

# Compositionality Principle in Recognition of Fine-Grained Emotions from Text

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## Abstract

The recognition of personal emotional state or sentiment conveyed through text is the main task we address in our research. The communication of emotions through text messaging and posts of personal blogs poses the ‘informal style of writing’ challenge for researchers expecting grammatically correct input. Our Affect Analysis Model was designed to handle the informal messages written in an abbreviated or expressive manner. While constructing our rule-based approach to affect recognition from text, we followed the compositionality principle. Our method is capable of processing sentences of different complexity, including simple, compound, complex (with complement and relative clauses), and complex-compound sentences. The evaluation of the Affect Analysis Model algorithm showed promising results regarding its capability to accurately recognize affective information in text from an existing corpus of personal blog posts.

## Introduction

*... in most emotion discourse, language is expressive, affecting, and constitutive*

Donald Brenneis (1990: 115)

Recently computational linguists demonstrate an increased interest in the tasks of text classification as subjective or of factual nature, of determination of orientation and strength of sentiment, and of recognition of attitude type expressed in text at various grammatical levels. To analyse contextual sentiment, rule-based approaches (Nasukawa and Yi 2003; Moilanen and Pulman 2007), and a machine-learning method using not only lexical but also syntactic features (Wilson, Wiebe, and Hoffmann 2005) were proposed. Advanced approaches targetting textual affect recognition at the sentence level are described in (Liu, Lieberman, and Selker 2003; Mulder et al. 2004; Alm 2008).

While constructing our rule-based approach to affect recognition from text, we took into account linguistic

features of text written in a free informal style. Our Affect Analysis Model was designed based on the compositionality principle, according to which we determine the emotional meaning of a sentence by composing a pieces that correspond to lexical units or other linguistic constituent types governed by the rules of aggregation, propagation, domination, neutralization, and intensification, at various grammatical levels.

## The Affect Analysis Model

In this work, the subset of emotional states defined by Izard (1971) (‘Anger’, ‘Disgust’, ‘Fear’, ‘Guilt’, ‘Interest’, ‘Joy’, ‘Sadness’, ‘Shame’, and ‘Surprise’) form the basis for affective text classification. The Affect database was created (see details in (Neviarouskaya, Prendinger, and Ishizuka 2007)) in order to support the handling of abbreviated language and the interpretation of affective features of lexical items. It includes the following tables: Emoticons, Abbreviations, Adjectives, Adverbs, Nouns, Verbs, Interjections, and Modifiers. Emotion categories with intensities (from 0.0 to 1.0) were manually assigned to the emotion-related entries of the database by three independent annotators. Considering the fact that some affective words may express more than one emotional state, annotators could relate words to more than one category (for ex., final annotation for noun ‘*enthusiasm*’ is ‘Interest:08, Joy:0.5’). Adverbs of degree along with some of the 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 (for ex., coeff(‘*barely*’) = 0.4).

Following the compositionality principle, we developed a rule-based algorithm for analysis of affect expressed by text at various grammatical levels.

In the *first stage* of the Affect Analysis Model, the sentence is tested for occurrences of emoticons, abbreviations, acronyms, interjections, ‘?’ and ‘!’ marks, repeated punctuation, and capital letters. Several rules are applied to define the dominant emotion in cases when multiple emoticons and emotion-related abbreviations

occur in a sentence. As interjections are added to sentence to convey emotion (e.g. ‘wow’, ‘alas’), they are analysed as well. If there are no emotion-related emoticons or abbreviations, we prepare the sentence for parser processing by replacing non-emotional abbreviations by their proper transcriptions found in the database (e.g., ‘I m [am] stressed bc [because] i have frequent headaches’).

The *second stage* is divided into two subtasks: (1) sentence analysis by the Connexor Machine Syntax<sup>1</sup> parser providing a full analysis of texts by showing how words and concepts relate to each other in sentences; (2) parser output processing. When handling the parser output, we represent the sentence as a set of primitive clauses (either independent or dependent). Each clause might include Subject formation (SF), Verb formation (VF), and Object formation (OF), each of which may consist of a main element (subject, verb, or object) and its attributives and complements. For the processing of complex or compound sentences, we build a so-called ‘relation matrix’, which contains information about dependences that the verbs belonging to different clauses have.

In the *third stage* (word-level analysis), the affective features of a word found in our database are represented as a vector of emotional state intensities  $e=[\text{Anger, Disgust, Fear, Guilt, Interest, Joy, Sadness, Shame, Surprise}]$  (e.g.,  $e(\text{‘love’})=[0,0,0,0,0.8,1.0,0,0,0]$ ). In the case of a modifier, the system identifies its coefficient. As our Affect 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 emotional adverb, if it is in comparative or superlative form, by multiplication on values 1.2 or 1.4, respectively.

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 on the overall meaning and affective bias of a statement. We have defined rules for processing phrases with regard to affective content:

1. Adjective phrase: modify the vector of adjective (e.g.,  $e(\text{‘extremely doleful’}) = \text{coeff}(\text{‘extremely’}) * e(\text{‘doleful’}) = 2.0 * [0,0,0,0,0,0.4,0,0] = [0,0,0,0,0,0.8,0,0]$ ).
2. Noun phrase: output vector with the maximum intensity within each corresponding emotional state in analysing vectors (for instance,  $e_1=[0..0.7..]$  and  $e_2=[0.3..0.5..]$  yield  $e_3=[0.3..0.7..]$ ).
3. Verb plus adverbial phrase: output vector with the maximum intensity within each corresponding emotional state in analysing vectors (e.g.,  $e(\text{‘shamefully deceive’})=[0,0.4,0,0,0,0,0.5,0.7,0]$  where  $e(\text{‘deceive’})=[0,0.4,0,0,0,0,0.5,0,0]$  and  $e(\text{‘shamefully’})=[0,0,0,0,0,0,0,0.7,0]$ ).
4. Verb plus noun phrase: if verb and noun phrase have opposite valences (e.g., ‘break favourite vase’, ‘enjoy bad weather’), consider vector of verb as dominant; if

valences are the same (e.g., ‘like honey’, ‘hate crying’), output vector with maximum intensity in corresponding emotional states.

5. Verb plus adjective phrase (e.g., ‘is very kind’, ‘feel bad’): output vector of adjective phrase.

The rules for modifiers are as follows: (1) adverbs of degree multiply or decrease emotional intensity values; (2) negations cancel (set to zero) vectors of the related words, i.e., ‘neutralize the emotional content’ (e.g., ‘Yesterday I went to a party, but nothing exciting happened there’); (3) prepositions such as ‘without’, ‘except’, ‘against’, ‘despite’ cancel vectors of related words (e.g., ‘I climbed the mountain without fear’ is neutralized due to preposition).

Statements with prefixed words like ‘think’, ‘believe’, ‘sure’, ‘know’, ‘doubt’, or with modal operators such as ‘can’, ‘may’, ‘would’ etc. are neutralized by our system. Conditional clause phrases beginning with ‘even though’, ‘if’, ‘unless’, ‘whether’, ‘when’, etc. are neutralized as well (e.g., ‘I eat when I’m angry, sad, bored...’).

There might be several emotional vectors within each of the SF, VF, or OF. 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.

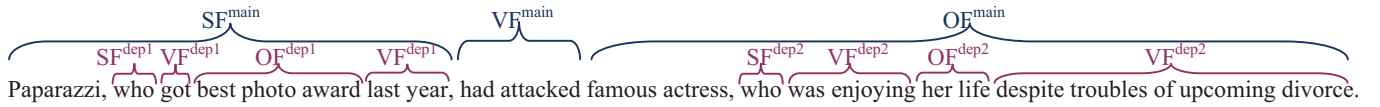
In the *fifth and final stage*, the overall emotion of a sentence and its resulting intensity degree are estimated. Our algorithm enables processing of different types of sentences, such as: simple, compound, complex, or complex-compound.

The emotional vector of a simple sentence (or a clause) is generated from Subject, Verb, and Object formation vectors resulting from phrase-level analysis. The main idea here is to first derive the 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: (1) if valences of Subject formation and Verb formation are opposite (e.g., SF = ‘my darling’, VF = ‘smashed’, OF = ‘his guitar’; or SF = ‘troubled period’, VF = ‘luckily comes to an end’), we consider the vector of the Verb-Object formation relation as dominant; (2) otherwise, we output the vector with maximum intensities in corresponding emotional states of vectors of Subject and Verb-Object formations.

In order to estimate the emotional vector of a compound sentence, first, we evaluate vectors of its independent clauses. Then, we define the resulting vector of the compound sentence based on the following rules: (1) with comma and 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.

<sup>1</sup> Connexor Machine Syntax.

<http://www.connexor.eu/technology/machinese/machinesyntax/>



### Steps in affect recognition:

- 1)  $e^{\text{dep1}}(\text{'who got best photo award last year'}) = \text{coeff}(\text{tense: 'past'; FPP: 'no'}) * e^{\text{dep1}}(\text{SF}^{\text{0dep1}} \& \text{VF}^{\text{0dep1}} \& \text{OF}^{\text{+dep1}}) = 0.4 * [0,0,0,0,0,0,0.42,0,0,0] = [0,0,0,0,0,0,0.17,0,0,0] = e^{\text{+dep1}}$ ;  
 $\text{SF}^{\text{main}} = \text{'Paparazzi'} \& e^{\text{+dep1}} = [0,0,0,0,0,0,0.17,0,0,0] = \text{SF}^{\text{+main}}$ ;
- 2)  $e^{\text{dep2}}(\text{'who was enjoying her life despite troubles of upcoming divorce'}) = \text{coeff}(\text{tense: 'past'; FPP: 'no'}) * e^{\text{dep2}}(\text{SF}^{\text{0dep2}} \& \text{VF}^{\text{+dep2}})$ , where  $\text{'troubles of upcoming divorce'}$  are neutralized due to  $\text{'despite'}$ , &  $\text{OF}^{\text{0dep2}} = 0.4 * [0,0,0,0,0,0,0.6,0,0,0] = [0,0,0,0,0,0,0.24,0,0,0] = e^{\text{+dep2}}$ ;  
 $\text{OF}^{\text{main}} = \text{'famous actress'} \& e^{\text{+dep2}} = [0,0,0,0,0,0,0.3,0,0,0.2] \& [0,0,0,0,0,0,0.24,0,0,0] = [0,0,0,0,0,0,0.3,0,0,0.2] = \text{OF}^{\text{+main}}$ ;
- 3)  $e^{\text{main}}(\text{'Paparazzi, who got best photo award last year, had attacked famous actress, who was enjoying her life despite troubles of upcoming divorce'}) = \text{coeff}(\text{tense: 'past'; FPP: 'no'}) * e^{\text{main}}(\text{SF}^{\text{+main}} \& \text{VF}^{\text{-main}} \& \text{OF}^{\text{+main}}) = 0.4 * ([0,0,0,0,0,0,0.17,0,0,0] \& [0.4,0,0,9,0,0,0,0,8,0,0] \& [0,0,0,0,0,0,0.3,0,0,0.2]) \text{ yield } [0.4,0,0,9,0,0,0,0,8,0,0] = [0.16,0,0,36,0,0,0,0,32,0,0] = e^{\text{-main}}$ .

Figure 1. Example of affect sensing in a complex sentence with relative clauses

To process a complex sentence with a complement clause (e.g., *'I hope that Sam will not harass my dog'*), first we derive the emotional vector of the complement clause, then create Object formation for the main clause using this vector, and finally estimate the resulting emotional vector of the main clause with added Object formation. In brief, we represent such sentence as a simple one, using the pattern *'who-SF does-VF what-OF'*, where object is represented as a complement clause.

Complex sentences containing adjective (relative) clauses introduced by *'who'*, *'whom'*, *'whose'*, *'that'*, *'which'*, or *'where'*, are analyzed in the following manner: (1) the emotional vector of adjective clause is estimated; (2) this emotional vector is added to the Subject or Object formation of the main clause depending on the role of the word to which the adjective clause relates (e.g., in a sentence *'The man who loved the woman robbed the bank'*, the clause *'who loved the woman'* relates to the subject *'man'*; and in a sentence *'The man robbed the bank where his beloved wife was working'*, the clause *'where his beloved wife was working'* relates to the object *'bank'*); (3) the emotional vector of the whole sentence is estimated. Figure 1 illustrates the analysis of a complex sentence with relative clauses: *'Paparazzi, who got best photo award last year, had attacked famous actress, who was enjoying her life despite troubles of upcoming divorce'*. In Figure 1,  $e = [\text{Anger, Disgust, Fear, Guilt, Interest, Joy, Sadness, Shame, Surprise}]$ ; the superscripts  $^0$ ,  $^-$ , and  $^+$  indicate *'neutral'*, *'negative'*, and *'positive'*, respectively;  $^{\text{main}}$  and  $^{\text{dep}}$  mean belonging to *'main'* and *'dependent'* clauses.

While processing complex-compound sentences (e.g., *'Max broke the china cup, with which Mary was awarded for the best song, so he regretted profoundly'*), first we generate emotional vectors of dependent clauses, then of complex sentences, and finally, we analyse the compound sentence formed by the independent clauses.

Our system enables the differentiation of the strength of the resulting emotion depending on the tense of a sentence and availability of first person pronouns. The dominant emotion of the sentence is determined according to the emotion state with the highest intensity within the final emotional vector.

## Experiment with Blog Entries

In order to evaluate the emotion recognition algorithm, we extracted 700 sentences from collection of diary-like blog posts provided by BuzzMetrics<sup>2</sup>. Three independent annotators labelled the sentences with one of nine emotion categories (or neutral) and a corresponding intensity value. Additionally, we interpreted these fine-grained annotations using three valence-based categories (positive emotion, negative emotion, and neutral) by merging *'Interest'*, *'Joy'*, and *'Surprise'* in positive emotion category, and *'Anger'*, *'Disgust'*, *'Fear'*, *'Guilt'*, *'Sadness'*, and *'Shame'* in negative emotion category. In our experiment, we considered the sentences and annotations, where two or three human raters completely agreed, as the *'gold standard'* for the evaluation of algorithm performance (in total, 656 sentences with fine-grained annotations, and 692 sentences with valence-based annotations).

To analyse the importance of words of different parts-of-speech in affect recognition, first we evaluated the performance of the Affect Analysis Model (AAM) with adjectives only, then we cumulatively added adverbs, verbs, and nouns to the algorithm. Averaged accuracy, precision, and recall at each step of this experiment are shown in Table 1 for each category. The obtained results indicate that consideration of all content parts of speech plays a crucial role in emotion recognition from text.

Next, we conducted *functional ablation* experiment. We compared complete AAM with all functionalities, core AAM without all additional functionalities, and five approaches where one specific functionality component (e.g., negation, neutralization due to modality, neutralization due to conditionality, modification by adverb-intensifiers, intensity correction) was ablated from complete AAM. Table 2 includes the results of this experiment, showing that AAM mostly benefits from rules on negation and conditionality.

<sup>2</sup> Weblog Data Collection. BuzzMetrics, Inc. <http://www.nielsenbuzzmetrics.com>

Table 1. Accuracy across sentences from blogs in the experiment with words of different parts-of-speech

Algorithm	Measure	Fine-grained categories										Merged labels		
		Neut	Ang	Disg	Fear	Guilt	Inter	Joy	Sad	Sh	Sur	Pos	Neg	Neut
AAM & adjectives	Averaged accuracy	0.389										0.439		
	Precision	0.15	0.77	0.69	0.61	0.73	0.62	0.79	0.78	0.50	0.82	0.85	0.92	0.14
	Recall	0.79	0.17	0.30	0.29	0.36	0.37	0.47	0.25	0.44	0.33	0.49	0.33	0.79
AAM & adjectives, adverbs	Averaged accuracy	0.416										0.470		
	Precision	0.16	0.67	0.69	0.60	0.75	0.59	0.79	0.80	0.50	0.87	0.84	0.93	0.15
	Recall	0.77	0.17	0.30	0.31	0.41	0.37	0.50	0.28	0.44	0.47	0.53	0.36	0.77
AAM & adjectives, adverbs, verbs	Averaged accuracy	0.640										0.720		
	Precision	0.28	0.91	0.59	0.72	0.73	0.63	0.86	0.78	0.55	0.86	0.86	0.94	0.25
	Recall	0.65	0.36	0.63	0.69	0.50	0.81	0.73	0.57	0.67	0.72	0.80	0.67	0.65
AAM & adjectives, adverbs, verbs, nouns	Averaged accuracy	0.726										0.816		
	Precision	0.46	0.83	0.63	0.76	0.75	0.56	0.87	0.78	0.57	0.85	0.85	0.92	0.41
	Recall	0.55	0.41	0.73	0.84	0.68	0.88	0.83	0.72	0.89	0.77	0.90	0.81	0.55

Table 2. Averaged accuracy in functional ablation experiment

Algorithm	Fine-grained categories	Merged labels
Complete AAM	0.726	0.816
Core AAM	0.659	0.772
AAM w/o negation	0.688	0.790
AAM w/o modality	0.720	0.814
AAM w/o conditionality	0.707	0.808
AAM w/o modification by adverb-intensifiers	0.723	0.814
AAM w/o intensity correction	0.723	0.816

The analysis of errors of complete AAM in the assignment of valence-based categories revealed that system requires common sense or additional context to deal with 28.5% of all errors. As human annotators labelled sentences only using fine-grained emotion categories and could assign ‘neutral’ to non-emotional but having strong valence cases, we can consider next type of errors (21%) as nonstrict one in the experiment with merged labels, where ‘gold standard’ was based on fine-grained emotion annotations. In 9% of cases, where system result did not agree with the ‘gold standard’ due to the rule of neutralization of negated phrases, the solution would be to reverse the valence of a statement, however, finding the pairs of opposite emotions might be problematic. The errors resulted from neutralization due to ‘cognition-related’ words (‘assume’, ‘know’ etc.) comprise 6.8% of errors. The failures also include some exceptional cases with connector ‘but’ (6%), errors caused by the lack of relevant terms in Affect database (6%), incorrect results from syntactical parser (4.5%), neutralization due to ‘can’, ‘could’, ‘may’, ‘would’ (3.8%), sense ambiguity (3%), neutralization due to condition (3%), and others.

## Conclusions

The Affect Analysis Model was designed based on the compositionality principle. The proposed rule-based algorithm enables analysis of emotions at various

grammatical levels. Our system showed promising results in affect recognition in sentences extracted from diary-like blog posts and fairy tales. Currently, the main limitations of the developed affect recognition module are: strong dependency on the source of lexicon, Affect database, and the commercially available syntactic parser; no disambiguation of word senses; and disregard of contextual information.

## References

- Alm, C.O. 2008. Affect in Text and Speech. Ph.D. diss., University of Illinois at Urbana-Champaign.
- Brenneis, D. 1990. Shared and Solitary Sentiments. In C. Lutz and L. Abu-Lughod (eds.), *Language and the Politics of Emotion*. Cambridge: Cambridge University Press.
- Izard, C.E. 1971. *The Face of Emotion*. New York: Appleton-Century-Crofts.
- Liu, H., Lieberman, H., and Selker, T. 2003. A Model of Textual Affect Sensing Using Real-World Knowledge. In *Proceedings of the International Conference on Intelligent User Interfaces*, 125-132.
- Moilanen, K. and Pulman, S. 2007. Sentiment Composition. In *Proceedings of the Recent Advances in Natural Language Processing International Conference*, 378-382.
- Mulder, M., Nijholt, A., den Uyl, M., and Terpstra, P. 2004. A Lexical Grammatical Implementation of Affect. In *Proceedings of the Seventh International Conference on Text, Speech and Dialogue*, 171-178. Berlin: Springer.
- Nasukawa, T., and Yi, J. 2003. Sentiment Analysis: Capturing Favorability using Natural Language Processing. In *Proceedings of Second International Conference on Knowledge Capture*, 70-77.
- Neviarouskaya, A., Prendinger, H., and Ishizuka, M. 2007. Textual Affect Sensing for Sociable and Expressive Online Communication. In *Proceedings of Second International Conference on Affective Computing and Intelligent Interaction*, 220-231. Springer LNCS 4738.
- Wilson, T., Wiebe, J., Hoffmann, P. 2005. Recognizing Contextual Polarity in Phrase-Level Sentiment Analysis. In *Proceedings of HLT/EMNLP Conference*, 347-354.