Distinguishing affective states in weblog posts

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Abstract
This short paper reports on initial experiments on the use of binary classifiers to distinguish affective states in weblog posts. Using a corpus of English weblog posts, annotated for mood by their authors, we trained support vector machine binary classifiers, and show that a typology of affective states proposed by Scherer’s et al is a good starting point for more refined analysis.

Introduction
We are investigating the subjective use of language in text and the automatic classification of texts according to their subjective characteristics, or ‘affect’. Our approach is to view affective states (such as ‘happy’, ‘angry’) as regions of Osgood’s Evaluation-Activation (EA) space (Osgood, Suci, & Tannenbaum 1957), and draws on recent work in psychology to construct a typology of such affective states (Scherer, Dan, & Flykt 2006). Our overall aim is to determine the extent to which such a typology can be validated and applied to the task of text classification using automatic methods. In this paper we describe some initial experiments aimed at validating a basic two dimensional classification of weblog posts, using Support Vector Machine (SVM) binary classifiers. The domain of weblogs is particularly well-suited for this task given its highly subjective nature and the availability of data, including data which have been author-annotated for ‘mood’.

Experimental method
We have collected from Livejournal a total of 346723 (mood-annotated by authors) weblog posts in English, from which almost half can be clearly identified as belonging to one of the four quadrant. In the following experiments we used a subset of this corpus (15662, 54940, 49779 and 35634 documents in quadrants Q1 to Q4 respectively, numbered clockwise from the top-right quadrant in Figure 1).

Our aim was to investigate to what extent the typology can serve as a basis for locating particular affects in the space. Our first hypothesis is that the classification of two disjoint (sets of) moods should yield a classification accuracy significantly above a baseline of 50%. Our second hypothesis is that the more geometrically distant two given moods are according to the typology, the more accurate a classifier is for these two moods, since each mood does not share many features with the other. In other words, the classification accuracy and the geometric distance between moods exhibits a positive correlation. We conducted a series of experiments using machine learning to classify weblog posts according to their mood, each class corresponding to one particular quadrant or an individual mood: annoyed, frustrated (in Q1); anxious, sad (in Q2); calm, hopeful (in Q3); excited, amused (in Q4). Using Support Vector Machines (Joachims 2001) with a few basic features (unigrams, POS and stems) and random samples of our corpus (1000 testing examples, 2000 and 4000 training examples for individual moods, plus 8000 and 16000 for each quadrant), we tested the binary classification. The set of features used varies for each of these tasks, they were selected by inspection of each (distinct) training data set. Two simple criteria were used for selecting features: no stop words and a number of occurrences of at least...
Results

Our first hypothesis is that, if the four quadrants proposed by Scherer are a suitable arrangement for affective states in the EA space, a classifier should perform significantly better than chance (50%). Table 1 shows the results for the binary classification of the quadrants. By micro-averaging accuracy, we obtain at least 60% accuracy for the four binary classifications of the quadrants. Our second hypothesis predicts a correlation between accuracy and distance in the EA space. Table 2 summarizes the results for all classification tasks carried out: the accuracy column represents the average over all sets of training examples, in ascending order, while the distance is a geometric measure of the distance between two moods (or the center of gravity for each quadrant, assuming a uniform distribution of moods in the random sample). The correlation column is the cumulated Pearson correlation coefficient. For instance, from 57.93% accuracy up to 65.35% accuracy, accuracy and distance displays a correlation coefficient of 0.423.

Analysis of results

Figure 1: how likely is it to classify 1000 weblogs and obtain at least 60% accuracy only by chance? A simple calculation using a binomial distribution (with $X=600$ successes, $n=1000$ trials and $p=0.5$) yields to a probability of $0.0000000001^3$. Therefore, it is safe to conclude that the typology is very helpful in improving the performance of a

\[^3P(X>600,n=1000,p=0.5) = 1-P(X\leq600) = 1-0.99999999999 = 0.0000000001\]
classifier into four distincts groups of affective states. These results show that the abstraction offered by the four quadrants in the model seems correct. This is also supported by the observation that the classifier shows no improvements over the baseline if trained over a random selection of examples in the entire space.

Figure 2: interpreting the results with regards to our second hypothesis is more difficult. For most of the way while moving upward along the accuracy dimension, the geometric distance between the two classes correlates positively. However, the general trend turns out to be a slightly negative correlation. We believe there are mainly two factors that can contribute to the distortion of the nature of the correlation between accuracy and distance:

- **Non-uniform distribution of moods**: We have assumed that the random selection of moods within a quadrant was uniform, i.e. covering the whole of the space uniformly. This is perhaps too optimistic, because moods that appear more often in the corpus are likely to be over-represented and therefore move the center of gravity of the quadrant away from the center.

- **Ambiguity of a mood location in the space**: There are two moods represented in the experiments which appear at more than one location in the typology: excited and sad. We have attempted to minimize the impact of such ambiguity in the results by taking a location in the middle, but this may have undesirable side-effects.

The obvious solution to the first problem is to make sure that we populate the training data with moods uniformly distributed in the space. If further research reveals that there are further subcategory within a single mood, then a solution to the second issue would be to create a distinctive tag for each subcategory.

## Future work

The next series of experiments should provide a more refined validation of the typology and some insights into the use of semantic orientation scores for the purpose of multi-mood classification of texts.

Whilst we have validated the proposed partitioning of the EA space for four regions as a whole, we now need to validate, for each quadrant, a more precise location for a number of individual, uncontroversial moods. This can be achieved by narrowing down the set of moods to those for which work in psychology exhibits a certain level of certainty with regards to their location, while at the same time are in agreement with our second hypothesis.

The long term aim of this work is to classify texts according to their mood, making it possible to classify a text according to more than two (positive vs negative or active vs passive) classes (angry, sad, happy, etc.). To achieve that, we will use directly the location of the affective states in the space in combination with automatic continuous “scores” (in the sense that they provide only a qualitative evaluation) of the E and A axis. Scores such as PMI-IR (Turney & Littman 2003) provide a real value for each axis. They can be converted to “measures” (in the sense that they offer a basis for comparison) between -1 and +1 by substituting the real PMI-IR scores for every semantically oriented phrase in a text with +1 or -1, and averaging over all phrases. By mapping the E and A measures to normalized values in the EA space, specific coordinates can be obtained and associated with surrounding affective states.

## References


