Understanding How Bloggers Feel: Recognizing Affect in Blog Posts

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Abstract
One of the goals of affective computing is to recognize human emotions. We present a system that learns to recognize emotions based on textual resources and test it on a large number of blog entries tagged with moods by their authors. We show how a machine-learning approach can be used to gain insight into the way writers convey and interpret their own emotions, and provide nuanced mood associations for a large wordlist.

Keywords
Affective computing, blogs, emotions

ACM Classification Keywords
H.3.1 [Information Storage And Retrieval]: Content Analysis and Indexing

Introduction
Automated recognition of human emotion has long been a goal of affective computing, not only providing us a richer understanding of cognitive processes, but also assisting us in creating computers that better react to human input. Existing research on affect recognition has mainly looked at sources of facial expressions [3], vocal intonation [2], and physiological signals that vary with affective states [8]. Surprisingly, although language is an important way to convey emotions, little

work has been conducted on detecting emotions based on the contents of verbal expressions. In this study, we demonstrate an automated process which can help better understand how writers feel.

Blogs as a Resource for Affective Texts

A blog is a web application that contains periodic entries on a common webpage. The vast majority of blogs can be viewed as personal diaries, where bloggers write about their experiences, opinions, and emotions. As a result, blogs provide naturally occurring windows into people's thoughts and feelings [1].

LiveJournal has over 9M users, of whom about 2M are active in some way (www.livejournal.com/stats/). One of the features of LiveJournal allows users to tag their posts with a *mood* tag and a *music* tag, as shown in Figure 1. The large number of mood-tagged entries presented us with the opportunity to attempt to build a system that can recognize human moods.

LiveJournal bloggers can choose from 132 predefined moods, including happy and sad, but also `bitchy`, `blah`, and `indescribable`. They can also type in any

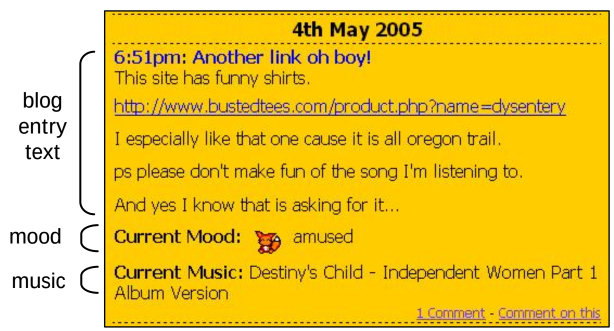

Figure 1. A LiveJournal blog entry with attached mood.

other mood, or leave this field blank. These moods are clearly not, for instance, the six 'basic' emotion categories enumerated by Ekman [3]. We deliberately decided to base our choice of mood categories on their actual use by bloggers: we want to understand how bloggers interpret their own moods, rather than presuppose any notion of whether a given term is or is not an emotion.

Affective Text Analysis Approaches

Given a large corpus, there are two primary approaches of automatic emotion recognition: linguistic analysis and machine learning text categorization.

Linguistic Analysis

This approach attempts to understand peoples' psychological states based on linguistic characteristics of their spoken or written expressions. Research shows it is possible to identify linguistic cues for writers' emotional states [1]. However, these approaches rely on the researcher's interpretations regarding linguistic representation, which may not correspond to the authors' conscious or unconscious intentions. Also, constructing the feature set can be costly in terms of human labor [9].

Automated Text Categorization

A second approach that can be applied is automated text categorization. For each document (blog entry), we attempt to identify, out of a set of possible emotions, the one that most closely characterizes the document text. For this task, various machine-learning techniques can be applied [9]. An inductive process, also called the *learner*, observes a formerly classified set of documents, the training set, and assembles the typical characteristics of classified documents. This assembly is the basis for the *classifier*, which in turn is fed by new documents, the test set, and does the actual categorization. Among a large variety of machine-learning techniques for text categorization, we chose Support Vector Machines [4] for our study. Studies have shown that SVMs perform best among several machine learning methodologies using large training sets [4,7].

An alternative approach involves knowledge engineering strategies. Liu et al, for instance, used a commonsense knowledge base to tag sentences with basic emotions [5]. While they generated an application felt to be intelligent and interactive by users, their method relies upon a labor-intensive hand-crafted repository.

Method

We randomly selected 100,000 LiveJournal blogs and downloaded their RSS feeds. About 10% of feeds contained no posts at all, about 10% contained only one post, and about 42% contained 25 posts (the maximum LiveJournal provides in an RSS feed), resulting in 1.4M blog posts. In about 58% of these, bloggers chose to attach moods to the entries, giving us a total dataset of 812,000 mood-tagged blog entries of average length 168 words. (This dataset is available on request.)

We found that the ten most frequently used moods are: `tired`, `amused`, `happy`, `bored`, `blah`, `cheerful`, `content`, `sleepy`, `excited`, and `calm`. As bloggers may type-in moods on top of the predefined ones, our sample included approximately 100,000 unique moods. To ensure sufficient data to apply the SVM, we only analyzed blog entries tagged with one of the fifty most frequent moods.

As an input for the algorithm, each blog entry was indexed into a feature vector using a standard tf/idf scheme. This information retrieval technique treats a document as a “bag of words”, assuming that the presence of words is significant, but their order is not, in contrast to, for example, [5,6]. As is standard practice in information retrieval, only the 5,000 most frequent words were indexed, excluding a standard list of stopwords, like ‘and’ or ‘is’. Too rare or frequent words do not assist in discriminating between categories, and thus ignoring them reduces computational needs.

We applied SVM^{light} learner (svmlight.joachims.org) on the 812,000 blog entry feature vectors of the training set. The results were used by the SVM^{light} classifier to classify the feature vectors of the test set that included a separate sample of 10,000 mood-tagged blog entries. We then compared the SVM’s decision with the actual mood of each entry in the test set to evaluate the performance of the algorithm.

Results

Word and Mood Associations

Our first result, provided by the SVM learner, is lists of words that characterize the moods. In Table 1, we show the ten words rated by the SVM learner as most characteristic for five moods. So, a blog entry tagged with the mood `loved` typically includes the words *valentine*, *sweetest*, and *roses*. As we might expect, some of these words are directly associated with the mood: *crying*, *sadness* and *upset* are all close in meaning to `sad`. However, the words *funeral* and *memories* are only indirectly associated with `sad`. These collections of words provide insight into what words typify moods *from the point of view of the author*, rather than terms predetermined by the researcher [1]. This list (available on request) has already been of interest to other researchers looking for a rapid method to extract affective information from blog and diary entries.

	sad	loved	hungry	happy	curious
1	sad	valentine	hungry	happy	curious
2	died	sweetest	starving	gorgeous	poll
3	crying	loved	craving	laughing	mystery
4	sadness	roses	food	coz	question
5	cry	kissed	eat	happiness	opinions
6	upset	arms	sauce	great	wondering
7	funeral	necklace	beef	awesome	memory
8	passed	eachother	muffin	beds	reminds
9	memories	layed	meal	seats	theory
10	cried	hugged	toast	greatest	wondered

Table 1. Five examples of moods and the words most associated with them

Word	Most likely Mood	Least likely Mood
computer	annoyed	contemplative
windows	annoyed	depressed
mac	happy	sad
britney	bored	happy
simpsons	happy	pissed off
mtv	bouncy	tired

Table 2. Examples of words associated with moods.

We can also reverse these associations: given a word, in which mood is it most likely to appear? For example, as shown in Table 2, the word *computer* is most likely to be included in an annoyed blog entry and least likely to be included in a `contemplative` blog entry. This could benefit, for example, corporations, entertainers, or politicians seeking to find a measure of the public's attitudes toward their names.

Mood Recognition Success

The binary SVM classifier looked at each mood category separately, and decided if a blog entry belongs to that mood or not. A positive decision meant the system predicted that the entry was tagged with the mood, and a negative decision meant the system predicted it was some other mood. Given this scheme, each decision resulted in one of four possible outcomes (see Figure 2): hit, false alarm, correct rejection, and miss.

		Blogger selected mood: Yes	Blogger selected mood: No
System decision	Positive	Hit	False Alarm
	Negative	Miss	Correct Rejection

$$Accuracy = \frac{\text{Hit} + \text{CR}}{\text{Hit} + \text{FA} + \text{Miss} + \text{CR}}$$

$$Precision = \frac{\text{Hit}}{\text{Hit} + \text{FA}} \qquad Recall = \frac{\text{Hit}}{\text{Hit} + \text{Miss}}$$

Figure 2. Binary decision outcomes and performance calculation.

Our system's *accuracy*, in terms of correctly guessing an entry to be or not to be an example of a mood, was 78%. If it made a positive prediction, it was correct 67% of the time, known as *precision*. However, given a positive example the system would only accurately predict it as positive 17% of the time: a low *recall* rate.

Topic-based text categorization systems often yield performance measures of around 80% [9]. Yet, the nature of blogs and the emotions we are trying to predict introduces noise into the task. For instance, having the bloggers themselves select the mood for their blog entry makes the selection subject to their understanding of the meaning of a mood. In contrast, given the distribution of positive and negative examples we chose for the SVM's input, a random guess would have yielded an accuracy level of 25%, as each positive example was accompanied by three randomly chosen negative examples from the remainder of the dataset.

Our results suggest that using a large corpus is powerful in achieving superior results, even with the simple bag-of-words approach: [6] applied a complex set of linguistic features on a smaller dataset from the same corpus and produced lower performance rates. Moreover, beyond the mere text categorization exercise he demonstrated, our work takes a broader perspective of exploring people's emotions through their writings.

To verify whether the large amount of moods accounted for the performance values, we manually sorted the moods into positive and negative classes. In discriminating between the two classes, our system had a 74% accuracy rate, a 72% precision rate, and an 80% recall rate, comparable to other sentiment classification studies [7]. This suggests that a simple method is promising for affective computing applications in which it is sufficient to know the user's mood valence.

anxious, artistic, bouncy, busy, cheerful, cold, content, crazy, ecstatic, excited, exhausted, happy, hyper, loved, accomplished	amused, awake, bored, calm, chipper, creative, sleepy, tired
confused, angry, crushed, curious, depressed, drained, frustrated, hopeful, hungry, sad, contemplative	annoyed, bitchy, blah, blank, cranky, crappy, lonely, pissed off, sick, aggravated
energetic	indescribable
good	okay
	mellow
	stressed

Figure 3. Clusters of moods, created by hierarchical cluster analysis based on similarity of word weights.

Mood Synonymy

The relevant words found by the SVM, discussed earlier, suggested that some moods may be fall within the same mood category. For example, the moods `angry` and `aggravated` both highly weigh the words *anger*, *bastard*, and *assholes* in their weighted word lists.

To estimate possible mood synonymy, we computed the similarity between the weight vectors created by the SVM learner, according to the formula:

$$\text{cosine}(\text{sim}(u,v)) = \sum_{i=1}^{n}(w_{iu} \times w_{iv}) \Big/ \sqrt{\sum_{i=1}^{n}(w_{iu}^2 \times w_{iv}^2)}$$, where

u and v represent two moods, and w_{ij} represents the weight of word i in the weight vector of mood j. Positive and negative values of this measure indicate similarity and dissimilarity between the two moods, respectively. The resulting similarity measures between all dyad moods were then clustered into ten groups using hierarchical clustering analysis, shown in Figure 3. Each cluster represents a group of moods that are synonymous on the hierarchy cut level. Clusters that are composed of a single mood imply that these moods are distinctly different from any other mood.

Some of the clusters are clearly clusters of positive or negative moods. However, while it is easy to understand how `sleepy` and `tired` appear together, it is surprising to find them with awake, `creative`, and `amused`. As predicted, the division into clusters does not necessarily match our intuitions about basic emotion categories, but it is rooted in bloggers' expressions of themselves. The clustering technique is not subject to anyone's preconceived judgment, but it simply groups moods that share similar patterns of word use. We are continuing to examine these results.

Conclusions

The results show that, to some degree, we can predict emotional states of bloggers from their writings. Affect recognition to date has often relied on classifying physiological measures such as facial expressions into a predetermined set of emotions. In contrast, our use of textual expressions and self-reported moods generated in the course of everyday life emphasizes the lived experience of mood by the writer. This can be a limitation: when bloggers select a mood, their purpose is not to correctly identify their emotional state and correlate it with the entry they have written. However, our testing strategy compares the automated prediction *to the users' perceptions of their own mood*.

A key element is the harvesting and use of a very large pre-existing corpus generated by many users. Even recognizing group blogs and multiple blogs written by single individuals, our N is still on the order of tens of thousands of users. By gathering examples from natural settings, we have a claim for ecological validity absent from many laboratory studies of emotion [2].

Our method has limitations: the bag-of-words approach ignores negation constructions ("not sad"), and we conflate all bloggers into a single dataset. Our results may not apply outside of the domain of blogs, although we expect it applies to other personally generated texts. We include moods that do not represent traditional emotions (e.g hungry). Our performance levels on the 50-mood set are low compared to other text classification tasks, probably because the mood set is very large relative to other studies [3,7], although it is ecologically valid. Our work on mood synonymy is a first step in applying this conclusion, and our current work involves identifying entries as one of these meta-categories.

Despite these limitations, we suggest that the resulting dataset of mood/word associations has significant utility for those aiming to automatically extract and analyze affective information from blogs and diaries, and potentially other informal writing such as email and IM.

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