Developing Document Classifiers for Recognizing Article Readers' Affects

Shiu-Li Huang
Department of Business Administration, National Taipei University
slhuang@mail.ntpu.edu.tw

Yi-Siou Chen
Department of Information Management, Ming Chuan University
es200283@msn.com

Abstract

Many researchers have devoted themselves to studying sentiment classification in order to classify unstructured texts with valuable information on the Web as having positive or negative sentiments. However, few of them addressed how to classify documents on the basis of readers' affects. This study developed affect classifiers based on basic emotions and moods as defined in psychology, instead of subjective emotion/mood categories, to decrease the complexity and confusion. The experimental results showed that this approach outperforms those of prior studies and that SVM (support vector machine) classifiers are more effective than naïve Bayes or SMO (sequential minimal optimization) classifiers.

Keywords: Document classification, sentiment classification, affect classification, basic affects, machine learning

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I. INTRODUCTION

To understand the needs and feelings of humans and increase humanness, affective computing has recently become important to human-computer interaction (HCI). Picard (1997) defined affective computing as "computing that relates to, arises from, or deliberately influences emotion or other affective phenomena." Affective computing enables computers to recognize affective states of humans and respond appropriately to these affective states. Since people demand more customized and intelligent interactions, affective computing is becoming more important in affect communication (Picard 2000). A number of HCI articles describe the efforts to design ''affective computers,'' or systems capable of recognizing and responding to users' feelings (Lopatovska et al. 2011). However, the state of knowledge about the role of emotions in HCI is still in its infancy.

The Internet is an essential part of our life. People search for information that they need and share their own opinions, experiences, or feelings on Internet forums, discussion groups, blogs, etc. It is a great resource for businesses and enables them to know the public or consumers' opinions and feelings about their products and services. For potential customers, the analysis of these reviews helps them make the right purchase decisions. The task of sentiment classification is to classify each document as either positive or negative (Liu 2007). However, most studies on sentiment classification focus on recognizing opinions rather than feelings expressed in documents. This study addresses how to classify each document into positive and negative on the basis of affect states. This effort is useful not only in analyzing customer reviews but also in delivering the best advertisement in the best context (Huang et al. 2012) and in predicting social and economic trends (Bollen et al. 2010).

The research objectives are as follows.

1. Develop document classifiers using the basic affects defined in psychology: To decrease the complexity of affect classification and provide standard affect categories, this study adopts the six basic emotions proposed by Shaver et al. (1987) and the twenty basic moods proposed by Watson & Clark (1988). To obtain a sufficient corpus, we map the emotion categories provided by the UDN News website (udn.com) to the basic emotion and mood categories and use the news articles as the training data.
2. Classify documents on the basis of readers' affects: The authors' or readers' affects are the focus when recognizing affects from documents. Most studies on emotion classification of documents focused on authors' emotions because a number of forums or blogs enable authors to indicate their emotions by inserting various emoticons into articles. In contrast, fewer studies explored the readers' emotions invoked by articles. Detecting readers' affects

induced by Web content is crucial to understand word-of-mouth effect on the Web and to devise advertising strategies.

II. LITERATURE REVIEW

2.1 Emotion Classification

Emotion classification is a kind of sentiment classification, and it focuses on feelings rather than opinions. Emotion classification aims to analyze the main emotions expressed by documents and classify documents into emotion categories. The emotion categories used by past studies for emotion classification are different. Generally, the researchers adopted the emotion categories predefined by the websites' emotion-tagging mechanisms. Machine learning and semantic approaches are the main approaches to recognize emotions from documents for emotion classification. This section briefly introduces them.

2.1.1. Machine learning approaches

Mishne (2005) presented preliminary experiments in classifying the moods of blog text. A corpus of blog posts was obtained from LiveJournal. Its users can select a mood from a predefined list of 132 moods while adding a blog entry. Support vector machines (SVM) were trained to classify blog text according to the mood reported by its author. The performance was not good (59.67% accuracy). The possible reasons were that the authors subjectively labeled their moods without following a guideline. Moreover, the average size of a blog entry was not enough to gather meaningful statistics and the predefined mood categories were highly subjective.

Leshed & Kaye (2006) used SVM to classify articles on the basis of bloggers' moods. They used LiveJournal as the data resource, which, as mentioned before, allows users to tag their posts with a mood tag from 132 predefined moods. The results demonstrated that it is viable to predict writers' emotional states from their articles.

Yang et al. (2007a) used emoticons from blog articles for building an emotional lexicon. They used SVM to classify blog sentences into emotion categories. They selected Yahoo! Kimo Blog articles as their data resource. Yahoo! Kimo Blog provides 40 emoticons that bloggers can insert into sentences when they edit articles. These emoticons were partitioned into four quadrants of the emotion space on the basis of their valence and arousal. The experimental result indicated that providing a larger collection of vocabularies and emotion senses makes for better performance than does a smaller collection of vocabularies and emotion senses.

Yang et al. (2007b) used SVM and conditional random field (CRF) approaches to study emotion classification of blog corpora. The emotion classifiers were trained at the sentence level and applied to the document level. They mainly used two emotion categories: positive and negative. Next, the positive emotion category was divided into two subcategories—happy and joy—and the negative category was similarly divided into two subcategories—sad and angry. The experimental result showed that bloggers expressed consistent emotions within a sequence of sentences, and most bloggers expressed positive emotions. When the previous sentences' emotions are known, CRF can achieve better performance than SVM.

Lin et al. (2007) focused on readers' emotions and tried to classify news articles into eight emotion categories provided by Yahoo! Chinese news. They used an SVM classifier and tried different combinations of features. The result showed that the combination of bigrams, words, metadata, and emotion categories of words achieves the best accuracy in readers' emotion classification.

Li et al. (2010) proposed a Chinese text emotion classification on the basis of readers' emotions. An emotion dictionary is created semi-automatically by using WordNet to build text vectors. The corpus included news articles from the website Sina that provided eight emotion categories. SVM and naïve Bayes classifiers were trained, and the results showed that the SVM classifier outperformed the naïve Bayes classifier.

The aforementioned studies did not map these emotion categories provided by the websites to basic emotion categories in psychology. Many emotion categories provided by websites were actually not emotions and confused taggers and analyzers. For instance, the tags—devil, nerd, pig, etc.—provided by Yahoo! Kimo Blog are difficult to treat as emotions.

2.1.2. Semantic approaches

A semantic approach is also known as a knowledge-based approach. It uses predefined affect dictionaries of opinion or emotion words to search the input words and analyze their effects (Khan et al. 2009).

Li & Ren (2008) classified blog articles according to seven emotion categories defined by Ekman et al. (1982), along with some important categories that are found in blogs with high use frequency. The emotion categories total 26 categories. They constructed a blog emotion-recognizing system. This system first analyzed lexical characteristics of the sentences and extracted words. Next, this system used an emotion dictionary to search for emotion categories of words and identified the emotion category of each sentence. Finally, this system computed the weight value of the emotion categories of all sentences. They used two different methods to find the main emotion from a blog article. Method 1 was to add all emotion weight values obtained in all sentences such that the emotion category with the biggest weight value was the main emotion of a blog article. Method 2 was to search for the central sentence according to its proportional distribution in the article to find the main emotion of a blog article. The experimental result showed that method 1 is more accurate than method 2 in emotion prediction, but method 1 requires much more time than method 2.

Quan & Ren (2010) constructed a blog emotion corpus for Chinese emotional expression analysis. The corpus contains manual annotation of eight emotional categories: emotion intensity, emotion holder/target, emotional word/phrase, degree word, negative word, conjunction, rhetoric, punctuation, and other linguistic expressions that indicate emotion. Therein, they found that verbs, nouns, adjectives, and adverbs are strong emotional parts of speech in Chinese. Furthermore, the emotion of text can be determined from its emotional keywords and phrases at a degree of about 69%.

2.2 Basic Affects

Affect is used as a generic label to refer to both moods and emotions (Forgas 1995). Emotion and mood are often used interchangeably, but are generally considered to be distinct. Beedie et al. (2005) reviewed academic papers and surveyed nonacademic respondents to investigate the differences between mood and emotion. Eight distinctions (cause, duration, consequences, intentionality, intensity, function, physiology, and awareness of cause) were cited by both academics and non-academics to distinguish between mood and emotion. Mood does not have a specific cause, but emotion has its specific cause. Mood can last for a long time, but emotion is transient in its duration. Mood is somehow the consequence of the emotion. Moreover, with regard to intentionality, mood usually does not intend to target anything, but emotion usually targets specific things. Emotion is high intensity, whereas mood is not. The differences between the functions of emotion and mood were not described by the respondents but were agreed to be distinct. However, it had been stated in the literature that emotion mediates customers' behavior, and mood mediates the cognition. The physiology differences are that emotions are manifested by physiological reactions, whereas moods, owing to low levels of arousal of the affective systems. Since the causes of a mood state are general, people are not likely to be aware of its cause. However, with a specific emotion, people are able to determine the cause.

2.2.1. Basic emotions

Psychologists claim that certain defined emotions are basic emotions for different reasons. The most common reason for proposing basic emotions is to provide an explanation of some routine observations about emotions (Ortony et al. 1990). For example, some basic emotions exist in all cultures, appear to be universally recognizable by characteristic facial expressions, and appear to serve identifiable biological functions related to survival needs. In affective computing researches, these definitions have been introduced as the baseline. However, some researchers have extended these definitions with additional emotions.

Shaver et al. (1987) used a prototype approach and hierarchical cluster analysis to explore the emotion hierarchy from ordinary people. They found that five or six clusters might reasonably be categorized as basic. The positive clusters are *love*, *joy*, and *surprise*; the negative clusters are *anger*, *sadness*, and *fear*. They thought the *surprise* cluster was questionable as a basic level category because the *surprise* cluster is clearly much smaller and less distinguished than the others.

Ortony and Turner (1990) explored basic emotions from different points of view. A common assumption in emotion theories is that there exists a small set of basic emotions. However, there is little agreement about how many emotions are basic and which emotions are basic. Several sets of basic emotions are proposed by emotion theorists according to different perspectives and opinions. Two facts can be found: one fact is that nearly every theorist posits that basic emotions include *anger*, *happiness*, *sadness*, and *fear*; the other fact is that the same emotion is often labeled differently by different researchers, for example, anger or rage, and happiness or joy.

This study adopts the basic emotions defined by Shaver et al. (1987), because the emotion hierarchy is a generic representation of emotions displayed by ordinary people, and the six basic emotions are expected to be suitable for communicating with ordinary people. Additionally, almost all emotion theorists agree that *joy* (*happiness*), *anger*, *sadness*, and *fear* are basic emotions. Although the emotion *surprise* does not perhaps qualify to be a basic emotion, this study retains it for reexamination.

2.2.2. Basic moods

Watson et al. (1988) developed two mood scales that comprise the Positive and Negative Affect Schedule (PANAS). They selected mood descriptors under the condition that the terms were relatively pure markers of either positive affect or negative affect; that is, terms that had a substantial loading on one factor but a near-zero loading on the other. Finally, they identified 10 terms for the positive mood scale and 10 terms for the negative mood scale. The terms for positive mood are *attentive*, *interested*, *alert*, *excited*, *enthusiastic*, *inspired*, *proud*, *determined*, *strong*, and *active*. The terms for negative mood are *distressed*, *upset*, *hostile*, *irritable*, *scared*, *afraid*, *ashamed*, *guilty*, *nervous*, and *jittery*. These PANAS terms can be randomly mentioned throughout the mood questionnaire, and subjects are asked to rate on a 5-point scale the extent to which they have experienced each mood state during a specified time frame. Watson and his colleagues conducted several experiments, and the results showed that the PANAS scales provide reliable, precise, and largely independent measures of positive and negative affects regardless of the subject population studied or the time frame used.

This study also considers readers' mood states that were induced by Web content; the PANAS scales in the Chinese version (Teng et al. 2006) are adopted for this investigation.

III. SYSTEM DESIGN

This study uses machine learning approaches to classify documents into either positive or negative affect categories on the basis of the basic affects in psychology. We mapped the emotion categories provided by UDN News into the six basic emotions and the twenty basic mood categories. The news articles tagged with basic emotions and moods were collected to train naïve Bayes, SVM, and sequential minimization optimization (SMO) classifiers.

First, a crawler retrieves news and blog articles from the Web. After news and blog articles are collected, the html parser parses these pages and extracts useful data such as article content and titles. This parser uses a Chinese word segmentation tool developed by the Chinese Knowledge and Information Processing (CKIP) group to segment words and tag each word with a part of speech. Thereby, the feature extraction mechanism can extract features easily. These collected articles with their segment words and part-of-speech tags are stored in the news and blog databases.

The feature extraction mechanism extracts adjectives, verbs, adverbs, and nouns that probably contain emotion information from articles (Quan et al. 2010). Next, the feature extraction mechanism uses X^2 statistic (CHI) and information gain (IG) feature selection methods to reduce the number of features and remove irrelevant and redundant features. Thus, an affect lexicon is generated. This study adopts and compares CHI and IG methods because they are the most effective feature selection methods for document classification (Tan et al. 2008; Yang et al. 1997).

The vector encoder transforms the news articles into vectors based on the affect lexicon. After that, the vectors of articles are stored in the training set and testing set databases. The training set is used to train the classifiers that are implemented using the Weka data mining software. Then, we compare the performances of these classifiers for affect classification. This study adopts and compares these classifiers because SVM and naïve Bayes are the most commonly used machine learning approaches for classification (Khan et al. 2009). In addition to the standard SVM training algorithm, this study also evaluates SMO, which is a faster algorithm for training support vector machines and less susceptible to numerical precision problems (Platt 1998).

IV. EXPERIMENTAL PROCEDURE

4.1 Data Collection

Read (2005) found that articles with informal language, for example, movie reviews and blogs, have a lot of noises such as mixed sentiment, sarcasm, and spelling mistakes. These noises will reduce the performance of sentiment analysis. In order to avoid this situation, we chose news articles as the training data. The source of news articles came from UDN News (udn.com). We collected news articles that contained more than ten emotion tags in the past week from each emotion category provided by UDN News. The system collected news articles once a week for five months—August to December 2010—as the training data; in total, 4882 articles were collected. Additionally, 1631 news articles during January and February of 2011 were collected as the testing data.

4.2 Affect Category Mapping

UDN News provides ten emotion tags: back you up (挺你), look forward to (期待), accurate (金準), funny (好笑), ignorant (白目), sad (悲傷), angry (生氣), nonsense (胡扯), lame (好冷), and trite (老套). Readers are allowed to label theses tags to news articles. These predefined emotions need to be mapped into the basic emotion and mood categories. We randomly chose 50 news articles from each emotion category, and therefore, 500 articles were selected. Four analysts who understood the definition of emotion and mood were invited to read the 500 news articles; each analyst was randomly assigned 250 news articles to read, and each news article was read by two analysts. After reading, they were asked to indicate their feelings on the basis of the basic emotions and moods by filling out the questionnaires for the basic emotions and moods, respectively. Each item in the questionnaires uses a 5-point Likert scale ranging from 1 to 5; a higher score indicates a stronger emotion or mood level. Thereby, the emotion categories predefined by the news website can be mapped into the six basic emotions and twenty basic mood categories.

We used a paired-samples *t* test to discover which emotion's positive value and negative value differ significantly. The positive (negative) value is the sum of all scores of individual positive (negative) affects according to the questionnaires. The results show that "look forward to," "lame," and "trite" are significantly positive, so these categories are mapped into positive emotions; on the other hand, "accurate," "sad," "angry," and "nonsense" are significantly negative, and therefore, these categories are mapped into negative emotions.

The results of mood mapping reveal that "back you up," "look forward to," and "funny" are significantly positive, so these categories are mapped into positive moods; "ignorant," "sad," "angry," and "nonsense" are significantly negative; hence, these categories are mapped into negative moods.

4.3 Classifier Training

We only considered the emotion categories provided by UDN News that can be mapped into positive or negative emotions or moods in psychology; therefore, 2161 articles out of the 4882 articles were used to train the emotion classifiers and 4522 articles out of the 4882 articles were used to train the mood classifiers. Additionally, we built another training set that contained the articles belonging to emotion- and mood-consistent categories, that is, "look forward to," "sad," "angry," and "nonsense," to train the classifiers for comparison.

Initially, 36,842 features from the articles in the emotion categories and 52,863 features from the articles in the mood categories were collected by using the CKIP word segmentation system. Then, we used CHI and IG feature selection methods to choose important features. Owing to the fact that the statistical significance of CHI can be tested by looking up a chi-square distribution table, we adopted the significance level of 0.05, and therefore, the chi-square value, 3.841, was used as a threshold. The features with a chi-square value higher than 3.841 were selected as important features. A comparison with the CHI method shows that the number of features selected by the IG approach was same as that selected by the CHI approach. In total, 1225 emotion features and 371 mood features were selected. We also used all the features to observe the performances of the classifiers. We found that some features were temporal owing to some events or activities happening, such as the presidential election. On the other hand, some features did not disappear with time. We call these timeless features that appeared in every month as stable features in this study. A total of 5277 stable emotion features and 8347 stable mood features were discovered. We used these stable features to train the classifiers as well and observed the performances.

4.4 Classifier Testing

The test news articles were used to test the classification ability of the classifiers. According to the results of affect category mapping, 753 articles out of the 1631 articles were mapped into the basic emotion categories and used to test the emotion classifiers; 1506 articles out of the 1631 articles were mapped into the basic mood categories and used to test the mood classifiers.

V. EXPERIMENTAL RESULT

The testing results are shown in Tables 1 and 2. Overall, SVM outperforms the other classifiers. However, the precision of SVM is worse than that of the other classifiers, particularly when using stable and all features. SVM tends to overfit the training data as the number of features increases. When the number of features is over a certain number, the performance of SVM begins to decrease (Yang et al. 2007b). The feature selection methods, CHI and IG, produce similar results; therefore, both of them are suitable for affect classifications. The performances of the naïve Bayes classifiers can be improved as the numbers of features increase.

Table 1. Testing results of emotion classifiers.

Training data	Classifier	Features	Accuracy	Precision	Recall	F-score
All training articles	Naïve Bayes	CHI	87.25%	0.834	0.873	0.851
		IG	87.64%	0.836	0.876	0.854
		Stable	84.86%	0.845	0.849	0.847
		All	90.57%	0.884	0.906	0.865
	SVM	CHI	90.43%	0.818	0.904	0.859
		IG	90.43%	0.818	0.904	0.859
		Stable	90.43%	0.818	0.904	0.859
		All	90.43%	0.818	0.904	0.859
	SMO	CHI	88.44%	0.84	0.884	0.858
		IG	88.44%	0.837	0.884	0.857
		Stable	84.32%	0.839	0.843	0.841
		All	88.71%	0.853	0.887	0.866
Emotion-mood consistent training articles	Naïve Bayes	CHI	91.89%	0.877	0.919	0.896
		IG	91.41%	0.876	0.914	0.894
		Stable	90.77%	0.879	0.908	0.892
		All	92.84%	0.871	0.928	0.899
	SVM	CHI	93.32%	0.871	0.933	0.901
		IG	93.32%	0.871	0.933	0.901
		Stable	93.32%	0.871	0.933	0.901
		All	93.32%	0.871	0.933	0.901
	SMO	CHI	92.36%	0.88	0.924	0.899
		IG	92.52%	0.881	0.925	0.9
		Stable	91.73%	0.89	0.917	0.902
		All	92.52%	0.881	0.925	0.9

Table 2. Testing results of mood classifiers.

Training data	Classifier	Features	Accuracy	Precision	Recall	F-score
All training articles	Naïve Bayes	CHI	55.11%	0.546	0.551	0.543
		IG	55.11%	0.546	0.551	0.543
		Stable	55.71%	0.554	0.557	0.555
		All	57.5%	0.571	0.575	0.568
	SVM	CHI	53.58%	0.498	0.536	0.41
		IG	53.58%	0.498	0.536	0.41
		Stable	54.05%	0.292	0.541	0.379
		All	54.05%	0.292	0.541	0.379
	SMO	CHI	55.31%	0.546	0.553	0.514
		IG	55.24%	0.545	0.552	0.513
		Stable	55.31%	0.552	0.553	0.552
		All	54.78%	0.546	0.548	0.547
Emotion-mood consistent training articles	Naïve Bayes	CHI	88.39%	0.88	0.884	0.882
		IG	88.39%	0.88	0.884	0.882
		Stable	92.05%	0.87	0.821	0.895
		All	93.16%	0.871	0.932	0.9
	SVM	CHI	93.32%	0.871	0.933	0.901
		IG	93.32%	0.871	0.933	0.901
		Stable	93.32%	0.871	0.933	0.901
		All	93.32%	0.871	0.933	0.901
	SMO	CHI	92.36%	0.886	0.924	0.901
		IG	92.36%	0.886	0.924	0.901
		Stable	90.36%	0.886	0.924	0.901
		All	92.52%	0.881	0.925	0.9

The overall performance of emotion classifiers is better than that of mood classifiers. The possible reason is that the number of emotion features is more than the number of mood features. Another possible reason is that mood does not have a specific cause and usually does not intend to target anything; therefore, moods are less attention grabbing than emotions and hard to correctly specify. If we only consider the emotion- and mood-consistent articles, the performances are significantly improved.

VI. CONCLUSION

Prior studies on emotion classification classified documents on the basis of the emotion tags provided by websites. However, many emotion tags were actually not emotions or moods defined in psychology. This study first associated documents with basic emotions and moods in psychology and then trained naïve Bayes, SVM, and SMO classifiers to classify documents into positive and negative emotions and moods. The SVM classifiers are more effective than the naïve Bayes and SMO classifiers. Table 3 compares this study with prior studies on affect classification at the document level and shows that affect classification based on basic emotions and moods in psychology is capable of improving performances.

Table 3. Comparison of studies on affect classifications.

Study	Author or Reader's affect	Training Data / Language	Classifier	Accuracy	Precision	Recall	F-score
Mishne (2005)	Author	Blog / English	SVM	60%	-	-	-
Leshed & Kaye (2006)	Author	Blog / English	SVM	74%	72%	80%	-
Yang et al. (2007b)	Author	Blog / Traditional Chinese	SVM	-	59%	59%	59%
Lin et al. (2007)	Reader	News / Traditional Chinese	SVM	87%	-	-	-
Li et al. (2010)	Reader	News / Simplified Chinese	SVM	-	84%	84%	84%
This Study	Reader	News / Traditional Chinese	SVM	93%	87%	93%	90%

- The study did not reveal the statistical data.

Some applications can be designed in future research. Online ad delivery systems can employ affect classifiers to deliver appropriate advertisements according to webpage readers' emotions or moods. Business intelligence systems acquire competitive intelligence by analyzing online reviews to understand what affects may be elicited about their and their competitors' products, services, and activities. It also can be applied to improve human-computer interaction. For instance, instant messengers or online chat rooms can detect the emotions expressed in sentences sent by users to change the user's feeling icons or pictures instantly.

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開發能識別文章讀者情感的文件分類器

黃旭立
國立臺北大學企業管理學系
slhuang@mail.ntpu.edu.tw

陳怡秀
銘傳大學資訊管理學系
es200283@msn.com

摘要

許多研究人員都致力於研究觀感分類，將網路上包含有用資訊的未結構化文章分類到正向或負向觀感裡。然而，如何依據讀者的情感將文件做分類，依然缺乏相關的研究。本研究基於心理學所定義的基本情緒與心情開發情感分類器，以識別文章所能觸發的讀者情感。採用基本情感可以減少情感分類時的複雜度並且提供標準的情感類別。實驗結果顯示本研究的分類器分類效果比過去研究所開發的分類器的效果還要好；支持向量機分類器的分類效果優於單純貝氏與序列最小優化分類器。

關鍵詞：文件分類、觀感分類、情感分類、基本情感、機器學習