Narrowing the Social Gap among People Involved in Global Dialog: Automatic Emotion Detection in Blog Posts

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Abstract
In this paper, we introduce a new approach to automatic emotion detection in blog posts. The purpose of our research is to develop an effective tool for recognition and interpretation of affect conveyed through written language. The main idea behind the proposed rule-based algorithm is to determine the prevailing emotion in each sentence of diary-like entry and to display the dynamics of emotion changes throughout the whole document by using simplified emotional faces.

Keywords
Affect sensing from text, affective user interface, blogs, emotions, sentiment analysis, social media.

1. Introduction
The emergence of social media such as Blogosphere has promoted the rapid evolution of global conversation. Integration of interactive online diaries, journals and personal blogs into our daily lives contribute to fulfilment of important aspects of social interaction needs. People use blogs to share feelings, thoughts, opinions, insights, experiences and perspectives with each other. Blogging, as a distinct social phenomenon, is attracting research communities from various fields.

The most challenging tasks for natural language researchers are recognition, classification and understanding of opinionated or emotional text [3], [5], [8]. Statistical language modelling techniques have been applied by researchers to learn the characteristics of 'happy' and 'sad' moods indicated in the blog entries [6], and to classify online diary posts by mood [4]. However, machine learning approaches to affect classification in blogs suffer from limitations such as: (1) subjective nature of the author's mood "annotations" due to widely-varying authors with different conceptualizations of moods; (2) small average size of an entry to gather meaningful statistics; (3) neglect of negation constructions and syntactical relations in sentences by the "bag-of-words" approach.

In this paper, we address the task of automatic emotion detection from text in blog posts. Emotion identification in such an environment can be useful for various socially oriented applications, such as affective assistance, filtering search results by emotion or its dynamics, assessment of emotional responses to consumer products etc. The proposed rule-based system employs natural language processing techniques for word/phrase/sentence-level analyses, and processes affective features of words and symbolic conventions (e.g. emoticons, abbreviations, acronyms) in order to determine the dominant emotion in a sentence. Our system is designed to handle not only correctly written language, but also messages typed in an evolving informal style [7]. For our research, we employed the Weblog Data Collection provided by BuzzMetrics [10].

2. Basis for text categorization
A fundamental task for any automatic emotion detection system is to first choose the basis for text categorization. We have decided to use (the relevant) nine emotional states taken from a set of ten emotions defined by Izard [2]: 'anger', 'disgust', 'fear', 'guilt', 'interest', 'joy', 'sadness' ('distress'), 'shame', and 'surprise'.

In order to handle abbreviated language and to interpret affective features of emoticons, abbreviations, and words, we created a special database. While accumulating database entries, we collected 364 emoticons, both of American and Japanese style, and the 337 most popular acronyms and abbreviations, both emotional and non-emotional. From the source of affective lexicon, WordNet-Affect [9], we have taken 1620 words: adjectives, nouns, verbs, and adverbs. Moreover, we included interjections and modifiers into our database.

Emotion category labels and numerical values of intensity were manually assigned to affect-related entries of database. Three independent annotators conformed to our guideline with the description of emotional state gradation within intensity levels. The range of intensity values that encode the degree of affective states from 'very weak' to 'very strong' is from 0.0 to 1.0. For example, 'annoyed', 'irritated', 'indignant', and 'enraged' all correspond to the 'angry' emotional state, but to a different level of intensity. Some affective words were annotated with more than one category. For instance, 'anger' and 'sadness' emotions are involved in the annotation of word "frustrated" with intensities 0.2 and 0.7, respectively. As for the modifiers, coefficients for intensity degree strengthening or weakening were given.

3. Emotion detection algorithm
Let us now consider the analysis process of emotional information conveyed by text. Initially, each blog entry is divided into separate sentences. Then, each single sentence of the blog is processed by the five levels of our analysis algorithm.

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At the first level, *symbolic cue analysis* is performed. The sentence is tested for occurrences of emoticons, abbreviations, acronyms, interjections, "?" and "!" marks, repeated punctuation and capital letters. Typically, people type emoticons and emotion-relevant abbreviations to accentuate an actual feeling, or to avoid misleading the readers, for instance, after irony or a joke. We defined the rules for cases when single or multiple such symbolic cues occur in the sentence.

The second level is devoted to *syntactical structure analysis*. Before parsing, non-emotional abbreviations and acronyms are replaced by their proper transcriptions found in the database. The used deep syntactical parser, Connexor Machinese Syntax [1], returns exhaustive information for analysed sentences. From the parser output in XML style, we can read off the characteristics of each token and the relations between them in a sentence (e.g. subject, verb, object, and their attributes).

After handling the result from the previous analysis level, the system transfers the data to *word-level analysis*. Here, the database is examined for presence of analysed words. The affective features of an emotional word found in the database are represented as a vector of emotional state intensities e = [anger, disgust, sadness, fear, guilt, interest, joy, shame, surprise] (e.g. e = [0.2, 0, 0.7, 0, 0, 0, 0, 0, 0] for word "frustrated"). In the case of a modifier, the system identifies its coefficient. Since the database contains words only in their dictionary form, the intensity of the emotional vector of an adjective in comparative or superlative form is multiplied by the values 1.2 or 1.4, respectively.

The purpose of the fourth level, *phrase-level analysis*, is to detect emotion involved in phrases. We have defined general types of phrases, and rules for processing them with regard to affective content: (1) adjective phrase: modify the vector of adjective; (2) noun phrase: output vector with the maximum intensity within each corresponding emotional state in analysing vectors; (3) verb plus noun phrase: if verb and noun phrase have opposite valences, we consider the vector of the verb as dominant; if valences are the same, output vector with maximum intensities in corresponding emotional states for positive, and output null vector for negative; (4) verb plus adjective phrase: output vector of adjective phrase.

The rules for modifiers are as follows:

- intensifiers multiply or decrease emotional intensity values;
- negation modifiers such as "no" or "not", and connector "neither…nor" cancel (set to zero) vectors of the related words, i.e. "neutralize the emotional content";
- prepositions such as "without", "except", "against", "despite" cancel vectors of related words.

Conditional clause phrases beginning with "if", "when", "whenever", "after", "before", and statements with words like "think", "believe", "sure", "know" and those with modal operators like "can", "may", "need" are disregarded by the system.

Sentence-level analysis is performed in the final stage. At this level, the overall affect of a sentence and its resulting intensity degree are estimated. The emotional vector of a simple sentence (or of a clause) is generated from emotional categories and their intensities resulting from phrase-level analysis. It is important to note that the developed system enables the differentiation of the strength of the resulting emotion depending on the tense of a sentence and availability of first person pronouns.

For compound sentences, we defined two rules: (1) with coordinate connectors "and" and "so": output the vector with the maximum intensity within each corresponding emotional state in the resulting vectors of both clauses; (2) with coordinate connector "but": the resulting vector of a clause following after the connector is dominant.

After all sentences of a blog post are analyzed and the dominant emotion of each sentence is determined, the dynamics of detected emotions can be visualized by means of simplified emotional faces that were designed to show emotions with varying degrees of intensities.

4. Conclusion

In this paper, we suggested a syntactical approach to automatic emotion recognition in blog posts. Our system employs a deep syntactical parser for sentence structure analysis and performs sentence processing at different levels, including symbolic cue analysis and word/phrase/sentence-level analyses. Each analyzed sentence is classified into one of nine emotions, or it is set as neutral. The proposed algorithm is capable of handling correct text documents as well as blog posts written in informal abbreviated style, contributing thus to better accuracy and larger coverage of online documents.

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