SEMANTICALLY DISTINCT VERB CLASSES INVOLVED IN SENTIMENT ANALYSIS

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ABSTRACT

The paper describes a novel rule-based approach to classification of opinion statements on the level of individual sentences. In contrast to existing approaches, the proposed method relies on the rules elaborated for semantically distinct verb classes. To deeply analyse the type, strength, and confidence level of expressed opinion, the system relies on the compositionality principle and lexicon of sentiment-conveying terms, functional words, modifiers, and modal expressions. The method is capable of processing sentences of different complexity, including simple, compound, complex (with complement and relative clauses), and complex-compound sentences.

KEYWORDS

Opinion mining, sentiment analysis.

1. INTRODUCTION AND RELATED WORKS

With rapidly growing online sources aimed at encouraging and stimulating people's discussions concerning public or social issues (news, blogs, discussion forums, etc.), there is a great need in development of computational tool for the analysis of people's attitudes. Thurstone (1931) considered people's opinions and beliefs to be verbal expressions of attitude with differing degrees of favorableness or unfavorableness toward the attitude object. According to the Appraisal Theory (Martin and White, 2005), attitude types define the specifics of appraisal being expressed: affect (personal emotional state), judgment (social or ethical appraisal of other's behaviour), and appreciation (evaluation of phenomena). Opinions have subjective nature, they are held with different levels of confidence, but are not substantiated by verification.

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, of recognition of attitude type expressed in text at various grammatical levels, and extraction of opinion related data (e.g., opinion holder, topic, attributes, values, etc.).

To support applications relying on recognition of textual subjectivity, sentiment orientation, and affective language, researchers created different sources: subjective (Wilson et al, 2005), affective (Strapparava and Valitutti, 2004), appraisal (Argamon et al, 2007) and polarity (Hatzivassiloglou and McKeown, 1997; Esuli and Sebastiani, 2006) lexicons.

Researchers have been approaching the task of measuring the word-level sentiment orientation and strength using (1) supervised learning algorithm determining semantic orientation of adjectives from the use of conjoint adjectives (Hatzivassiloglou and McKeown, 1997); (2) Latent Semantic Analysis and Pointwise-

Mutual Information (Turney and Littman, 2003); (3) WordNet structure relations (Kamps and Marx, 2002; Kim and Hovy, 2004; Andreevskaia and Bergler, 2006).

To analyse sentiment on the phrase/clause/sentence level, simple methods for combination of individual sentiments of sentiment-bearing words were proposed by Kim and Hovy (2004): polarities combination where "negatives cancel one another out"; harmonic and geometric means of the sentiment strengths within analyzed textual level. Some researchers employed unsupervised (Yu and Hatzivassiloglou, 2003) and supervised (Alm et al, 2005) statistical techniques. Machine-learning method using not only lexical but also syntactic features was proposed in (Wilson et al, 2005). However, strong dependency of statistical based techniques on domain, topic, language style, and large amounts of data to gather meaningful statistics, as well as neglect of discourse and syntactical structure, affect on the accuracy of sentiment classification at small textual composition levels.

Rule-based approaches targeting the analysis of contextual sentiment were proposed in (Nasukawa and Yi, 2003; Mulder et al, 2004; Moilanen and Pulman, 2007). Nasukawa and Yi (2003) developed method to extract and classify local sentiment expressions (as positive or negative) for given specific subjects. The limitations of this approach are domain-dependent manually developed lexicon, no anaphora resolution, and inability to deal with long complex sentences containing embedded clauses due to shallow parsing. The lexical, grammatical approach introduced by Mulder et al. (2004) focused on the propagation of affect towards an object. Moilanen and Pulman (2007) proposed a theoretical composition model for sentiment analysis at various grammatical levels. The experiments with the developed lexical system revealed the crucial dependency of this approach on a wide-coverage lexicon, accurate parsing, and sentiment sense disambiguation. The model of integration of machine learning approach with compositional semantics is described in (Choi and Cardie, 2008).

Kessler's (2008) research focuses on the modeling of semantic framework, that consists of 12 classes of linguistic elements ("Veridicality Elements") having the potential to change the stance toward the proposition, and development of rule-based approach to true/false classification of beliefs expressed in preposition statement. Given a proposition and its sentential context, the proposed system determines if its writer agrees with, denies, or takes no stance towards the proposition's truth-value.

The detailed algorithm for scoring the combinations of adverbs, verbs, and adjectives on a scale from -1 ("maximally negative") to +1 (maximally positive) is described in (Subrahmanian and Reforgiato, 2008). For opinion mining, researchers employed only certain categories of verbs that positively or negatively reinforce the expressed opinion, and completely ignored the sentiment of nouns, thus greatly narrowing the potential of their approach.

Casey et al. (2005) used machine learning (SVM) with fine-grained semantic distinctions in features (attitude type, namely affect, judgment, and appreciation; and orientation) in combination with 'bag of words' to classify movie reviews. However, the concentration of the researchers only on adjectives, that express appraisal, and their modifiers, is the limitation of this approach, as it was proved that all content parts of speech play crucial role in sentiment analysis (Neviarouskaya et al, 2009a).

The main limitations of existing approaches are: (1) lexicon-based systems for sentiment analysis suffer from limitation in lexicon coverage; (2) rules for polarity score combinations are too generalized; (3) semantics of lexical terms and sense ambiguity are ignored; (4) concentration on contextual valence shifters is shallow; (5) no or little attention is paid to modality and confidence level in relation to expressed opinion.

In this paper we describe the compositionality principle applied to classification of opinion statements on the level of individual sentences, and introduce a novel way of deep sentiment analysis based on the rules elaborated for semantically distinct verb classes. The developed system identifies opinion type, strength, confidence level, and related reasons. To our knowledge, this is the only work extensively dealing with semantics of verbs in opinion mining.

2. BUILDING THE LEXICON

We built the lexicon for sentiment analysis that includes: (1) sentiment-conveying terms with assignments of attitude type, prior polarity orientation (positive and negative), and the strength of sentiment; (2) functional words; (3) modifiers; and (4) modal operators.

2.1 The Core of Sentiment Lexicon

As a core of sentiment lexicon, we employ SentiFul database (Neviarouskaya et al, 2009b), which contains in total 10657 sentiment-conveying entries: 3445 adjectives (e.g., '*euphoric*', '*hostile*'), 834 adverbs (e.g., '*luckily*', '*miserably*'), 4431 nouns (e.g., '*fright*', '*mercy*'), and 1947 verbs (e.g., '*reward*', '*blame*'), which are annotated by sentiment polarity, polarity scores and weights. In our work, for both opposite valences (positive and negative), the bounds of the polarity score are 0.0 (indicating the absence of given orientation of sentiment) and 1.0 (the utmost value). Some examples of SentiFul entries are listed in Table 1.

Since we aim to classify opinion expressions using not only polarity orientation, but also attitude type, we extended the SentiFul annotations of adjectives, adverbs, nouns, and verbs using the following categories from the Appraisal Theory (Martin and White, 2005): 'affect', 'judgment', and 'appreciation'.

Table 1. Examples of words with sentiment annotations from SentiFul

POS	Lemma	Polarity scores		Polarity weights	
		Pos_score	Neg_score	Pos_weight	Neg_weight
adjective	*lovable*	0.85	0.0	1.0	0.0
	tremendous	0.75	0.1	0.67	0.33
adverb	*advantageously*	0.3	0.0	1.0	0.0
	frightfully	0.0	0.95	0.0	1.0
noun	*success*	0.67	0.0	1.0	0.0
	spoilage	0.133	0.3	0.167	0.833
verb	*privilege*	0.2	0.0	1.0	0.0
	regret	0.0	0.15	0.0	1.0

2.2 Functional Words

Inspired by the works of Nasukawa and Yi (2003) and Polanyi and Zaenen (2004), we distinguish the following types of functional words:

(1) 'reversal' type of adjectives (e.g., '*reduced*'), nouns (e.g., '*reduction*', '*termination*'), and verbs (e.g., '*to reduce*', '*to limit*'), which reverse the prior polarity of related words;

(2) 'propagation' type of verbs, which propagate the sentiment towards the arguments (e.g., positive polarity of '*respect*' is propagated to the object in '*to respect OBJ*', or negative polarity of '*fail*' is propagated to the subject in '*SUBJ fail*');

(3) 'transfer' type of verbs, which transmit sentiments among the arguments (e.g., positive or negative polarity of object is transmitted to the subject in '*SUBJ serve OBJ*').

The 'propagation' and 'transfer' types of verbs, as proposed in (Nasukawa and Yi, 2003), are useful for the task of detection of local sentiments for given subjects.

2.3 Modifiers

We collected modifiers that have an impact on contextual sentiment features of neighbouring words, related phrases, or clauses. The modifiers include:

(1) adverbs of degree (e.g., '*significantly*', '*slightly*' etc.) that influence on the strength of sentiment of the related words;

(2) negation words (e.g., '*never*', '*nothing*', '*no*' etc.) that reverse the polarity of related statement;

(3) adverbs of doubt (e.g., '*scarcely*', 'hardly' etc.) that reverse the polarity of related statement;

(4) prepositions (e.g., '*without*', '*despite*' etc.) that neutralize the sentiment of related words;

(5) condition operators (e.g., '*as if*', '*if*', '*even though*' etc.) that neutralize the sentiment of related words.

Adverbs of degree affect on neighbouring verbs, adjectives, or another adverb, and are used to mark that the extent or degree is either greater or less than usual. Two annotators gave coefficients for intensity degree strengthening or weakening (from 0.0 to 2.0) to each of 112 collected adverbs, and the result was averaged (e.g., coeff('*perfectly*') = 1.9, coeff('*slightly*') = 0.2).

2.4 Modal Operators

Modality is concerned with assertions of probability, possibility, permission, intention, obligation and the like (Hoye, 1997). We consider two types of the modal operators as indicators of the confidence level of expressed opinion: (1) modal auxiliaries (e.g., '*can*', '*may*', '*might*', '*must*', '*should*'); (2) modal adverb satellites (e.g., '*definitely*', '*inevitably*', '*probably*', '*possibly*'). Two annotators assigned the level of confidence to each of the collected modal operators using scale from 0.0 to 1.0.

3. COMPOSITIONALITY PRINCIPLE

'*The full story of how lexical items reflect attitudes is more complex than simply counting the valences of terms*' (Polanyi and Zaenen, 2004)

Words in a sentence are interrelated and, hence, each of them can influence on the overall meaning and attitudinal bias of a statement. The algorithm for the classification of opinion type is designed based on the *compositionality principle*, according to which we determine the attitudinal meaning of a sentence by composing a pieces that correspond to lexical units or other linguistic constituent types governed by the rules of *polarity reversal*, *aggregation (fusion)*, *propagation*, *domination*, *neutralization*, and *intensification*, at various grammatical levels.

The rule of *polarity reversal* is applied in three cases: (1) negation word-modifier in relation with sentiment-conveying statement (e.g., '*never*' & POS('*succeed*') => NEG('*never succeed*')); (2) adverb of doubt in relation with sentiment-conveying statement (e.g., 'scarcely' & POS('relax') => NEG('*scarcely relax*')); (3) functional word of 'reversal' type in relation with sentiment-conveying statement (e.g., adjective '*reduced*' & POS('*enthusiasm*') => NEG('*reduced enthusiasm*')).

The rules of *aggregation (fusion)* are as follows: (1) if polarities of sentiment-conveying terms in adjective-noun, noun-noun, adverb-adjective, adverb-verb phrases have opposite directions, mixed polarity with dominant polarity of descriptive term is assigned to the phrase (e.g., POS('*beautiful*') & NEG('*fight*') => POS-neg('*beautiful fight*'); NEG('*shamelessly*') & POS('*celebrate*') => NEG-pos('*shamelessly celebrate*')); otherwise (2) the resulting polarity is based on the equal polarities of terms, and the strength of sentiment is measured as a maximum between polarity scores of terms (*max*(score1,score2)).

The rule of *propagation* is applied when functional verb of 'propagation' or 'transfer' type is used in a phrase/clause and it is necessary to detect the sentiment of a term that has prior neutral polarity (e.g., PROP-POS('*to admire*') & NEUT('*his behaviour*') => POS('*his behaviour*'); NEUT('*Mr. X*') & TRANS('*supports*') & NEG('*crime business*') => NEG('*Mr. X*')).

The rules of *domination* are as follows: (1) if polarities of verb (this rule is applied only for certain classes of verbs) and object in a clause have opposite directions, the resulting polarity is prevailing polarity of verb (e.g., NEG('*to deceive*') & POS('*hopes*') => NEG('*to deceive hopes*')); (2) if compound sentence joints clauses using coordinate connector 'but', the sentiment features of a clause following after the connector is dominant (e.g., 'NEG(*It was hard to climb a mountain all night long*), *but* POS(*a magnificent view rewarded the traveler at the morning*).' => POS(sentence)).

The rule of *neutralization* is applied when preposition-modifier or condition operator relate to the sentiment-conveying statement (e.g., '*despite*' & NEG('*troubles*') => NEUT('*despite troubles*')).

The rule of *intensification* means strengthening or weakening the polarity score, and is applied when (1) adverb of degree relates to sentiment-conveying term (e.g., Pos_score('*extremely happy*')=coeff('*extremely*')*Pos_score('*happy*')=2.0*0.6 > Pos_score('*happy*')=0.6); (2) adjective or adverb is used in comparative or superlative form (e.g., Neg_score('*sad*')=0.9 < Neg_score('*sadder*')=0.9*1.2 < Neg_score ('*saddest*')=0.9*1.4).

Our method is capable of processing sentences of different complexity, including simple, compound, complex (with complement and relative clauses), and complex-compound sentences. To understand how words and concepts relate to each other in a sentence, we employ syntactical parser, Connexor Machinese Syntax (*http://www.connexor.eu/*) that returns lemmas, parts of speech, dependency functions, syntactic function tags, and morphological tags. When handling the parser output, we represent the sentence as a set of primitive clauses. Each clause might include Subject formation, Verb formation and Object formation, each of which may consist of a main element (subject, verb, or object) and its attributives and complements. The developed algorithm can detect not only subjects represented by noun phrases, but also subjects represented by gerund (non-finite verb form) as in the sentence '*Walking on the beach is a pleasure*', by an infinitive as in the sentence '*To offend the youngest child is an obscene action*', or by a full clause, introduced by 'that', itself containing a subject and a predicate like in the sentence '*That tomorrow weather will be sunny is great*'. For the processing of complex or compound sentences, we build a so-called 'relation matrix', which contains information about dependences (e.g., coordination, subordination, condition, contingency, etc.) between different clauses in a sentence. While applying the compositionality principle, we consecutively assign sentiment features to words, phrases, formations, clauses, and finally, to the whole sentence.

4. CONSIDERATION OF THE SEMANTICS OF VERBS

All sentences must include a verb, because the verb tells us what action the subject is performing. In order to elaborate rules for sentiment analysis based on the semantics of verbs, we investigated VerbNet (Kipper et al, 2006), the largest on-line verb lexicon that is organized into verb classes characterized by syntactic and semantic coherence among members of a class. Based on the thorough analysis of 270 first-level classes of VerbNet and their members, 73 verb classes (1) were found useful for the task of sentiment analysis, and (2) were further classified into 22 classes differentiated by the role that members play in sentiment analysis and by rules applied to them. Our classification is shown in Table 2. For each of our verb classes, we developed set of rules that are applied to sentiment analysis on the phrase/clause-level.

Table 2. Verb classes defined for sentiment analysis

Verb class	Verb samples	Examples of VerbNet classes
1 Psychological state or emotional reaction		
1.1 Object-centered (oriented) emotional state	*appreciate*, *distrust*	Admire-31.2, Care-88.1 etc.
1.2 Subject-driven change in emotional state (trans.)	*charm*, *inspire*, *bother*	Amuse-31.1 etc.
1.3 Subject-driven change in emotional state (intrans.)	*appeal to*, *grate on*	Appeal-31.4
2 Judgment		
2.1 Positive judgment	*bless*, *honor*	Judgment-33-pos.
2.2 Negative judgment	*blame*, *punish*	Judgment-33-neg. etc.
3 Favorable attitude	*accept*, *allow*, *tolerate*	Allow-64, Appoint-29.1 etc.
4 Adverse (unfavorable) attitude	*discourage*, *elude*, *forbid*	Forbid-67, Refrain-69 etc.
5 Favorable or adverse calibratable changes of state	*grow*, *decline*	Calibratable_cos-45.6
6 Verbs of removing		
6.1 Verbs of removing with neutral charge	*delete*, *remove*	Remove-10.1
6.2 Verbs of removing with negative charge	*deport*, *expel*	Banish-10.2-neg., Fire-10.10 etc.
6.3 Verbs of removing with positive charge	*evacuate*, *cure*	Banish-10.2-pos., Free-80 etc.
7 Negatively charged change of state	*break*, *crush*, *smash*	Break-45.1
8 Bodily state and damage to the body	*sicken*, *injure*	Change_bodily_state-40.8.4 etc.
9 Aspectual verbs		
9.1 Initiation, continuation of activity, and sustaining	*begin*, *continue*, *maintain*	Begin-55.1, Sustain-55.6 etc.
9.2 Termination of activity	*quit*, *finish*	Complete-55.2, Stop-55.4
10 Preservation	*defend*, *insure*	Defend-85
11 Verbs of destruction and killing	*damage*, *poison*	Destroy-44, Murder-42.1 etc.
12 Disappearance	*disappear*, *die*	Disappearance-48-2
13 Limitation and subjugation	*confine*, *restrict*	Limit-76, Subjugate-42.3
14 Assistance	*succor*, *help*	Help-72
15 Obtaining	*win*, *earn*	Get-13.5.1
16 Communication indicator/reinforcement of attitude	*guess*, *complain*, *deny*	Advise-37.9, Conjecture-29.5 etc.
17 Verbs of leaving	*abandon*, *desert*	Leave-51.2, Resign-10.11
18 Changes in social status or condition	*canonize*, *widow*	Orphan-29.7
19 Success and failure		
19.1 Success	*succeed*, *manage*	Succeed-74-pos.
19.2 Failure	*fail*, *flub*	Succeed-74-neg.
20 Emotional nonverbal expression	*smile*, *weep*	Nonverbal_expression-40.2
21 Social interaction	*marry*, *divorce*	Correspond-36.1, Marry-36.2 etc.
22 Transmitting verbs	*supply*, *provide*	Fulfilling-13.4.1 etc.

Some verb classes include verbs annotated by prior positive or negative polarity (dominant scores were taken from SentiFul): "Psychological state or emotional reaction", "Judgment", "Verbs of removing with negative charge", "Verbs of removing with positive charge", "Negatively charged change of state", "Bodily state and damage to the body", "Preservation", and others. The sentiment features of phrases, which involve positively or negatively charged verbs from such classes, are context-sensitive, and are defined by means of rules designed for each of the class.

As an example, below we provide short description and rules elaborated for the subclass **"Object-centered (oriented) emotional state"**.

Features: subject experiences emotions towards some stimulus; verb prior polarity: positive or negative; context-sensitive.

Verb-Object rules (subject is ignored):

1. **"Interior perspective"** (subject's side, emotion state or attitude):

S & V+('*admires*') & O+('*his brave heart*') => (fusion, *max*(V_score,O_score)) => pos. affect.

S & V+('*admires*') & O-('*mafia leader*') => (verb valence dominance, V_score) => pos. affect.

S & V-('*disdains*') & O+('*his honesty*') => (verb valence dominance, V_score) => neg. affect.

S & V-('*disdains*') & O-('*criminal activities*') => (fusion, *max*(V_score,O_score)) => neg. affect.

2. **"Exterior perspective"** (social/ethical judgment):

S & V+('*admires*') & O+('*his brave heart*') => (fusion, *max*(V_score,O_score)) => pos. judgment.

S & V+('*admires*') & O-('*mafia leader*') => (verb valence reversal, *max*(V_score,O_score)) => neg. judgment.

S & V-('*disdains*') & O+('*his honesty*') => (verb valence dominance, *max*(V_score,O_score)) => neg. judgment.

S & V-('*disdains*') & O-('*criminal activities*') => (verb valence reversal, *max*(V_score,O_score)) => pos. judgment.

3. In case of neutral object: prior polarity of verb and verb score (V_score).

Verb-PP (prepositional phrase) rules:

1. In case of negatively charged verb and PP starting with '*from*', verb valence dominance:

S & V-('*suffers*') & PP-('*from illness*') => (interior: neg.); (exterior: neg.).

S & V-('*suffers*') & PP+ ('*from love*') => (interior: neg.); (exterior: neg.).

2. In case of positively charged verb and PP starting with '*in*'/'*for*', treat PP same as object (see above):

S & V+('*believes*') & PP-('*in evil*') => (interior: pos.); (exterior: neg.).

S & V+('*believes*') & PP+('*in kindness*') => (interior: pos.); (exterior: pos.).

In majority of rules the strength of sentiment is measured as a maximum between polarity scores of verb and object (*max*(V_score,O_score)), because strength of overall sentiment depends on both scores. For example, sentiment conveyed by '*to suffer from grave illness*' is stronger than that of '*to suffer from slight illness*'.

In contrast to the rules of **"Object-centered (oriented) emotional state"** subclass, which ignore sentiment features of a subject in a sentence, the rules elaborated for the **"Subject-driven change in emotional state (trans.)"** disregard the sentiment features of object, as in sentences involving members of this subclass object experiences emotion, and subject causes the emotional state. For example (due to limitation of space, here and below we provide only some cases):

S('*Classical music*') & V+('*calmed*') & O-('*disobedient child*') => (interior: pos.); (exterior: pos.).

S-('*Fatal consequences of GM food intake*') & V-('*frighten*') & O('*me*') => (interior: neg.); (exterior: neg.).

The Verb-Object rules for the subclasses **"Positive judgment"** and **"Negative judgment"** (verbs from **"Judgment"** class relate to a judgment or opinion that someone may have in reaction to something) are very close to those defined for the subclass **"Object-centered (oriented) emotional state"**. However, Verb-PP rules have some specifics: for both positive and negative judgment verbs, we treat PP starting with '*for*'/'*of*'/'*as*' same as object in Verb-Object rules. For example:

S('*He*') & V-('*blamed*') & O+('*innocent person*') => (interior: neg. judgment); (exterior: neg. judgment).

S('*They*') & V-('*punished*') & O('*him*') & PP-('*for his misdeed*') => (interior: neg. judgment); (exterior: pos. judgment).

Verbs from classes **"Favorable attitude"** and **"Adverse (unfavorable) attitude"** have prior neutral polarity and positive or negative reinforcement, correspondingly, that means that they only impact on the polarity and strength of non-neutral phrase (object in a sentence written in active voice, or subject in a sentence written in passive voice, or PP in case of some verbs).

Rules:

1. If verb belongs to the "Favorable attitude" class and the polarity of phrase is not neutral, then polarity score of the phrase is intensified (we use symbol '^' to indicate intensification):

S('*They*') & [V pos. reinforcement]('*elected*') & O+('*fair judge*') => positive; O_score^.

S('*They*') & [V pos. reinforcement]('*elected*') & O-('*corrupt candidate*') => negative; O_score^.

2. If verb belongs to the "Adverse (unfavorable) attitude" class and the polarity of phrase is not neutral, then polarity of the phrase is reversed and score is intensified:

S('*They*') & [V neg. reinforcement]('*prevented*') & O-('*the spread of disease*') => positive; O_score^.

S+('*His achievements*') & [V neg. reinforcement]('*were overstated*') => negative; S_score^.

Below are some examples of processing the sentences with verbs belonging to **"Verbs of removing"** class.

"Verbs of removing with neutral charge":

S('*The tape-recorder*') & [V neutral rem.]('*automatically ejects*') & O-neutral('*the tape*') => neutral.

S('*The safety invention*') & [V neutral rem.]('*ejected*') & O('*the pilot*') & PP-('*from burning plane*') => positive; PP_score^.

"Verbs of removing with negative charge":

S('*Manager*') & [V neg. rem.]('*fired*') & O-('*careless employee*') & PP('*from the company*') => positive; *max*(V_score,O_score).

"Verbs of removing with positive charge":

S('*They*') & [V pos. rem.]('*evacuated*') & O('*children*') & PP-('*from dangerous place*') => positive; *max*(V_score,PP_score).

Along with modal auxiliarities and modal adverb satellites, members of **"Communication indicator/reinforcement of attitude"** verb class also indicate the confidence level or degree of certainty concerning given opinion.

Features: subject (communicator) expresses statement with/without attitude; statement is PP starting with '*of*', '*on*', '*against*', '*about*', '*concerning*', '*regarding*', '*that*', '*how*' etc.; ground: positive or negative; reinforcement: positive or negative.

Rules:

1. If the polarity of expressed statement is neutral, then sentiment is neutral:

S('*Professor*') & [V pos. ground, pos. reinforcement, confidence:1.0]('*dwelled*') & PP-neutral('*on a question*') => neutral.

2. If the polarity of expressed statement is not neutral and reinforcement is positive, then polarity score of the statement (PP) is intensified:

S('*Jane*') & [V neg. ground, pos. reinforcement, confidence:1.0]('*is complaining*') & PP-('*of a headache again*') => negative; PP_score^; confidence:1.0.

3. If the polarity of expressed statement is not neutral and reinforcement is negative, then polarity of the statement (PP) is reversed and score is intensified:

S('*Max*') & [V neg. ground, neg. reinforcement, confidence:0.2]('*doubt*') & PP-{'*that*' S+('*his good fortune*') & [V termination]('*will ever end*')} => positive; PP_score^; confidence:0.2.

In the last example, to measure the sentiment of PP, we apply rule for the verb '*end*' from the **"Termination of activity"** class, which reverses the non-neutral polarity of subject (in intransitive use of verb) or object (in transitive use of verb). For example, sentiment of a sentence with positive PP '*They discontinued helping children*' is negative.

5. CONCLUSION

In this paper, we introduced a novel rule-based approach to the analysis of opinion statements on the level of individual sentences. We developed the classification of verbs relevant for sentiment analysis, and elaborated rules for each verb class. The advantage of our method is consideration of semantics of verbs, which allows accurate and robust automatic analysis of opinion type, strength, and confidence level, and broadens the coverage of sentences with complex contextual sentiment. The limitations include dependency on lexicon, on accuracy of the parser, and lack of term sense disambiguation. The primary objective for the future research is to implement a procedure for automatic update of the sentiment lexicon.

REFERENCES

Alm, C.O., Roth, D., and Sproat, R., 2005. Emotions from Text: Machine Learning for Text-based Emotion Prediction. *Proceedings of the Human Language Technology Conference and Conference on Empirical Methods in Natural Language Processing*, pp. 579-586.

Andreevskaia, A. and Bergler, S., 2006. Mining WordNet for Fuzzy Sentiment: Sentiment Tag Extraction from WordNet Glosses. *Proceedings of the 11th Conference of the European Chapter of the Association for Computational Linguistics*, pp. 209-216.

Argamon, S. et al, 2007. Automatically Determining Attitude Type and Force for Sentiment Analysis. *Proceedings of the 3rd Language and Technology Conference*.

Casey, W., Garg, N., and Argamon, S., 2005. Using Appraisal Groups for Sentiment Analysis. *Proceedings of the 14th ACM International Conference on Information and Knowledge Management*, CIKM, Bremen, DE.

Choi, Y., Cardie, C., 2008. Learning with Compositional Semantics as Structural Inference for Subsentential Sentiment Analysis. *Proceedings of Conference on Empirical Methods in Natural Language Processing*, pp. 793-801.

Esuli, A. and Sebastiani, F., 2006. SentiWordNet: a Publicly Available Lexical Resource for Opinion Mining. *Proceedings of the 5th International Conference on Language Resources and Evaluation*, pp. 417-422.

Hatzivassiloglou, V. and McKeown, K.R., 1997. Predicting the Semantic Orientation of Adjectives. *Proceedings of the 35th Annual Meeting of the Association for Computational Linguistics and the 8th Conference of the European Chapter of the ACL*, pp. 174-181.

Hoye, L., 1997. *Adverbs and Modality in English*. Addison Wesley Longman Inc., New York, US.

Kamps, J. and Marx, M., 2002. Words with Attitude. *Proceedings of the Belgian-Dutch Conference on Artificial Intelligence*, pp. 449-450.

Kessler, J.S., 2008. Polling the Blogosphere: a Rule-Based Approach to Belief Classification. *Proceedings of the International Conference on Weblogs and Social Media*.

Kim, S.-M. and Hovy, E., 2004. Determining the Sentiment of Opinions. *Proceedings of the Conference on Computational Linguistics*, COLING, pp. 1367-1373.

Kipper, K. et al, 2006. A Large-scale Extension of VerbNet with Novel Verb Classes. *Proceedings of the EURALEX*.

Martin, J.R. and White, P.R.R., 2005. *The Language of Evaluation: Appraisal in English*. Palgrave, London, UK.

Moilanen, K. and Pulman, S., 2007. Sentiment Composition. *Proceedings of the Recent Advances in Natural Language Processing International Conference*, pp. 378-382.

Mulder, M. et al, 2004. A Lexical Grammatical Implementation of Affect. *Proceedings of the 7th International Conference on Text, Speech and Dialogue*, Springer, pp. 171-178.

Nasukawa, T. and Yi, J., 2003. Sentiment Analysis: Capturing Favorability using Natural Language Processing. *Proceedings of the 2nd International Conference on Knowledge Capture*, pp. 70-77.

Neviarouskaya, A., Prendinger, H., and Ishizuka, M., 2009a. Compositionality Principle in Recognition of Fine-Grained Emotions from Text. *Proceedings of the International Conference on Weblogs and Social Media*, AAAI, San Jose, US, pp. 278-281.

Neviarouskaya, A., Prendinger, H., and Ishizuka, M. 2009b. SentiFul: Generating a Reliable Lexicon for Sentiment Analysis. *Proceedings of the International Conference on Affective Computing and Intelligent Interaction*, IEEE, Amsterdam, Netherlands.

Polanyi, L. and Zaenen, A., 2004. Contextual Valence Shifters. *In Working Notes of the AAAI Spring Symposium on Exploring Attitude and Affect in Text: Theories and Applications*.

Strapparava, C. and Valitutti, A., 2004. WordNet-Affect: an Affective Extension of WordNet. *Proceedings of the International Conference on Language Resources and Evaluation*, pp. 1083-1086.

Subrahmanian, V.S. and Reforgiato, D., 2008. AVA: Adjective-Verb-Adverb Combinations for Sentiment Analysis. *In Intelligent Systems*, IEEE, Vol. 23, No. 4, pp. 43-50.

Thurstone, L.L., 1931. The Measurement of Attitudes. *In Journal of Abnormal and Social Psychology*, Vol. 26, pp. 249-269.

Turney, P.D. and Littman, M.L., 2003. Measuring Praise and Criticism: Inference of Semantic Orientation from Association. *In ACM Transactions on Information Systems*, Vol. 21, No. 4, pp. 315-346.

Wilson, T., Wiebe, J., and Hoffmann, P., 2005. Recognizing Contextual Polarity in Phrase-level Sentiment Analysis. *Proceedings of Human Language Technology Conference and Conference on Empirical Methods in Natural Language Processing*. Vancouver, Canada, pp. 347-354.

Yu, H. and Hatzivassiloglou, V., 2003. Towards Answering Opinion Questions: Separating Facts from Opinions and Identifying the Polarity of Opinion Sentences. *Proceedings of the Conference on Empirical Methods in Natural Language Processing*, pp. 129-136.