Textual Affect Sensing for Sociable and Expressive Online Communication

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Abstract. In this paper, we address the tasks of recognition and interpretation of affect communicated through text messaging. The evolving nature of language in online conversations is a main issue in affect sensing from this media type, since sentence parsing might fail while syntactical structure analysis. The developed Affect Analysis Model was designed to handle not only correctly written text, but also informal messages written in abbreviated or expressive manner. The proposed rule-based approach processes each sentence in sequential stages, including symbolic cue processing, detection and transformation of abbreviations, sentence parsing, and word/phrase/sentence-level analyses. In a study based on 160 sentences, the system result agrees with at least two out of three human annotators in 70% of the cases. In order to reflect the detected affective information and social behaviour, an avatar was created.

Keywords: Affective sensing from text, affective user interface, avatar, emotions, online communication, language parsing and understanding, text analysis.

1 Introduction

Emotions and feelings accompany us throughout the span of our lives and colour the way we build and maintain the basis for interactions with people in a society. This phenomenon also takes place in the virtual communities, where "*you can't kiss anybody and nobody can punch you in the nose, but a lot can happen within those boundaries. To the millions who have been drawn into it, the richness and vitality of computer-linked cultures is attractive, even addictive.*" [24]. The online world of computer-mediated communication is such an environment where people can remain in touch virtually with their relatives and friends to exchange experiences, share opinions and feelings, and satisfy their social need of interpersonal communication. Since affect is an important component of effective social interaction, consideration of human emotions while constructing human-human online environments and human-computer systems [7] might enrich their interactivity and expressiveness. Affect-driven software may even benefit a person's well-being, as demonstrated in the research on simulating user-adapted persuasion dialogs about healthy eating [8].

In the past decade, issues of recognition, interpretation and representation of affect have been extensively investigated by researchers in the field of affective computing.

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A wide range of modalities have been considered, including affect in speech, facial display, posture, and physiological activity [21]. Recently, textual information is gaining increased attention by researchers interested in studying different kinds of affective phenomena, including sentiment analysis, subjectivity and emotions.

The focus of our work is on textual affect sensing and visualization in virtual communication environments, specifically, in Instant Messaging (IM), where people tend to use an informal style of writing. The evolving language observed in online communication poses a challenge for text processing tasks. We have thus taken into account the peculiarity of this communication medium (details are given in [18]) when designing our rule-based Affect Analysis Model. In order to make the user's experience in online communication enjoyable, exciting and fun, we have developed a system for the recognition and interpretation of affect conveyed through text, and complementary, the visual reflection of affective states and communicative behaviour through the use of a 2D cartoon-like avatar.

The remainder of the paper is structured as follows. Section 2 discusses related work. Section 3 describes the basis for text classification. The developed Affect Analysis Model and preliminary experimental results are discussed in Section 4 and Section 5, respectively. In Section 6, we briefly discuss and conclude the paper.

2 Related Work

In order to analyse affect communicated through written language, researchers in the area of natural language processing proposed a variety of approaches, methodologies and techniques.

WordNet-Affect, a linguistic resource for the lexical representation of affective knowledge, was created by Strapparava and Valitutti [26] with the aim to support applications relying on language recognition and generation. [25] described automatic textual emotion recognition and its visualization by kinetic typography (text animation). In order to analyse affective content, the authors were using not only affective words from WordNet-Affect, but also an affective lexicon derived from the evaluation of the semantic similarity between generic terms and affective concepts.

Kamps and Marx [10] investigated measures for affective or emotive aspects of meaning obtained from the structure of the WordNet lexical database. To classify sentiment and affect represented in text, methods employing Pointwise-Mutual Information calculation were introduced [23,28]. An approach to analysing affect content in free text using fuzzy logic techniques was proposed by Subasic and Huettner [27]. [2] presented a method for extracting sentiment-bearing adjectives from Word-Net using the Sentiment Tag Extraction Program. Kim and Hovy [11] developed an automatic algorithm for classifying opinion-bearing and non-opinion-bearing words, and described a method for the detection of sentence-level opinion.

Statistical language modelling techniques have been applied by researchers to analyse moods conveyed through online diary posts [12,14,15]. However, the main limitation of those "bag-of-words" approaches to textual affect classification is that they neglect the negation constructions and syntactical relations in sentences. Pang et al. [20] reported promising results on the classification of film reviews into "positive" and "negative" by using support vector machines. In contrast to classifying documents by their overall sentiment, Wilson et al. [30] presented experiments in which they automatically distinguish prior and contextual polarity of individual words and phrases in sentiment expressions.

Some researchers employed a keyword spotting technique to recognize emotion from text [19] or expressed in a multi-modal way (for example, speech signals along with textual content [31]). However, the use of a simple word-level analysis model cannot handle cases where affect is expressed by phrases requiring complex phrase/sentence-level analyses, since words are interrelated and influence each other's affect-related interpretation (like in the sentence "*I use the ability to breathe without guilt or worry*"), or when a sentence carries affect through underlying meaning (for example, "*I punched my car radio, and my knuckle is now bleeding*").

Advanced approaches targeting at textual affect recognition performed at the sentence-level are described in [5,13,16]. The lexical, grammatical approach introduced by Mulder et al. [16] focused on the propagation of affect towards an object. Boucouvalas [5] developed the Text-to-Emotion Engine based on word tagging and analysis of sentences. However, the proposed system employs the parser that generates emotional output only if an emotional word refers to the person himself/herself and the sentence is in present continuous or present perfect continuous tense. We think that such limitations greatly narrow the potential of textual emotion recognition. An approach for understanding the underlying semantics of language using large-scale real-world commonsense knowledge was proposed by Liu et al. [13], who incorporated the created affect sensing engine into an affectively responsive email composer called EmpathyBuddy.

3 Foundation for Affective Text Classification

Here we address the basis of affective text classification as an important first task for the development of an automatic emotion recognition system.

3.1 Emotion and Communicative Function Categories

Why do people prefer to communicate and interact with a person who is expressive? In face-to-face communication, displayed emotions signal that the speaker is more sociable, open and humorous. All types of expressive means (such as gaze, intonation, facial expressions, gestures, body postures and movements etc.) potentially carry communicative power and promote better understanding [1,22].

Thus we believe that interaction in online conversations might benefit from the automation of multiple expressive channels, so that the user does not have to worry about visual self-presentation or misunderstandings as in standard IM systems, but can focus on the content of the conversation. Thus, we aim at recognizing and visualizing not only emotions in text messages, but also communicative functions. Both can then be "acted out" by our avatar. Since the purpose of affect recognition in an IM system is to relate text to avatar emotional expressions, emotional categories were confined to those that can be visually expressed and easily understood by users. For affect categorization, we have decided to use the subset of emotional states defined by Izard [9]: 'anger', 'disgust', 'fear', 'guilt', 'interest', 'joy', 'sadness' (‘distress’), ‘shame’, and ‘surprise’. As to communicative functions, ‘greeting’, ‘thanks’, ‘posing a question’, ‘congratulation’, and ‘farewell’ form the basis for communicative behaviour identification.

3.2 Affect Database

In order to support the handling of abbreviated language and the interpretation of affective features of emoticons, abbreviations, and words, a special database was created using MySQL 5.0 [17].

While accumulating affect database entries, we collected 364 emoticons, both of American and Japanese style (for example, “:”>” and “=^_^=” for ‘blushing’), and the 337 most popular acronyms and abbreviations, both emotional and non-emotional (for example, “BL” for ‘belly laughing’, “cul8r” for ‘see you later’, and “bc” – ‘because’). From the source of affective lexicon, WordNet-Affect [26], we have taken 1627 words: adjectives, nouns, verbs, and adverbs. We added not only words that refer directly to emotions, mood, traits, cognitive states, behaviour, attitude, sensations, but also words that carry the potential to elicit affective states in humans to our database (for example, “beautiful”, “disaster”, “break”, “deceive”, “violate” etc.). In addition to affect-related words, we were taking into account words standing for communicative functions listed in the previous subsection. Since interjections, such as “alas”, “wow”, “yay”, “ouch”, etc. are specific indicators of communicated emotion caused by unexpectedness, a long-awaited joyful event, or pain, they were collected as well. Moreover, we included 112 modifiers (e.g. “very”, “extremely”, “slightly”, “hardly”, “less”, “not” etc.) into our database because they influence the strength of related words and phrases in a sentence.

Emotion categories and intensities were manually assigned to affect-related entries of the database by three independent annotators. Intensity values range from 0.0 to 1.0, and describe the intensity degree of affective states from ‘very weak’ to ‘very strong’. Annotators conformed to our guideline with the description of emotional state gradation within intensity levels. For example, ‘cheerful’, ‘glad’, ‘happy’, ‘joyful’ and ‘elated’ all correspond to the ‘joy’ emotional state, but to a different degree of intensity. Emoticons and emotional abbreviations were transcribed and related to named affective states, whereby each entry was assigned to only one category (examples are listed in Table 1). The inter-rater agreement was calculated using Fleiss’ Kappa statistics. The Kappa coefficients for emoticons and abbreviations are 0.94 and 0.93, respectively, showing good annotation reliability.

Since some affective words may express more than one emotional state, annotators could relate words to more than one category. For instance, in the annotation of the word “frustrated”, both ‘anger’ and ‘sadness’ emotions are involved, with intensities 0.2 and 0.7, respectively (Table 2).

Assignments of emotion labels to the same word might differ among annotators. We only considered emotion categories that occur in the assignments of at least two annotators. The most frequent emotion labels in resulting sets were ‘joy’ and ‘sadness’ (34.3% and 30.0% of overall number of affective words, respectively) whereas the least frequent was ‘guilt’ (3.1%). The distribution of affective words with one, two, and three emotion labels is 67%, 29%, and 4%, respectively.

Table 1. Examples of emoticons and abbreviations taken from affect database

Symbolic representation	Meaning	Category	Intensity
:-)	happy	Joy	0.6
:-o	surprise	Surprise	0.8
:-S	worried	Fear	0.4
\(^O^)/	very excited	Joy	1.0
(~_~)	grumpy	Anger	0.3
m(._.)m	bowing, thanks	Thanks	-
JK	just kidding	Joy	0.3
4gv	forgive	Guilt	0.6
PPL	people	-	-

Table 2. Examples of words taken from affect database

Affective word	Part of speech	Category	Intensity
cheerfulness	Noun	Joy	0.3
astonished	Adjective	Surprise	1.0
frustrated	Adjective	Anger	0.2
		Sadness	0.7
dislike	Verb	Disgust	0.4
remorsefully	Adverb	Guilt	0.8
		Sadness	0.5

In intensity estimation, variance of data from the mean was taken into consideration. If the variance was not exceeding a predetermined threshold, the resulting intensity was measured as the average of intensities given by three annotators. Otherwise, the intensity value responsible for exceeding the threshold was removed, and only the remaining values were taken into account. Regarding the emotion intensity annotations of affective words, we observed interesting statistics within each of the nine emotion categories. Fig. 1 shows the percentage of cases with valid variance of given intensities within each emotion category.

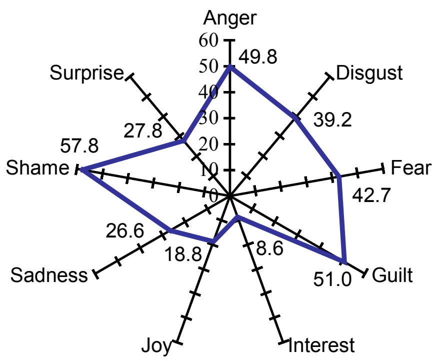

Fig. 1. The percentage of cases with valid variance of intensities within each emotion category

As seen from the diagram, annotators easily agreed in intensity assignments to 'shame', 'guilt', and 'anger' categories, in contrast to frequent disagreement in cases of 'interest', 'joy', and 'sadness'. We can only speculate that disagreement is related to the huge diversity of 'joyful' and 'sad' synonymous words with different emotional colorations, and due to the fuzziness of the 'interest' concept (some of psychologists do not consider 'interest' as an emotional state at all).

Adverbs of degree have an impact on neighbouring verbs, adjectives, or another adverb, and are used to mark that the extent or degree is either greater or less than usual [4]. In [3], authors use adverbs of degree to modify the score of adjectives in sentiment analysis. In our work, such adverbs along with some of prepositions constitute the set of modifiers. Two annotators gave coefficients for intensity degree strengthening or weakening (from 0.0 to 2.0) to them, and the result was averaged (see Table 3).

Table 3. Examples of modifier coefficients

Modifier	Category	Coefficient
perfectly	adverb of affirmation	1.9
seemingly	adverb of doubt	0.6
immensely	strong intensifying adverb	1.8
slightly	weak intensifying adverb	0.2
hardly	negation	0.0

4 Affect Analysis Model

The algorithm for analysis of affect in text consists of five stages: (1) symbolic cue analysis, (2) syntactical structure analysis, (3) word-level analysis, (4) phrase-level analysis, and (5) sentence-level analysis. The working flow of the Affect Analysis Model is presented in Fig. 2.

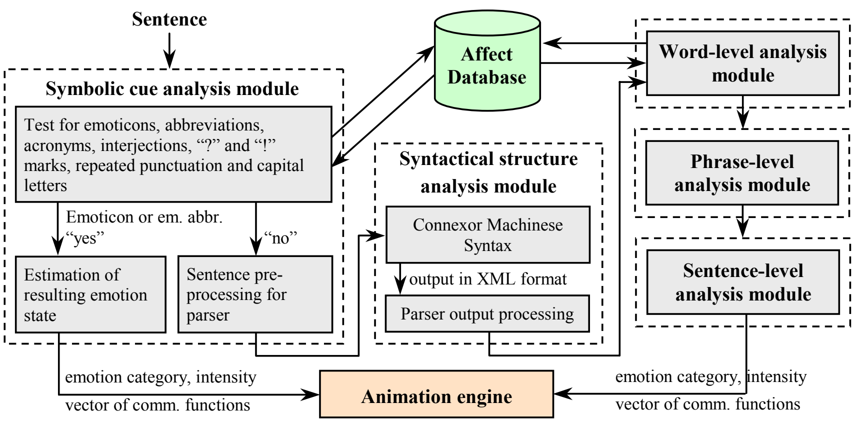

Fig. 2. Working flow of the Affect Analysis Model

4.1 Symbolic Cue Analysis

In the *first stage*, the sentence is tested for occurrences of emoticons, abbreviations, acronyms, interjections, "?" and "!" marks, repeated punctuation and capital letters.

If there is an emoticon or abbreviation related to an emotional state, no further analysis of affect in text is performed based on the simplifying assumption that the emoticon (or abbreviation) dominates the affective meaning of the entire (simple or compound) sentence. It is known that people type emoticons and emotional abbreviations to show actual feeling, or to avoid misleading the other participants, for instance, after irony, joke, or sarcasm (e.g. "*Thank you so much for your kind encouragement :-(*"). On the other hand, if there are multiple emoticons or emotion-relevant abbreviations in the sentence, we determine the prevailing (or dominant) emotion based on the following two (tentative) rules: (1) when emotion categories of the detected emoticons (or abbreviations) are the same, the higher intensity value is taken for this emotion; (2) when they are different, the category (and intensity) of the emoticon occurring last is dominant.

If there are no emotion-relevant emoticons or abbreviations in a sentence, we prepare the sentence for parser processing: emoticons and abbreviations standing for communicative function categories are excluded from the sentence; and non-emotional abbreviations and acronyms are replaced by their proper transcriptions found in the database (e.g. "*I m* [am] *stressed bc* [because] *i have frequent headaches*"). In such a way, the problem of correct processing of abbreviated text by syntactical parser is settled.

4.2 Syntactical Structure Analysis

The *second stage* is devoted to syntactical structure analysis. The used Connexor Machinese Syntax parser [6] returns exhaustive information for analysed sentences, including word base forms, parts of speech, dependency functions, syntactic function tags, and morphological tags. From the parser output, we can read off the characteristics of each token and the relations between words in a sentence. While handling the parser output, we represent the sentence as a set of primitive clauses (either independent or dependent). Each clause might include Subject formation, Verb formation and Object formation, each of which may consist of main element (subject, verb, or object) and its attributives and complements.

4.3 Word-Level Analysis

For each word in the database we built (see Sect. 3.2), either the communicative function category is taken as a feature or the affective features of a word are represented as a vector of emotional state intensities e = [anger, disgust, sadness, fear, guilt, interest, joy, shame, surprise]. For example, e("rude")=[0.2,0.4,0,0,0,0,0,0,0]; e("brotherly")=[0,0,0,0,0,0,0.2,0,0]; and e("love")=[0,0,0,0,0,0.8,1,0,0]. In the case of a modifier, the system identifies its coefficient.

Since the database contains words only in their dictionary form, one important system function at this stage is to increase the intensity of the emotional vector of an adjective (or adverb) if it is in comparative or superlative form (e.g. "gladder", "gladdest").

4.4 Phrase-Level Analysis

In the *fourth stage*, phrase-level analysis is performed. The purpose of this stage is to detect emotions involved in phrases, and then in Subject, Verb, and Object formations. Words in a sentence are interrelated and, hence, each of them can influence the overall meaning and affective bias of a statement.

We have defined general types of phrases, and rules for processing them with regard to affective content:

- adjective phrase (“extremely sad”): modify the vector of adjective;
- noun phrase: output vector with the maximum intensity within each corresponding emotional state in analysing vectors (e.g. e(“brotherly love”)= =[0,0,0,0,0,0.8,1,0,0]);
- verb plus adverbial phrase: output vector with the maximum intensity within each corresponding emotional state in analysing vectors;
- verb plus noun phrase: if verb and noun phrase have opposite valences (“break favourite vase”, “enjoy bad weather”), consider vector of verb as dominant; if valences are the same (“like honey”, “hate crying”), output vector with maximum intensity in corresponding emotional states;
- verb plus adjective phrase: output vector of adjective phrase.

The rules for modifiers are as follows:

- adverbs of degree multiply or decrease emotional intensity values;
- negation modifiers such as “no”, “not”, “never”, “any”, “nothing” 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 (e.g. statement “*despite his endless demonstrations of rude power*” is neutralized due to preposition).

Statements with prefixed words like “think”, “believe”, “sure”, “know”, “doubt” or with modal operators such as “can”, “may”, “must”, “need”, “would” etc. are not considered by our system because they express a modal attitude towards the proposition. Conditional clause phrases beginning with “if”, “even if”, “when”, “whenever”, “after”, “before”, and “although”, “even though”, etc. are disregarded as well (e.g. “*I eat when I'm angry, sad, bored…*”, or “*If only my brain was like a thumbdrive, how splendid it would be*.”).

There might be several emotional vectors within each of the Subject, Verb, or Object formations. During this stage, we apply the described rules to phrases detected within formation boundaries. Finally, each formation can be represented as a unified vector encoding its emotional content.

4.5 Sentence-Level Analysis

In the *fifth and final stage*, the overall emotion of a sentence and its resulting intensity degree are estimated. The emotional vector of a simple sentence (or of a clause) is generated from Subject, Verb, and Object formation vectors.

The main idea here is to first derive emotion vector of Verb-Object formation relation. It is estimated based on the “verb plus noun phrase” rule described above. In order to apply this rule, we automatically determine valences of Verb and Object formations using their unified emotion vectors (particularly, non-zero-intensity emotion categories). The estimation of the emotion vector of a clause (Subject plus Verb-Object formations) is then performed in the following manner: if valences of Subject formation and Verb formation are opposite (e.g. Subject formation = "my darling", Verb formation = "smashed", Object formation "his guitar"; or Subject formation = "troubled period", Verb formation = "luckily comes to an end"), we consider the vector of the Verb-Object formation relation as dominant; otherwise, we output the vector with maximum intensities in corresponding emotional states of vectors of Subject and Verb-Object formations.

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. In our approach, the emotional vector of a simple sentence (or of a clause) is multiplied by the corresponding empirically determined coefficient of intensity correction (details are given in [18]).

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 (e.g. "*They attacked, but we luckily got away!*").

After the dominant emotion of the sentence is determined (according to the highest intensity in the resulting vector), the relevant parameters are sent to the animation engine of our avatar.

5 System Evaluation

For system evaluation, we collected 160 sentences from a corpus of online diary-like blog posts [29]. Three annotators labeled the sentences with one of nine emotion categories discussed in Sect. 3.1 (or neutral) and a corresponding intensity value. The annotations from human raters are considered as "gold standard" for the evaluation of algorithm performance. The measured Fleiss' Kappa coefficient was low (0.58), and suggests that persons' comprehension, interpretation and evaluation of emotions are individual and might depend on personality type and emotional experience.

When comparing system results with human raters' annotations, we found that the percentage of cases where the dominant emotion category obtained by our algorithm matches with at least one of three raters' annotation is 79.4% (from which 84.3% are categorized as emotional, and 15.7% - neutral) of all sentences. In view of the variety of considered emotions (9 categories and neutral), the accuracy of our system seems reasonably high. In 70%, system output agrees with at least two annotators.

We also evaluated the system performance with regard to intensity estimation. The percentage of emotional sentences according to the measured distance between

Table 4. Percentage of emotional sentences according to the range of intensity difference between human annotations and output of algorithm

Range of intensity difference	[0.0 – 0.2]	(0.2 – 0.4]	(0.4 – 0.6]	(0.6 – 0.8]	(0.8 – 1.0]
Percentage of sentences %	68.2	26.2	4.7	0.9	0.0

intensities given by human raters (averaged values) and those obtained by Affect Analysis Model is shown in Table 4. As seen in the table, our system achieved satisfactory results for emotion intensity estimation.

6 Discussion and Conclusions

In this paper, we describe a rule-based approach to affect sensing from text at a sentence-level. A preliminary evaluation of the Affect Analysis Model algorithm shows promising results regarding its capability to recognize affective information in text from an existing corpus of informal online communication.

The salient features of the proposed algorithm are: (1) analysis of nine emotions on the level of individual sentences (which remains a challenge for machine learning based approaches); (2) the ability to handle the evolving language of online communications; (3) consideration of syntactic relations and dependences between words in a sentence; (4) basis on database of affective words, interjections, emoticons, abbreviations and acronyms, modifiers; (5) analysis of negation, modality, and conditionality; and (6) emotion intensity estimation. Moreover, we implemented a test interface with an avatar based on the Affect Analysis Model (see Fig. 3).

On the other hand, the system strongly depends on the created source of lexicon, affect database. This limits its performance if indirectly emotion-related words occur in analysed sentence (e.g. "*Oh yes, not forgetting, they had a mini chocolate fountain!*"). Furthermore, the Affect Analysis Model does not yet disambiguate word meanings (e.g. word "kill" is typically associated with negative emotions, but the phrase "to kill the audience" conveys 'surprise') and it fails to process expression-modifiers such as "to no end", "to death" (e.g. "*I love my ipod to death* "), etc.

We also encountered the problem of annotating sentences in isolation, i.e, without context. For example, the sentence "*There are no other terms that could really put me in a better position*" was rated as 'sad' by two annotators, as 'joy' by one, and as

Fig. 3. Test application of Affect Analysis Model

'neutral' by our system, whereas originally it belongs to a 'sad' monologue. Therefore, when analysing text messages in IM, we should also take into account the emotion dynamics throughout the conversation, or its "overall mood".

In our future study we will investigate those issues and explore the possibilities to overcome current limitations of the system.

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References

1. Allwood, J.: Bodily Communication Dimensions of Expression and Content. In: Multimodality in Language and Speech Systems, pp. 7–26. Kluwer Academic Publishers, Netherlands (2002)
2. Andreevskaia, A., Bergler, S.: Mining WordNet for Fuzzy Sentiment: Sentiment Tag Extraction from WordNet Glosses. In: Proceedings of EACL'06, Italy (2006)
3. Benamara, F., Cesarano, C., Picariello, A., Reforgiato, D., Subrahmanian, V.: Sentiment Analysis: Adjectives and Adverbs are Better than Adjectives Alone. In: Proceedings of ICWSM'07,, OMNIPRESS, Boulder, Colorado (2007)
4. Biber, D., Johansson, S., Leech, G., Conrad, S., Finegan, E., Quirk, R.: Longman Grammar of Spoken and Written English. Pearson Education Limited (1999)
5. Boucouvalas, A.C.: Real Time Text-to-Emotion Engine for Expressive Internet Communications. In: Being There: Concepts, effects and measurement of user presence in synthetic environments, pp. 306–318. IOS Press, Amsterdam (2003)
6. Connexor Oy, http://www.connexor.com/
7. Cowie, R., Douglas-Cowie, E., Tsapatsoulis, N., Votsis, G., Kollias, S., Fellenz, W., et al.: Emotion Recognition in Human-Computer Interaction. IEEE Signal Processing Magazine 1, 32–80 (2001)
8. De Rosis, F., Mazzotta, I., Miceli, M., Poggi, I.: Persuasion Artifices to Promote Wellbeing. In: Proceedings of First International Conference on Persuasive Technology for Human Well-being, Netherlands, pp. 84–95 (2006)
9. Izard, C.E.: Human Emotions. Plenum Press, New York, NY (1977)
10. Kamps, J., Marx, M.: Words with Attitude. In: Proceedings of BNAIC'02, pp. 449–450 (2002)
11. Kim, S.-M., Hovy, E.: Automatic Detection of Opinion Bearing Words and Sentences. In: Proceedings of IJCNLP'05 (2005)
12. Leshed, G., Kaye, J.: Understanding How Bloggers Feel: Recognizing Affect in Blog Posts. Extended Abstracts of CHI'06, 1019–1024 (2006)
13. Liu, H., Lieberman, H., Selker, T.: A Model of Textual Affect Sensing using Real-World Knowledge. In: Proceedings of IUI'03, pp. 125–132 (2003)
14. Mihalcea, R., Liu, H.A: Corpus-based Approach to Finding Happiness. In: Proceedings of the AAAI Spring Symposium on Computational Approaches to Weblogs (2006)
15. Mishne, G.: Experiments with Mood Classification in Blog Posts. In: Proceedings of the First Workshop on Stylistic Analysis of Text for Information Access (2005)

16. Mulder, M., Nijholt, A., den Uyl, M., Terpstra, P.: Lexical Grammatical Implementation of Affect. In: Proceedings of the 7th International Conference on Text, Speech and Dialogue, pp. 171–178. Springer, Heidelberg (2004)
17. MySQL 5.0, http://www.mysql.com/
18. Neviarouskaya, A., Prendinger, H., Ishizuka, M.: Analysis of Affect Expressed through the Evolving Language of Online Communication. In: Proceedings of IUI'07, pp. 278–281. ACM Press, New York (2007)
19. Olveres, J., Billinghurst, M., Savage, J., Holden, A.: Intelligent, Expressive Avatars. In: Proceedings of WECC'98, pp. 47–55 (1998)
20. Pang, B., Lee, L., Vaithyanathan, S.: Thumbs up? Sentiment Classification Using Machine Learning Techniques. In: Proceedings of the Conference on Emprirical Methods in Natural Language Processing (2002)
21. Picard, R.: Affective Computing. The MIT Press, Cambridge, MA (1997)
22. Poggi, I., Pelachaud, C.: Performative Faces. Speech Communication 26, 5–21 (1998)
23. Read, J.: Recognising Affect in Text using Pointwise-Mutual Information. Master thesis, University of Sussex (2004)
24. Rheingold, H.: The Virtual Community: Homesteading on the Electronic Frontier. Wesley Publishing, Menlo Park, CA (1993)
25. Strapparava, C., Valitutti, A., Stock, O.: Dances with Words. In: Proceedings of IJCAI'07, Hyderabad, India, pp. 1719–1724 (2007)
26. Strapparava, C., Valitutti, A.: WordNet-Affect: an Affective Extension of WordNet. In: Proceedings of LREC'04, pp. 1083–1086 (2004)
27. Subasic, P., Huettner, A.: Affect Analysis of Text Using Fuzzy Semantic Typing. In: IEEE Transactions on Fuzzy Systems 9(4), 483–496 (2001)
28. Turney, P.D.: Thumbs Up or Thumbs Down? Semantic Orientation Applied to Unsupervised Classification of Reviews. In: Proceedings of ACL'02, USA (2002)
29. Weblog Data Collection. BuzzMetrics, Inc., http://www.nielsenbuzzmetrics.com
30. Wilson, T., Wiebe, J., Hoffmann, P.: Recognizing Contextual Polarity in Phrase-level Sentiment Analysis. In: Proceedings of HLT/EMNLP-2005, Vancouver, Canada (2005)
31. Chuang, Z.-J., Wu., C.-H.: Multi-Modal Emotion Recognition from Speech and Text. In: Computational Linguistic and Chinese Language Processing 9(2), 45–62 (2004)