CHAPTER 1

INTRODUCTION

The burst of new computer-based media for communication and expression has caused an increasing need for human-computer interaction to acknowledge human emotions. The work presented in this paper focuses on emotion recognition in English text. The fact that online communication is still to a great extent text-based justifies such an approach. The domain is online communication in the form of short messages, such as real-time instant messages (chat), comments on social media and social networking sites, or microposts (e.g., tweets). Previous research [1] has shown that such communication is beneficial for social relations, and that users consider chat a medium for fulfilling, versatile, and engaging communication.

The proposed recognition algorithm classifies the text of a sentence according to the following emotional categories: happiness, sadness, anger, fear, disgust, and surprise [2]. The proposed algorithm estimates emotional weights for each emotional category (how intense the emotion is) in the form of a numerical vector. The vector is used to determine the dominant emotional type (the emotional type with the highest weight) and the overall emotional valence of a sentence (is the emotion positive, negative, or neutral). If the vector is zero or close to zero, the sentence is considered emotionally neutral. Users of our software may determine their criteria for neutrality.

To recognize emotions in sentences, we use a hybrid of a keyword-spotting method and a rule-based method. The keyword-spotting approach is based on the use of a lexicon of words and expressions related to emotions. The main contribution is threefold. First, in order to construct a word lexicon, use of both the power of human judgment and the power of WordNet, a lexical database for English language. Specifically, a survey based word lexicon to automatically search WordNet for all semantic relatives of the initial word set. Second, we take into account “:)”s, “>:O”s, and “ROFL”s through an extensive emoticon lexicon. Third, trying to overcome some of the problems associated with keyword-spotting techniques with several heuristic rules. An argument that the proposed technique is suitable for analyzing fragmented online textual interaction that is abundant in colloquialisms.

This approach is implemented with a software framework called Synesketch. Since emotion recognition software is rarely available online, a consideraton as our important additional contribution that Synesketch is an entirely free open-source library. Before Synesketch, there was only one such library with emotion recognition features—Concept-Net2. Nevertheless, the latest and current version of ConceptNet does not include that feature. Several Synesketch-based projects and applications have been developed, both by the authors and by third-party developers and designers, underpinning the practical and creative value of our contribution. An evaluation study has been conducted of the recognition algorithm, which gave us promising results. In particular, the results show high classification accuracy and underline the importance of the emoticon lexicon. The study method and results are presented.

CHAPTER 2

OVERVIEW

2.1 Affect Lexicons and WordNet

Most textual sentiment and affect recognition research includes building and employing lexical resources with emotional keywords, i.e., words typically associated with certain emotion types. Especially relevant to our work are those approaches that use WordNet, a lexical database for English language that also contains semantic connections between words. So far, WordNet has been primarily used for sentiment analysis. For example, creation of a SentiWordNet lexicon based on WordNet synsets collected from synonymous terms. Three numerical weights, defining to what degree the terms are positive, negative, or neutral, were associated with each WordNet set of synonyms. Similarly, a presentation of a method for extracting sentiment-bearing adjectives from WordNet and assigning them positive or negative tags. A description of a WordNet-grounded method to automatically generate and score a sentiment lexicon, called SentiFul, and expand it through direct synonymy, antonymy, and hyponymy relations, derivation, and compounding with known lexical units. In the field of emotion recognition, WordNet was used for creation of fine-grained emotion lexicons. For example, a development was made on WordNet-Affect, a lexicon of affective concepts, based on a subset of WordNet set of synonyms. Affective labels for the concepts related to emotional state, moods, traits, situations evoking emotions or emotional responses were assigned to the WordNet- Affect entries. Later it was extended as WordNet- Affect with a set of hierarchically organized emotional categories. Nevertheless, this organization is only partially compliant with the Ekman classification. For example, it includes labels such as “apprehension” (negative emotion), “anticipation” (positive), or “apathy” (neutral), which cannot fit well into Ekman’s scheme. Ma et al. searched WordNet for emotional words for all six emotional types defined by Ekman, and assigned to those words weights according to the proportion of synsets with emotional connotation those words belong to.

2.2 Keyword-Spotting Approach

A traditional and the most intuitive approach to emotion recognition is based on spotting emotional keywords. While some techniques take into account only words, others associate words with certain numerical weights. The Affective Reasoner being one of the simple approaches, searches for emotional keywords in text and uses a small lexicon of unambiguously affective words. Apply a more complex language parser in conjunction with a tagged dictionary of common words. Then the association of words with numerical weights, grounding the method in fuzzy logic. Similarly, uses a lexicon with numerical weights in conjunction with sentence-level processing. The use a weighted lexicon with a simple rule-based system, not taking emoticons into account.

In the realm of sentiment analysis, especially interesting is a keyword-spotting method who use emoticons and heuristics. However, their approach is limited to three emotional types (positive, negative, and neutral) and is heavily grounded on human coder subjective Judgments. Although keyword-based methods are praised for their intuitiveness, accessibility, and economy, they have been criticized for being based on shallow analysis capable of recognizing only surface features of the prose, and ignoring many semantic subtleties. For example, these methods can fail to account for negation and rely on keyword sets which may be difficult to define. Moreover, they have problems with word sense disambiguation.

2.3 Statistical Approach

The most common alternative to keyword spotting is based on statistics and the use of machine learning algorithms trained with a large textual corpus. For example, few people used supervised machine learning with the SNoW learning architecture in order to classify emotions in text. As a domain, the authors use children's fairytales. Furthermore, few others utilize a machine learning model with corpus-based features (unigrams). As a corpus, they use a collection of blog posts. Others also employ a supervised system based on a unigram model. Similarly, Latent Semantic Analysis (LSA) technique and a Naïve Bayes classifier trained on the corpus of blog posts annotated with emotions. Few others utilize emoticons as classification labels for the emotion classification task. Other researchers who used statistical language modelling techniques to analyse moods in text include opted for a hybrid approach that combines keyword-spotting with statistical approaches. However, this alternative to keyword spotting has problems too: the lack of semantic precision (as opposed to keyword-based approaches), large corpora needed for solid performance, and, more often than not, neglect of negation and other syntactical constructs. Statistics-grounded techniques are also popular within the related field of sentiment analysis and classification. As previously said, sentiment analysis seeks to determine if a piece of text has a positive or a negative connotation. Especially interesting is the approach by Read, which utilizes several positive and negative emoticons in Usenet groups in order to train their software. Similarly, use of smiling emoticons and expressions such as "LOL" as one of the strategies for detecting irony in text. And also the use emoticons in order to determine the sentiment of the text.

2.4 Ruled-Based and Hybrid Approaches

There are other approaches, such as advanced rule-based linguistic approaches targeting textual affect recognition at the sentence level. Introduction an original approach based on a large-scale common sense knowledge base. The authors ground their affect models in Open Mind Common Sense, an open-source database of general common sense knowledge. This approach is implemented through ConceptNet, an open source toolkit. Even though this approach is innovative and seems to offer a lot of potential, the presented evaluation results do not provide enough evidence of this technique's emotion classification accuracy. Rule-based systems are also employed in the field of sentiment analyses. Furthermore, there are some hybrid approaches to emotion recognition. For instance, a system was proposed that consists of both a keyword recognizing engine and an emotion classifier. The classifier employs Knowledge- Based Artificial Neural Network (KBANN), which uses approximate domain knowledge and rules. Finally, another rule-based linguistic approach was proposed for affect recognition from text, called the Affect Analysis Model (AAM). The authors employ a lexicon that consists not only of words, but also of emoticons and informal language. However, unlike the majority of approaches that rely on Ekman's six types of emotions, their model introduces nine emotional categories.

CHAPTER 3
TEXTUAL EMOTION RECOGNITION

Our hybrid keyword spotting technique is based on a lexicon and several heuristic rules. The lexicon consists of two parts: 1) a word lexicon, and 2) an emoticon lexicon. The word lexicon is semi-automatically generated using the WordNet lexical database for English language. The emoticon lexicon, which also includes common abbreviations and informal language common in Netspeak, is constructed manually. Each lexicon entry (word or emoticon) is associated with six emotional weights that correspond to six basic emotional categories defined by Ekman: happiness, sadness, anger, fear, disgust, and surprise. The value of each weight is between 0 and 1. We opted for Ekman's model since it is the most common in the field of emotion classification. Some researchers refer to these emotional types as the "Big Six." As shown in the Appendix table more than half of the presented emotion classification techniques use the Ekman's model.

3.1 Word Lexicon

The technique we use to generate the word lexicon is based on a simple idea. The emotional weight of a word taken from WordNet can be calculated as a proportion of emotional senses among all senses of the word. First, we start with a small initial collection of unambiguously emotional words and use it as a starting point for collecting the lexical "relatives" of these words from WordNet. The assumption of our technique is that words semantically close to this initial set of emotional words themselves carry a stronger emotional connotation than other words. So, in order to create the initial collection, we conducted a 20-person study. People were asked to list for each emotion type at least five words that they unambiguously associate the most with the given type. Words that were mentioned three or more times were considered good indicators of the corresponding emotion type and were added to the collection of words for that type. Such words were, for example, "happy" or "beautiful" for happiness, "lonely" for sadness, "terror" for fear, "rotten" for disgust, "suddenly" for surprise, etc. Then, we used WordNet 1.6 to search for synsets of the words from the initial collection. A synset is a set of semantically equivalent words within WordNet. Since most words carry more than one meaning, they belong to several synsets. Our lexicon is created through the analysis of semantic relationships of words and synsets, as described below.

The lexicon generation algorithm consists of the following steps:

1. six (empty) sets of emotional synsets Sk, k 2 E, and the (empty) word set W are created. E is the set of six emotional types (happiness, sadness, anger, fear, disgust, surprise); E ={ fh, sd, a, f, d, sug}.

2. WordNet is searched for synsets of words from the initial sets of emotional keywords Vk, k 2 E. These initial synsets are added to Sk, k 2 E, sets of emotional synsets for a given emotional type k.

3. This step is repeated d times. In each iteration l (l ¼ 1; 2; . . . ; d), WordNet is searched for synsets semantically akin to the synsets from the Sk, via WordNet's pointer type SimilarTo. The extended synsets are added to Sk, k 2 E. However, since these synsets are obtained indirectly, they are attached a penalty coefficient p, which is computed in the
following manner:

$$p_{kj} = 0.1 * l;\ \ k \in \{h, s, a, f, d, su\}, j = 1, 2, \ldots, q_{ki}.$$

qki is the number of emotional synsets for the given word i and the given emotional type k (the emotional synset of type k is the one contained in the set Sk). The penalty grows in each iteration, which corresponds to the intuition that synsets semantically closer to the initial set of emotional keywords carry a stronger emotional meaning.

In practice, the value of d is 3. The value of 0.1 (in (1)) and d ¼ 3 resulted from a series of lab experiments that we have conducted on the test corpus of five sentences
for each emotional type (not the corpus we used for evaluation). We varied this number and discussed the results with students and fellow researchers, and finally agreed on these values.

4. When all synsets are acquired, words from the synset sets Sk, k 2 E, are added to the final set of words, W. The total number of words in W is m.

5. The emotional weights wki, k 2 E, i ¼ 1; 2; . . .;m, are calculated for each word from W. For each word, the algorithm collects all the synsets in WordNet the word belongs to. For a given word i, the number of all synsets from WordNet is ni. Some of these synsets also belong to the synset sets Sk—those are considered the emotional ones. Other synsets, though being part of WordNet, do not belong to the sets of emotional synsets. The emotional weight for each word and for each emotional type is calculated as a quotient between the number of emotional synsets (of a given emotional type) and the number of all synsets the word belongs to, diminished by using the average penalty of all its emotional synsets. This can be formally expressed in the following manner:

$$w_{ki} = \frac{q_{ki}}{n_i}\left(1 - \frac{\sum_{j=1}^{q_{ki}} p_{kj}}{q_{ki}}\right) = \frac{1}{n_i}\left(q_{ki} - \sum_{j=1}^{q_{ki}} p_{kj}\right)$$

$$i = 1, 2 \ldots, m;\ k \in \{h, s, a, f, d, sp\}.$$

The word lexicon formed this way consists of 3,725 words. A small part of the lexicon is shown in Table 1.

TABLE 1

A Small Portion of the Word Lexicon, with Emotional Weights Given for Several Words; Emotional Types Include: Happiness (H), Sadness (Sd), Anger (A), Fear (F), Disgust (D), and Surprise (Su)

Word	H	Sd	A	F	D	Su
joyful	1.0	0.0	0.0	0.0	0.0	0.0
severe	0.0	0.133	0.133	0.5	0.133	0.0
fierce	0.0	0.0	0.75	0.2	0.2	0.0
popeyed	0.0	0.0	0.0	0.0	0.0	0.45
repellent	0.0	0.0	0.0	0.0	0.25	0.0
somber	0.0	0.4	0.0	0.4	0.0	0.0

3.2 Emoticon Lexicon

An emoticon is a typographical symbol (or a combination of symbols) that represents a facial expression, such as :), ;), and the like. By using emoticons, writers tag their sentences with a certain emotion or mood, indicating in a more explicit way how the sentence should be interpreted. The idea of an emoticon-like symbol is actually older than the Internet itself; for example, Ludwig Wittgenstein debated the power of a face-like symbol drawn by only four hand drawn strokes to express a wide range of emotions. Emoticons arguably express human feelings more directly than words. Considering the widespread use of these symbols, we strongly argue that any textual sensing algorithm that focuses on online communication (such as chat) should consider emoticons. Unfortunately, emoticons are not part of WordNet or any other lexical database that we know of. Therefore, it was not possible to create an emoticon lexicon automatically—we had to do it manually. So, we first collected the most frequent text-based emoticons from the list of emoticons used by the most popular chat systems: GTalk,7 Skype,8 MSN Messenger,9 and Yahoo! Messenger,10 appended by the Wikipedia list of Western emoticons11 as well as the list created by Gajadhar and Green [37]. Our list also includes common abbreviations, such as “LOL” or “OMG.” In addition, the emoticon lexicon is appended with the common vulgarisms or informal exclamations (“damn” or “yuck,” for instance), which though not emoticons, do not exist in lexical databases, yet carry an undeniable affective connotation. Although the emoticons’ emotional semantics is most often obvious and self-explanatory, we consulted Wikipedia’s definitions of emoticons’ emotional meanings. We consider this source relevant in this particular context since it is the result of a social consensus among many active Web users. However, Wikipedia descriptions do not comply with Ekman’s categories for all emoticons from our collection, so we have conducted a study in order to define emotional vectors (with an emotional weight for each of the six emotional types) for each emoticon, as that information was not available. In order to ground the opinion in the common viewpoint, we contacted 174 participants on popular social networks using the Snowball sampling technique. All participants use social networks and chat regularly. Their ages vary between 16 and 40 years. Participants were asked to assign emotional weights to emoticons taken from the collection according to their perception of the emotions expressed by those emoticons. The choice of values for weights was: 1.0 (direct emotional meaning, the way happiness is associated with “:-)”), 0.5 (partial emotional meaning, the way fear, sadness, or disgust may (or may not) be associated with “:/”), or 0 (no emotional meaning). After the study, we assigned to the each emoticon a majority weight given by participants. A small portion of the emoticon lexicon is presented in Table 2. The entire emoticon lexicon consists of 128 symbols and abbreviations. Both word and emoticon lexicons are available online.

TABLE 2
A Small Portion of the Emoticon Lexicon

Emoticon	H	Sd	A	F	D	Su
:-)	1.0	0.0	0.0	0.0	0.0	0.0
>:-(	0.0	0.5	1.0	0.0	0.5	0.0
lol	1.0	0.0	0.0	0.0	0.0	0.0
yuck	0.0	0.0	0.0	0.0	1.0	0.0

3.3 Emotion Recognition and Heuristic Rules

In a nutshell, our recognition algorithm gets one sentence an its input, parses the text into words, compares these words with the ones from the lexicons, and then employs several heuristic rules. Parsing is done using the Java Break Iterator class. In the process of text parsing, emoticons are used in the following way: If an emoticon is followed by a word with the first letter in uppercase, the word is considered the beginning of the next sentence. Heuristic rules, grounded in common sense, are intended to overcome some of the problems associated with keyword spotting methods, such as negation detection, the effect of punctuation marks, etc.

Finally, the algorithm calculates the overall emotional state for the input sentence. The overall emotional state consists of an overall vector with six emotional weights and an emotional valence. The emotional valence can take values of _1, 0, or _1, showing if the emotion is negative, neutral, or positive, respectively.

Sentence-level rules, which apply to a whole sentence, are the following:

a. If there is a negation14 in a part of a sentence (divided from the rest of the sentence by a comma, semicolon, colon, dash, or hyphen) where an emotional word is spotted, the emotional valence of the whole sentence is flipped. It means that the values switch between the happiness weight and the weights of the negative emotions (sadness, anger, fear, or disgust). For example, the algorithm would flip the valence of the sentence "I am not happy, that was hard," but would not flip the valence of the sentence "I am happy, that was not easy." Moreover, if the valence changes from positive to negative, the algorithm would assign the happiness weight to all four negative emotions (sadness, anger, fear, and disgust). The approach to handling negation in terms of its use of clausal punctuation could be found. However, the current version of our algorithm has certain limitations (for example, flipping all four negative emotions and handling double negation). The current work is based on a new version of the algorithm in order to fix these limitations.

b. The more exclamation marks ("!") a sentence has, the more intense its emotions become. For each new mark, emotional weights get intensified by 20 per cent.

c. If a sentence possesses a combination of characters such as "?!" or "!?", there is an emotion of surprise in it (the surprise weight is set to 1.0).

Word-level rules, which apply to single words, are the following:

d. The more characteristic signs a spotted emoticon has, the more intense the emotions of that sentence become. For example, this emoticon ":))))" is clearly more "happy" than this one ":)". For each new mark, related emotional weight (in this case happiness weight) gets intensified by 20 percent.

e. If a spotted emotional keyword is uppercase, the emotion associated with the word gets intensified by 50 percent.

f. If a spotted emotional keyword is preceded by an intensifying word (such as “extremely,” “very,” “exceedingly,” etc.), the emotion associated with the word gets intensified by 50 percent. The values of 20 percent and 50 percent resulted from a series of lab experiments mentioned (test corpus of five sentences for each emotional type).

Our algorithm consists of the following steps:

1.1 The input sentence is processed by applying sentence-level rules: a, b, and c.

2.2 The input sentence is parsed into words.

3.3 Each word is compared to keywords from both lexicons.

4.4 If a keyword is spotted, word-level rules—d, e, and f —are applied to it.

5.5 Emotional weights of a keyword are updated based on the applied (word-level) rules.

6.6 The keyword is added into an emotion words set. This is done for all spotted emotion-related keywords.

7.7 The overall emotional state of the sentence, the overall vector that corresponds to the entire sentence, is calculated using the emotion words set with updated weights.

Emotional weights of the overall vector are based on the max value of all keywords of the same emotion type from the emotion words set. Emotional valence depends on whether or not the sum of overall happiness weight outweighs the overall weight of the dominant negative emotion (sadness, anger, fear, or disgust weights).

Let the value wsk denote the overall emotional weight and the value v the emotional valence for a given sentence and for a given emotional type k, k 2 fh; sd; a; f; d; sug. The given sentence contains m emotional words. Let the value wki denote the emotional weight for a given word i,

i ¼ 1; 2; . . .;m, and a given emotional type k.

Then, the overall emotional weights and the emotional valence the sentence can be calculated in the following manner:

$$ws_k = max(w_{ki}); i = 1, 2, \ldots, m;\ k \in h, sd, a, f, d, su\}$$

$$v = \begin{cases} -1, & w_{hi} - max_{u \in \{sd,a,f,d\}}(w_{ui} < 0 \\ 0, & w_{hi} - max_{u \in \{sd,a,f,d\}}(w_{ui}) = 0\,; i = 1, 2, \ldots, m. \\ 1, & w_{hi} - max_{u \in \{sd,a,f,d\}}(w_{ui} > 0 \end{cases}$$

CHAPTER 4
APPLICATIONS

The affect sensing approach is implemented through a textual emotion recognition engine called Synesketch. In addition to the emotion recognition, Synesketch also provides software modules for emotion visualization in the form of abstract generative animation art. Synesketch is written in Java. Its first version was published online as a free open-source project (under the GNU General Public License) in November 2008. The library was improved over time. The version we describe in this paper is the final version downloadable from the website. The goal of the visualization is to foster and expand the means and forms of human on-line communication and expression, by not only communicating emotions, but also evoking emotions in the users. Synesketch may be used in a variety of contexts, from market research based on finegrained emotion analysis, through e-learning, to creative applications used for making user experience more enjoyable and fun. In fact, Synesketch has already been integrated into a couple of real-world apps.

CHAPTER 5

SYNESKETCH VISUALIZATION

We developed two default visualization systems. Both of them transfer a sequence of sentences (written during a chat session, for example) into a generative animation. Each sentence triggers one type of animation, which is active until suppressed by the animation created for the next sentence. Generative animation art represents recognized emotions using a variety of colour palettes, shapes, sizes, frame rates, and animation properties. Images of one of the visualizations are shown in fig1.

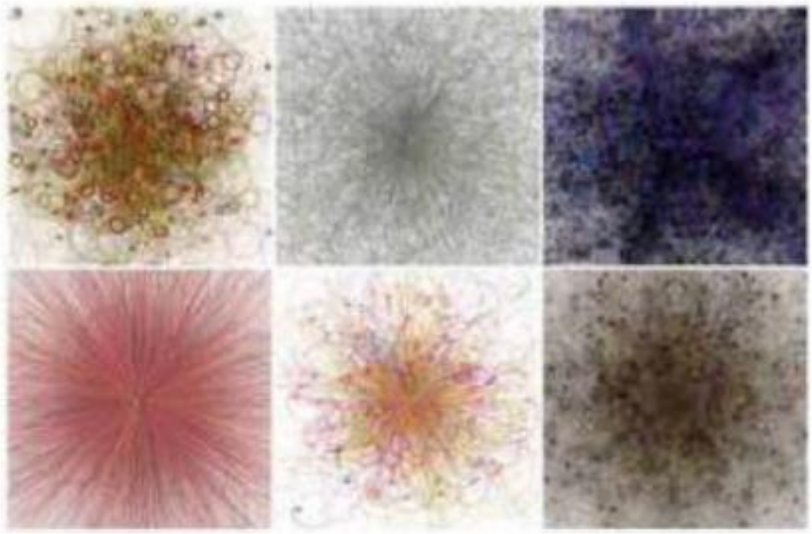

FIG 1 : SYNESKETCH VISUALS REPRESENTATION

For instance, the results show that Synesketch visualizations are highly effective in communicating emotions and, compared to other common emotion visualization techniques (specifically, animated chat emoticons and avatars), they are (statistically) significantly Better in evoking emotions. However, these visualizations are only the default ones; Synesketch supports and promotes building visualizations by third-party designers.

CHAPTER 6

EVALUATION

Different approaches are analysed in terms of :

1. Classification type
2. Classification method
3. Method features (inclusion of emoticons/abbreviations, based on rules, based on WordNet)
4. Availability of test data, and
5. Applications (free software, available online, open source, has real-world apps based on it, has visualization).

	Synesketch	Elliott [15]	Boucouvalas and Zhe [33]	Subasic and Huettner [17]	Ma *et al.* [14]	Olveres *et al.* [18]	Devillers *et al.* [19]	Mishne [29]	Alm *et al.* [25]	Aman and Szpakowicz [26]	Katz *et al.* [27]	Strapparava and Mihalcea [28]	Leshed and Kaye [30]	Neviarouskaya *et al.* [24]	Seol *et al.* [23]	Liu *et al.* (ConceptNet) [22, 48]	Calix *et al.* [49]	Chuang and Wu [42]	Purver and Battersby [43]	Yuan and Purver [44]	Keshtkar [52]	Francisco and Gervas [53]	Go *et al.* [45]	Pak and Paroubek [46]	Thelwall *et al.* [47]	Mihalcea and Liu [31]	Read [6]	Carvalho *et al.* [8]
Classification Type																												
1. Sentiment Analysis																							x	x	x	x	x	x
2. Emotion Analysis: 6 Ekman	x		x		x				x	x	x	x				x	x	x	x	x	x							
3. Emotion Analysis: other		x		x		x	x	x					x	x	x		x				x	x						
Emotion Detection Method																												
1. Keyword spotting	x	x	x	x	x	x	x						x	x	x	x		x			x	x			x	x		x
1.1. Keyword weights	x			x	x	x	x							x				x				x			x			
1.2. (Semi)Autom. lex.	x				x									x								x			x			x
2. Statistical methods								x	x	x	x	x	x		x		x		x	x	x		x	x	x	x	x	
3. Other		x		x			x								x	x										x		
Method Features																												
1. Emoticons/abbr.	x													x					x	x	x		x	x	x		x	x
2. Rule-based	x				x	x	x							x	x			x				x		x	x			x
3. Word-net based	x				x				x	x		x		x			x				x	x						
Evaluation																												
Test data available	x								x			x																
Applications																												
1. Free software	x															x			x^1	x^1					x^3			
2. Available online	x																		x^2	x^2			x		x			
3. Open Source	x															x												
4. Real-world apps	x		x		x									x		x			x	x			x		x			
5. Visualization	x				x	x								x		x	x		x	x			x		x			

x^1 – Only the basic version of the software is free.

x^2 – Software is available online with limited features (sentiment instead of emotion analysis, not all emotional types).

x^3 – The software has a free basic version, available only for academic research.

CONCLUSION AND FUTURE ENHANCEMENT

An approach is presented for textual affect recognition positioned within the context of computer-mediated human interaction. The recognition algorithm receives a text sentence as an input and classifies it according to the six emotional types defined by Ekman [2]. The output emotional vector can be used to determine the dominant emotional type and the emotional valence of the sentence. Our contribution is based on the way lexicons are created and how they are used in conjunction with heuristic rules. The usage of the WordNet-based word lexicon and a lexicon of emoticons, abbreviations, and vulgarisms.

The affect recognition approach is illustrated through a software system, Synesketch. Besides the affect recognition engine, Synesketch includes an engine for generating emotion-related abstract animation in real time. Most of Synesketch-based applications, created by third-party developers and designers, are located within the context of computer-mediated human communication (such as emotional visual chat).

- Synesketch is, to the extent of our knowledge, the only free open source textual emotion recognition software published on the web.
- The evaluation study presents promising results in terms of high classification accuracy, underlining the importance of the emoticon lexicon.
- Future efforts will be centered on refining the algorithm and the lexicon. At the moment we are working on the improved version of negation detection.
- To allow the users to evaluate emotion recognition while using Synesketch. The program would continuously follow this feedback and would adjust the lexicon accordingly.
- The users will be allowed to add words, emoticons, abbreviations, etc., and annotate them with appropriate affects. The software would then search for recurrent patterns and add those to the lexicon.

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