SentiFul: A Lexicon for Sentiment Analysis

Alena Neviarouskaya, Helmut Prendinger, and Mitsuru Ishizuka, *Member*, *IEEE*

Abstract—In this paper, we describe methods to automatically generate and score a new sentiment lexicon, called SentiFul, and expand it through direct synonymy and antonymy relations, hyponymy relations, derivation, and compounding with known lexical units. We propose to distinguish four types of affixes (used to derive new words) depending on the role they play with regard to sentiment features: propagating, reversing, intensifying, and weakening. Besides derivation, we considered important process of finding new words such as compounding, which is a highly productive process, especially in the case of nouns and adjectives. We elaborated the algorithm for automatic extraction of new sentiment-related compounds from WordNet using words from SentiFul as seeds for sentiment-carrying base components and applying the patterns of compound formations. In the paper, the importance of considering modifiers, contextual valence shifters, and modal operators, which are integral parts of the SentiFul lexicon for robust sentiment analysis, is also discussed.

Index Terms—Linguistic processing, mining methods and algorithms, thesauruses.

1 Introduction

Sentiment analysis today is a rapidly developing field with a variety of emerging approaches targeting the recognition of sentiment reflected in written language. Sentiment-related information can be encoded lexically within the actual words of the sentence, syntactically, and morphologically through changes in attitudinal shades of word meaning using suffixes [1].

To support applications relying on the recognition of textual subjectivity, semantic orientation, and affective language, researchers created different resources: subjective [2], affective [3], appraisal [4], and polarity [5], [6] lexicons. Methods for extracting and annotating subjective terms include: machine learning approaches examining the conjunction relations between adjectives [5], clustering adjectives according to distributional similarity based on a small amount of annotated seed words [7], pattern-bootstrapping algorithms to extract nouns [8], consideration of Web-based mutual information in ranking subjective adjectives [9], bootstrapping employing a small set of seed subjective terms and an online dictionary, plus filtering the candidates based on a similarity measure [10], and morphosyllabic sentiment tagging [11].

A useful sentiment lexicon would contain assignments of polarity orientation (positive and negative) and also the strength of sentiment or, in some cases, the degree of centrality to the sentiment category. To determine the word-level strength of sentiment, Latent Semantic Analysis (LSA) [12], the pointwise mutual information (PMI) technique [12], [13], and methods employing WordNet [14] structure relations [15], [16], [17] were proposed.

Most lexicon-based systems for analysis of sentiment on sentence or document levels face the difficulty of assigning sentiment scores to words that are not available in their databases. To deal with limitation in lexicon coverage, we will therefore propose methods (based on our previous work [18]) to automatically build and expand the sentiment lexicon (SentiFul) represented by sentiment-conveying words, which are annotated by sentiment polarity, polarity scores, and weights. The examples of applications that may be supported by SentiFul include public opinion mining, analysis of trends in consumers' subjective feedback, sentiment-based recommendation system, integration into online communication media, and social networks, etc.

Although many researchers have already attempted to extract and score new words through synonymy and antonymy relations, derivation of new sentiment lexemes by manipulation with morphological structure of words, as well as compounding using sentiment-conveying terms as key elements, were not well explored. To our knowledge, the only works employing morphological analysis for sentiment tagging of words are [11] (English words are transformed and compared with known sentiment lemmas and affixes) and [19] (polarities of Chinese opinion-related compound words are predicted based on the analysis of their morphological structure).

In our work, we approach the problem from the opposite direction: Based on sentiment-scored lemmas and types of affixes, new words are automatically built and scored. We also developed an algorithm to extract sentiment-conveying compounds, and elaborated the rules for scoring them based on the patterns according to which the compounds are created. In addition to the sentiment-related entries, we are proposing to collect 1) modifiers and intensifying/reversing words that influence the contextual sentiment (or its strength) of phrases or sentences, and 2) modal operators that indicate the confidence degree with which the opinion statement is expressed.

- A. Neviarouskaya and M. Ishizuka are with the Department of Information and Communication Engineering, Graduate School of Information Science and Technology, University of Tokyo, Eng. Bldg. 2, 7-3-1 Hongo, Bunkyo-ku, Tokyo 113-8656, Japan.
E-mail: lena@mi.ci.i.u-tokyo.ac.jp, ishizuka@i.u-tokyo.ac.jp.
- H. Prendinger is with the Digital Content and Media Sciences Research Division, National Institute of Informatics, 2-1-2 Hitotsubashi, Chioda-ku, Tokyo. E-mail: helmut@nii.ac.jp.

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The remainder of the paper is structured as follows: In Section 2, we report on related work. In Section 3, we describe the core of our sentiment lexicon, SentiFul.[1] The possibility of expanding SentiFul by means of the SentiWordNet lexicon [6] is explored in Section 4. Methods for extracting new sentiment-related terms and their evaluations are detailed in Sections 5 and 6, respectively. In Section 7, we discuss the types of modifiers and intensifying/reversing words. Section 8 describes modal operators. In Section 9, we conclude the paper.

2 Related Work

First, we discuss methods for extracting subjective terms and assigning sentiment polarity to them. Hatzivassiloglou and McKeown [5] assumed that, given the set of adjectives with predetermined orientation labels (positive or negative) and the pairs of adjectives conjoined using the conjunctions "*and*," "*or*," "*but*," "*either-or*," "*neither-nor*," it is possible to predict the orientation of two conjoined adjectives. A log-linear regression model that was automatically constructed based on the constraints on the orientations of conjoined adjectives from the corpus, in combination with supplementary morphology rules, predicted whether two conjoined adjectives are of the same or opposite orientation with a high level of accuracy (82 percent). Wiebe [7] proposed a method for identifying strongly subjective adjectives clustered according to distributional similarity. Two bootstrapping algorithms aimed at the generation of lists of subjective nouns by exploiting extraction patterns (e.g., "*expressed* <dobj>," "*voiced* <dobj>," etc.), which are discovered to be associated with 20 seed subjective nouns (e.g., "*delight*," "*embarrassment*," etc.), are described in [8]. The main assumption behind this bootstrapping approach is that words of the same semantic class appear in similar pattern contexts. Baroni and Vegnaduzzo [9] proposed ranking a large list of adjectives according to a subjectivity score by employing a small set of manually selected subjective adjectives and computing the mutual information of pairs of adjectives (seed adjective and adjective to be ranked) using frequency and co-occurrence frequency counts on the Web. The spin model for prediction of polarity of words based on analysis of semantic relations (synonymy, antonymy, and hyponymy) and glosses was introduced by Takamura et al. [20]. To assign subjectivity labels to word senses, methods relying on distributional similarity [21] and on semi-supervised minimum cut algorithm [22] were proposed.

Next, we describe methods that assign not only polarity orientation, but also strength or degree of sentiment to the sentiment-conveying words. Turney and Littman [12] proposed an approach to measure the semantic orientation of a given word based on the strength of its association with a set of seven context-insensitive positive words (e.g., "*good*," "*excellent*," etc.), minus the strength of its association with a set of seven negative words (e.g., "*bad*," "*poor*," etc.). Researchers compared two different statistical measures of word association, PMI and LSA, and found that the method relying on PMI is less accurate and less stable than the LSA method. Limitations of these statistical methods include: size of corpora required for good performance, long processing time, and problem of word sense disambiguation. Kamps and Marx [15] investigated measures for affective and emotive aspects of meaning obtained from the structure of the WordNet lexical database. Since the meaning of a concept in WordNet is determined by its position relative to other concepts, the authors decided to evaluate individual words (specifically, adjectives) by determining their relation (or distance) to the words "*good*" and "*bad*," and assigning values in the interval $[-1; 1]$. To determine word-level sentiment, Kim and Hovy [16] developed two models which expand the list of a small amount of seed verbs and adjectives, manually annotated with sentiment labels (positive or negative), by means of exploration of basic semantic relations in WordNet such as synonymy and antonymy relations. For each word, both positive and negative strengths were computed. Research on mining WordNet for fuzzy sentiment was conducted by Andreevskaia and Bergler [17], who proposed a method for extracting sentiment-bearing adjectives from WordNet using a set of positive and negative seed words. After expanding the list of seed words by their synonyms, antonyms, and hyponyms found in WordNet, the algorithm analyzed all WordNet glosses and extracted the terms which contained in their definitions the sentiment-conveying words from the compiled list. The method developed by Esuli and Sebastiani [6] quantitatively analyzes the glosses associated with synsets of adjectives, adverbs, nouns, and verbs, and assigns three numerical scores (objectivity, positivity, and negativity) to each synset of WordNet.

3 Generating the Core of Sentiment Lexicon

The first step in building lexicon of sentiment-conveying terms involves the collection of relevant content words and the assignment of prior polarity scores (positivity score and negativity score) to each lexical unit. By "sentiment polarity score," we mean the strength or degree of intensity of sentiment (for example, "*cheerful*," "*happy*," and "*elated*" have different strengths of positivity). In our work, for both opposite valences, the bounds of the polarity score are 0.0 (indicating the absence of given orientation of sentiment) and 1.0 (the utmost value of intensity).

For the generation of the core of our sentiment lexicon, we employ the Affect database [23], which contains, in total, 2,438 direct and indirect (having the potential to elicit affective states in humans) emotion-related entries: 918 adjectives (e.g., "*euphoric*," "*hostile*," "*beautiful*"), 243 adverbs (e.g., "*luckily*," "*miserably*"), 900 nouns (e.g., "*fright*," "*mercy*," "*disaster*"), and 377 verbs (e.g., "*reward*," "*blame*," "*deceive*"). The affective features of each distinct word in this database are encoded using nine emotions ("anger," "disgust," "fear," "guilt," "interest," "joy," "sadness," "shame," and "surprise" [24]), and are represented as a vector of emotional state intensities that range from 0.0 to 1.0. Using emotional vectors, we interpreted the sentiment of Affect database entries by means of polarity scores and polarity weights. Polarity weight means the rate of the number of positive (negative) emotions with intensity

1. SentiFul is freely available upon request for research purposes.

TABLE 1
Examples of Words with Sentiment Annotations from SentiFul

Affective word	POS	Non-zero-intensity emotions from Affect database emotional vector	Polarity scores		Polarity weights	
			Pos_score	*Neg_score*	*Pos_weight*	*Neg_weight*
tremendous	adjective	'surprise:1.0', 'joy:0.5', 'fear:0.1'	0.75	0.1	0.67	0.33
pensively	adverb	'sadness:0.2', 'interest:0.1'	0.1	0.2	0.5	0.5
success	noun	'joy:0.9', 'interest:0.6', 'surprise:0.5'	0.67	0.0	1.0	0.0
regret	verb	'guilt:0.2', 'sadness:0.1'	0.0	0.15	0.0	1.0

greater than 0.0 to the total number of emotions with intensity greater than 0.0 in the emotional vector (positive and negative weights add up to 1.0). We considered three emotions ("interest," "joy," and "surprise") as having mainly positive orientation, and six emotions ("anger," "disgust," "fear," "guilt," "sadness," and "shame") as negatively valenced.

Positivity and negativity scores were calculated using (1) and (2). Based on (3) and (4), we derived the polarity weights.

$$Pos\_score = \left[\frac{\sum_{i=1}^{pos} Intensity(i)}{pos}\right], \tag{1}$$

$$Neg\_score = \left[\frac{\sum_{i=1}^{neg} Intensity(i)}{neg}\right], \tag{2}$$

$$Pos\_weight = \left[\frac{pos}{pos + neg}\right], \tag{3}$$

$$Neg\_weight = \left[\frac{neg}{pos + neg}\right], \tag{4}$$

whereby *Intensity* is the intensity value of the corresponding emotion in the emotional vector; *pos* (*neg*) is the number of positive (negative) emotions having $Intensity > 0.0$ in the emotional vector, respectively.

We named our sentiment database "SentiFul." Some examples of SentiFul entries are listed in Table 1. The main drawback of a sentiment analysis approach which relies upon a lexicon of sentiment-conveying terms is the lack of scalability since the recall of the lexicon-based method depends on the coverage of the database used. Thus, to expand SentiFul, we first investigated the possibility of taking advantage of sense-level scores from SentiWordNet (version 1.0) [6].

4 Examining SentiWordNet

SentiWordNet was developed based on WordNet [14] synsets comprised from synonymous terms. Motivated by the assumption that "*different senses of the same term may have different opinion-related properties*," Esuli and Sebastiani [6] developed a method employing eight ternary classifiers and quantitatively analyzing the glosses associated with synsets. Three numerical scores ($Obj(s)$, $Pos(s)$, and $Neg(s)$), which characterize to what degree the terms included in a synset are objective, positive, and negative, were automatically determined based on the proportion of classifiers assigning the corresponding label to the synset. The scores range from 0.0 to 1.0 and sum up to 1.0.

The question "*How reliable is SentiWordNet?*" arose at the very beginning of its exploration, just after analyzing the scores of synsets that include the adjective "*happy*" (Table 2). Three out of six synsets are characterized by negativity predominance ($Neg(s)$ is greater than both $Pos(s)$ and $Obj(s)$); in two synsets the scores of positivity prevail ($Pos(s)$ is greater than both $Neg(s)$ and $Obj(s)$); and one synset is completely objective ($Obj(s) = 1.0$) in SentiWordNet. A sentiment analysis system employing a sense disambiguation algorithm might yield counterintuitive results on the sentence "*Those were happiest days, I never felt such elation!*" if scores for the {happy(5), euphoric(1)} synset were considered.

TABLE 2
SentiWordNet Scores for Synsets Containing Adjective "Happy"

Synset with corresponding sense	*Pos(s)*	*Neg(s)*	*Obj(s)*
{happy(1)}: enjoying or showing or marked by joy or pleasure or good fortune; '*a happy smile*'; '*spent many happy days on the beach*'; '*a happy marriage*'	**0.625**	0.25	0.125
{happy(2), pleased(3)}: experiencing pleasure or joy; '*happy you are here*'; '*pleased with the good news*'	0.0	**0.75**	0.25
{happy(3), felicitous(2)}: marked by good fortune; '*a felicitous life*'; '*a happy outcome*'	**0.875**	0.0	0.125
{happy(4)}: satisfied; enjoying well-being and contentment; '*felt content with her lot*'; '*quite happy to let things go on as they are*'	0.0	**0.75**	0.25
{happy(5), euphoric(1)}: exaggerated feeling of well-being or elation	0.125	**0.5**	0.375
{happy(6), well-chosen(1)}: well expressed and to the point; '*a happy turn of phrase*'; '*a few well-chosen words*'; '*a felicitous comment*'	0.0	0.0	**1.0**

Let us now turn to the analysis of possibilities to extend the SentiFul lexicon using SentiWordNet. As we restricted polarity scores and polarity weights in SentiFul to distinct lexemes (sentiment features of different senses of a term are unified), we considered two approaches to derive scores for each lexeme from SentiWordNet: 1) Method "*FS*": take $Pos(s)$, $Neg(s)$, and $Obj(s)$ scores of first synset for each lemma in SentiWordNet; 2) Method "*UNI*": calculate unified positivity and negativity scores for each lemma in SentiWordNet using (5) and (6) and derive weights of positivity, negativity, and objectivity based on (7), (8), and (9). As there are synsets where $Pos(s) = Neg(s) > 0$, all weights need to be normalized.

$$Uni\_Pos\_score = \left[\frac{\sum_{i=1}^{pos} Pos(s)(i)}{pos}\right], \quad (5)$$

$$Uni\_Neg\_score = \left[\frac{\sum_{i=1}^{neg} Neg(s)(i)}{neg}\right], \quad (6)$$

$$Pos\_weight = \left[\frac{pos}{senses}\right], \quad (7)$$

$$Neg\_weight = \left[\frac{neg}{senses}\right], \quad (8)$$

$$Obj\_weight = \left[\frac{obj}{senses}\right], \quad (9)$$

whereby *pos* is the number of lemma senses having $Pos(s)(i) >= Neg(s)(i)$ and $Pos(s)(i) > 0$; *neg* is the number of lemma senses having $Neg(s)(i) >= Pos(s)(i)$ and $Neg(s)(i) > 0$; *obj* is the number of lemma senses having $Obj(s)(i) = 1$; *senses* is the total number of lemma synsets.

Using the "*FS*" and "*UNI*" methods, we obtained scores for all 152,050 distinct lemmas in SentiWordNet. In particular, the total numbers of distinct lemmas having either $Obj(s) <= 0.5$ (from "*FS*") or $Obj\_weight <= 0.5$ (from "*UNI*") are 14,918 and 37,414, respectively. In order to evaluate the appropriateness of scores derived from SentiWordNet, we created a gold standard based on SentiFul entries (originating from the manually annotated Affect database) and their scores. For the gold standard, we considered only those SentiFul entries that also occur in SentiWordNet: 750 adjectives, 237 adverbs, 894 nouns, 372 verbs. The evaluation was based on the comparison of the valence of the dominant score from SentiWordNet with the valence of the dominant score from the gold standard.

The rule for the determination of valence of the dominant score for a lemma in the gold standard is: if *Pos_score* > = *Neg_score* & *Pos_weight* > *Neg_weight* = > positive, else if *Pos_score* > *Neg_score* & *Pos_weight* = *Neg_weight* = > positive, else if *Neg_score* = > *Pos_score* & *Neg_weight* > *Pos_weight* = > negative, else if *Neg_score* > *Pos_score* & *Neg_weight* = *Pos_weight* = > negative, else if *Pos_score* = *Neg_score* & *Pos_weight* = *Neg_weight* = > random, else if *Pos_score* > *Neg_score* = > positive, else negative.

To obtain the valence of the dominant score within scores derived from SentiWordNet using "*FS*" and "*UNI*" methods, we propose four ways:

1. "*FS_strength*" (disregarding $Obj(s)$): If $Pos(s) > Neg(s) =>$ positive, else if $Neg(s) > Pos(s) =>$ negative, else if $Pos(s) = Neg(s) = 0.0 =>$ neutral, else random.
2. "*FS_obj*": If $Obj(s) > 0.5 =>$ neutral, else if $Pos(s) > Neg(s) =>$ positive, else if $Neg(s) > Pos(s) =>$ negative, else random.
3. "*UNI_strength*" (disregarding *Obj_weight*): If *Uni_Pos_score*>*Uni_Neg_score* = > positive, else if *Uni_Neg_score*>*Uni_Pos_score* = > negative, else if *Uni_Pos_score* = *Uni_Neg_score* = 0.0 = > neutral, else random.
4. "*UNI_weight*": If *Obj_weight* >0.5 = > neutral, else if *Uni_Pos_score* = > *Uni_Neg_score* & *Pos_weight* > *Neg_weight* = > positive, else if *Uni_Pos_score* > *Uni_Neg_score* & *Pos_weight* = *Neg_weight* = > positive, else if *Uni_Neg_score* = > *Uni_Pos_score* & *Neg_weight* > *Pos_weight* = > negative, else if *Uni_Neg_score* > *Uni_Pos_score* & *Neg_weight* = *Pos_weight* = > negative, else if *Uni_Pos_score* = *Uni_Neg_ score* & *Pos_weight* = *Neg_weight* = > random, else if *Uni_Pos_score* > *Uni_Neg_score* = > positive, else negative.

Table 3 includes some examples of the obtained results. The results of the evaluation of different methods for obtaining scores for adjectives, adverbs, nouns, and verbs based on SentiWordNet are displayed in Fig. 1. As seen from the diagrams, more accurate scores were obtained for adjectives, and the worst results were obtained for scoring the verbs. This is not surprising, as the mean polysemy for adjectives is very low, while verbs typically have a lot of senses. The "*UNI*" method performed better than the method based on the consideration of scores of the first synset in SentiWordNet ("*FS*" method). The results we obtained when examining SentiWordNet were not satisfying, and hence we decided to explore other ways to extend the SentiFul lexicon.

5 Methods for Expanding SentiFul

5.1 Finding New Lexical Units through Synonymy Relation

To find new sentiment-related words, the most direct way is to derive them through the synonymy relation with known lexemes. Undoubtedly the deep meaning of any lexical unit is unique. However, we can take advantage of considering pairs of words that have similar senses and assign sentiment scores to them. The process of finding and scoring new words through a synonymy relation consists of three main steps, which are applied to adjectives, adverbs, nouns, and verbs independently.

Step 1. Given a word from SentiFul, we derive[2] all related synsets found in WordNet. For example, four synsets were found for verb "*congratulate*": {"*compliment*," "*congratulate*"}, {"*congratulate*," "*felicitate*"}, {"*pride*," "*plume*," "*congratulate*"}, and {"*preen*," "*congratulate*"}.

Step 2. In each multiple-word synset from the previous step, we retrieve words that are already included in SentiFul, then calculate averages of scores and weights within synsets that have new terms, and finally assign these values to remaining words within corresponding synset. For the above example, all synonyms of the verb "*congratulate*," except

2. For the exploration of WordNet relations, we employed Java API for WordNet Searching (JAWS): http://lyle.smu.edu/~tspell/jaws.

TABLE 3
Examples of the Comparison of Results from Different Methods with the Gold Standard

Lemma (POS)	Method	*Pos_score*	*Neg_score*	*Pos_weight*	*Neg_weight*	Dominant	Result
weakness (noun)	SentiWordNet sense #1	0.0	0.125				
	SentiWordNet sense #2	0.125	0.625				
	SentiWordNet sense #3	0.0	0.375				
	SentiWordNet sense #4	0.5	0.125				
	SentiWordNet sense #5	0.0	0.875				
	SentiFul gold standard	**0.0**	**0.2**	**0.0**	**1.0**	**negative**	
	'FS_strength'	0.0	0.125	-	-	negative	**hit**
	'FS_obj'	0.0	0.125	-	-	neutral	**neutral no hit**
	'UNI_strength'	0.5	0.5	0.2	0.8	random	**random hit**
	'UNI_weight'	0.5	0.5	0.2	0.8	negative	**hit**
congratulate (verb)	SentiWordNet sense #1	0.25	0.125				
	SentiWordNet sense #2	0.0	0.125				
	SentiWordNet sense #3	0.0	0.375				
	SentiWordNet sense #4	0.0	0.5				
	SentiFul gold standard	**0.4**	**0.0**	**1.0**	**0.0**	**positive**	
	'FS_strength'	0.25	0.125	-	-	positive	**hit**
	'FS_obj'	0.25	0.125	-	-	neutral	**neutral no hit**
	'UNI_strength'	0.25	0.333	0.25	0.75	negative	**no hit**
	'UNI_weight'	0.25	0.333	0.25	0.75	negative	**no hit**

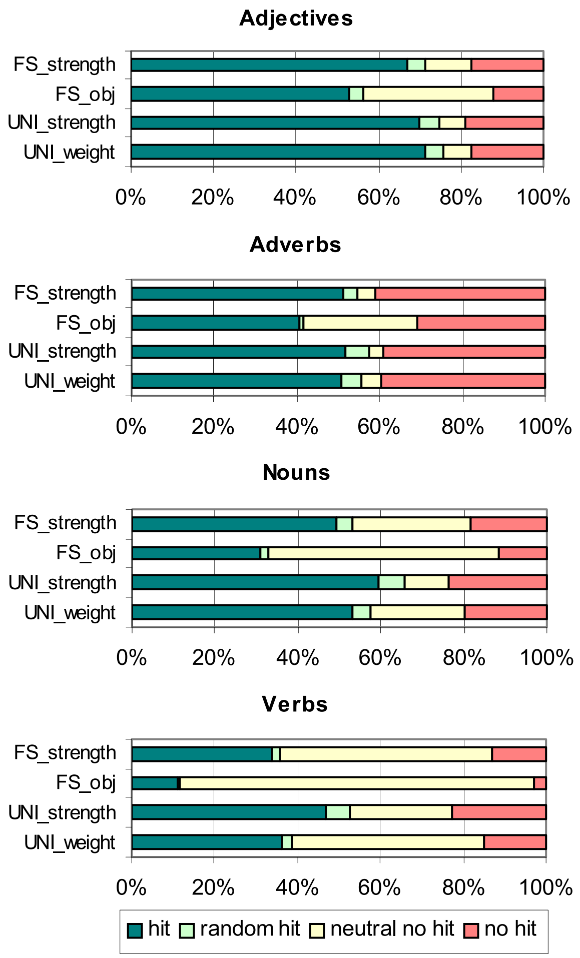

Fig. 1. Accuracy of different methods for obtaining scores based on SentiWordNet.

"*compliment*" in the first synset and "*felicitate*" in the second synset, are already in SentiFul. Therefore, scores of "*congratulate*" (*Pos_score* = 0.4, *Neg_score* = 0.0, *Pos_ weight* = 1.0, and *Neg_weight* = 0.0) are propagated to "*complement*" and "*felicitate*." In case the verb "*pride*" from the third synset was new for SentiFul, we would take the averages of polarity scores and averages of weights of both "*plume*" and "*congratulate*."

Step 3. After *Steps 1* and *2* are completed for all original SentiFul entries (we consider only their direct synonyms), we eliminate duplicates of new words, as they can obtain assignments from different synsets derived using different words from SentiFul, and calculate their new scores as averages of assignments of those redundantly produced words.

Relying on direct synonymy relations, we automatically extracted 4,190 new words from WordNet (see examples in Table 4): 1,122 adjectives, 107 adverbs, 1,731 nouns, and 1,230 verbs. We decided not to iterate the above procedure on these new words, because nondirect synonyms are not necessarily carrying similar sentiment features as the original concepts (e.g., "*healthy*"-"*intelligent*"-"*thinking*").

5.2 Examining Direct Antonymy Relation

The next step in enriching the SentiFul database is to analyze antonymy relations. We concentrated on the extraction of direct antonyms of words available in SentiFul from WordNet. Direct antonymous words are conceptual opposites that represent lexical pairs (indirect antonyms are not lexically paired).

Given a word from SentiFul and its class (adjective, adverb, noun, verb), we retrieve its direct antonyms from WordNet. Then, if these newly retrieved words are not available in SentiFul, we assign sentiment-related scores

TABLE 4
Examples of Newly Derived Words
Based on Direct Synonymy Relations

POS	Lemma	*Pos_score* / *Neg_score*	*Pos_weight* / *Neg_weight*
adjective	*appealing*	0.333 / 0.033	0.833 / 0.167
	barbarous	0.0 / 0.625	0.0 / 1.0
	confounded	0.1 / 0.2	0.167 / 0.833
adverb	*advantageously*	0.3 / 0.0	1.0 / 0.0
	frightfully	0.0 / 0.95	0.0 / 1.0
	poorly	0.0 / 0.334	0.0 / 1.0
noun	*authority*	0.383 / 0.05	0.875 / 0.125
	defect	0.0 / 0.6	0.0 / 1.0
	impetuosity	0.65 / 0.65	0.5 / 0.5
verb	*exhaust*	0.2 / 0.375	0.167 / 0.834
	glorify	0.3 / 0.0	1.0 / 0.0
	privilege	0.2 / 0.0	1.0 / 0.0

TABLE 5
Examples of Newly Derived Words
Based on Direct Antonymy Relations

POS	Word (direct antonym of words from SentiFul)	*Pos_score* / *Neg_score*	*Pos_weight* / *Neg_weight*
adj.	*attractive* (*repulsive, unattractive*)	0.8 / 0.0	1.0 / 0.0
	maleficent (*beneficent*)	0.0 / 0.3	0.0 / 1.0
	wise (*foolish*)	0.9 / 0.0	1.0 / 0.0
adv.	*carelessly* (*carefully*)	0.0 / 0.1	0.0 / 1.0
	honorably (*dishonorably*)	1.0 / 0.0	1.0 / 0.0
	painlessly (*painfully*)	0.4 / 0.0	1.0 / 0.0
noun	*penalty* (*reward*)	0.0 / 0.2	0.0 / 1.0
	safety (*danger*)	0.7 / 0.0	1.0 / 0.0
	truth (*falsehood, falsity*)	0.9 / 0.0	1.0 / 0.0
verb	*bless* (*curse*)	0.25 / 0.0	1.0 / 0.0
	defend (*attack*)	0.7 / 0.0	1.0 / 0.0
	deteriorate (*recuperate*)	0.0 / 0.2	0.0 / 1.0

and weights to them based on the assumption that direct antonyms possess sentiment features that are opposite to those of the original word from SentiFul. Hence, the original *Pos_score* and *Neg_score* trade places (the same procedure for weights) in case of direct antonyms. If the same antonyms are retrieved using different original words from SentiFul, we calculate averages of scores and weights. For example, using the nouns "*falsehood*" and "*falsity*" from SentiFul, we retrieved duplicate entries of their direct antonym "*truth*" from WordNet, and calculated averages of the reversed scores and weights of the original words. The examination of direct antonymy relations of SentiFul entries allowed us to automatically extract 288 new words from WordNet (some examples are listed in Table 5): 123 adjectives, 13 adverbs, 73 nouns, and 79 verbs.

5.3 Examining Hyponymy Relations

The most important semantic relation in organizing nouns in WordNet is a relation between lexicalized concepts, or a relation of subordination [25]. In WordNet, the lexical hierarchy of nouns is represented using hypernym-hyponym relations between the appropriate synsets. At the top of the hierarchy, there are a few generic terms which can characterize many specific terms at the lower levels. The semantic relation known as hyponymy goes from the generic term to a more specific one, thus representing specialization (e.g., "*attainment*" = > "*success*" = > "*winning*", whereas the hypernymy relation points in the opposite direction, i.e., from a specific term to a more generic one (e.g., "*winning*" = > "*success*" = > "*attainment*").

Miller [25, p. 31] defines hyponymy as follows: "*when the features characterizing synset {A} are all included among the features characterizing synset {B}, but not vice versa, then {B} is a hyponym of {A}*." Hyponymy relation between nouns is our particular interest, as we assume that sentiment features of a sentiment-conveying term (e.g., "*success*"), along with other features, are to some extent inherited by its hyponym (e.g., "*winning*"). On the other hand, hypernymy relation represents generalization and it is not necessarily true that sentiment features of a sentiment-conveying term (e.g., "*success*") will characterize its hypernym (e.g., "*attainment*"), which is located at a higher level of the lexical hierarchy.

Our algorithm for hyponymy retrieval from a lexical inheritance system of WordNet takes into account only one level of specialization. Given a noun from SentiFul, we automatically retrieve a list of corresponding hyponyms from WordNet, and propagate sentiment features (scores and weights) of the original term to its hyponyms. If the hyponymy relation of different nouns from SentiFul results in the same term, we eliminate duplicates and consider averages of their scores and weights as the resulting assignment. The examples of nouns retrieved from WordNet through examination of hyponymy relations are shown in Table 6. In total, 1,085 new nouns were added to the SentiFul lexicon.

5.4 Method to Derive and Score Morphologically Modified Words

We are proposing to expand our SentiFul lexicon through manipulations with morphological structure of known lemmas that result in the formation of new lexical units [26]. Adjectives, adverbs, nouns, and verbs form open classes whereby membership is indefinite and unlimited [27]. We can easily form new words playing with bases and affixes. Derivation is a process responsible for building new lexemes by either adding derivational prefixes (attachments to the front of the base) or suffixes (attachments to the end of the base). Suffixes typically have less specific meanings than prefixes. The main contribution to the meaning of many suffixes is that which follows from a change of the grammatical class. We intentionally do not consider conversions, as nouns and verbs having the same dictionary form often have different meanings, especially in terms of sentiment.

We distinguish four types of affixes, depending on the role they play with regard to sentiment features:

TABLE 6
Examples of Nouns Retrieved Based on Hyponymy Relations

Retrieved Word	*Pos_score* / *Neg_score*	*Pos_weight* / *Neg_weight*	Is a hyponym of [word from SentiFul]	*Pos_score* / *Neg_score*	*Pos_weight* / *Neg_weight*
amity	0.25 / 0.0	1.0 / 0.0	*friendliness*	0.3 / 0.0	1.0 / 0.0
			peace	0.2 / 0.0	1.0 / 0.0
aspersion	0.0 / 0.55	0.0 / 1.0	*attack*	0.0 / 0.7	0.0 / 1.0
			depreciation	0.0 / 0.4	0.0 / 1.0
betise	0.0 / 0.35	0.0 / 1.0	*error*	0.0 / 0.3	0.0 /1.0
			fault	0.0 / 0.6	0.0 /1.0
			mistake	0.0 / 0.15	0.0 /1.0
consonance	0.4 / 0.0	1.0 / 0.0	*harmony*	0.4 / 0.0	1.0 / 0.0
fiasco	0.0 / 0.5	0.0 / 1.0	*collapse*	0.0 / 0.5	0.0 / 1.0
reprehensibility	0.0 / 0.9	0.0 / 1.0	*evil*	0.0 / 0.9	0.0 / 1.0

1. *Propagating* affixes preserves sentiment features of the original lexeme and propagate them to newly derived lexical unit (e.g., *"en-"*+*"rich"* = > *"enrich,"* *"harmony"*+*"-ous"* = > *"harmonious,"* *"scary"*+*"-fy"* = > *"scarify"*).
2. *Reversing* affixes changes the orientation of sentiment features of the original lexeme (e.g., *"dis-"*+*"honest"* = > *"dishonest,"* *"harm"*+*"-less"* = > *"harmless"*).
3. *Intensifying* affixes increases the strength of sentiment features of the original lexeme (e.g., *"super"* +*"hero"* = > *"superhero,"* *"over"*+*"awe"* = > *"overawe"*).
4. *Weakening* affixes decreases the strength of sentiment features of the original lexeme (e.g., *"semi"*+*"sweet"* = > *"semisweet"*).

Table 7 summarizes our classification with respect to the type of an affix, class of a base lexeme (*a* stands for adjective, *adv* for adverb, *n* for noun, and *v* for verb), and class of a newly formed word.

TABLE 7
Our Classification of Affixes Attached to a Base Lexeme to Form New Word

Type of affix	Prefix (+class of base lexeme); (class of base lexeme+) suffix	Examples
	Adjective formation	
Propagating	pro- (+*a*); (*a*+) -ish; (*v*+) {-able, -ant, -ent, -ible, -ing}; (*n*+) {-al, -en, -ful, -ic, -like, -type, -y}; (*v*/*n*+) {-ate, -ed, -ive, -ous}	*attacking*, *advanced*, *harmonious*, *careful*, *lovable*, *messy*
Reversing	{a-, ab-, an-, anti-, contra-, counter-, de-, dis-, dys-, il-, im-, in-, ir-, mal-, mis-, non-, pseudo-, un-, under-} (+*a*); (*n*+) -less	*intolerant*, *dishonest*, *misleading*, *guiltless*, *harmless*
Intensifying	{extra-, hyper-, mega-, super-, ultra-} (+*a*)	*superfine*
Weakening	semi- (+*a*)	*semisoft*
	Adverb formation	
Propagating	pro- (+*adv*); (*a*+) -ly; (*n*+) {-wise, -wards}	*charmingly*, *defectively*
Reversing	{a-, ab-, an-, anti-, contra-, counter-, de-, dis-, dys-, il-, im-, in-, ir-, mal-, mis-, non-, pseudo-, un-, under-} (+*adv*);	*imperfectly*, *ungratefully*
Intensifying	{extra-, hyper-, mega-, super-, ultra-} (+*adv*)	
Weakening	semi- (+*adv*)	
	Noun formation	
Propagating	{neo-, re-} (+*n*); (*v*+) {-age, -al, -ant, -ation, -ent, -ication, -ification, -ion, -ment, -sion, -tion, -ure}; (*a*+) {-ity, -ness}; (*n*+) {-ful, ist, -ship}; (*v*/*a*+) {-ance, -ence, -ee}; (*v*/*n*+) {-er, -ing, -or}; (*a*/*n*+) {-cy, -dom, -hood}; (*v*/*n*/*a*+) {-ery, -ry}	*awfulness*, *deceiver*, *offender*, *savagery*
Reversing	{anti-, counter-, dis-, dys-, in-, mal-, mis-, non-, pseudo-, under-} (+*n*)	*nonviolence*, *underachiever*
Intensifying	{arch-, hyper-, mega-, super-, ultra-} (+*n*)	*superego*
Weakening	{mini-, semi-} (+*n*); (n+) {-ette, -let}	*mini-recession*
	Verb formation	
Propagating	{be-, co-, fore-, inter-, pre-, pro-, re-, trans-} (+*v*); {em-, en-} (+*n*/*a*); (*n*/*a*+) {-ate, -en, -fy, -ify, -ise, -ize}	*enrich*, *scarify*, *agonize*
Reversing	{de-, dis-, dys-, mis-, un-, under-} (+*v*)	*devalue*, *disagree*, *mistrust*
Intensifying	{out-, over-} (+*v*)	*outfight*, *overawe*

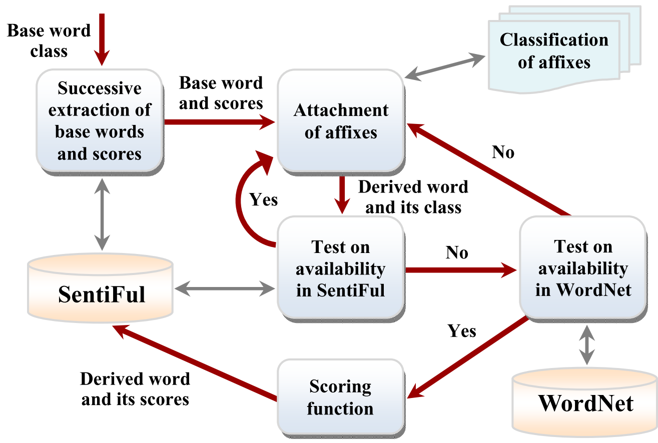

Fig. 2. The algorithm of derivation and scoring of the new words.

Our algorithm for building new words receives the following parameters: class of the base word, class (prefix or suffix) and type of the affix, affix, and the class of derived word. The processing is as follows (please see schematic illustration in Fig. 2): 1) Given the class of the base word, the system successively extracts each corresponding lemma from SentiFul and its sentiment-related scores, 2) depending on the affix class, affix is attached either to the front or to the end of the lemma to form new word, and 3) given the class of a derived word and the newly formed word itself, SentiFul is scanned on the presence of this lemma and, if the result is positive, this lemma is not considered for inclusion; else, WordNet is examined on the availability of this lemma and, if this word exists, it is considered for future inclusion in SentiFul along with sentiment-related scores.

Based on the type of the affix and sentiment-related scores of the original word, the scoring function assigns polarity scores and weights to the derived word. In the case of *Propagating* affix, original scores and weights are transferred to the new word without variation. The original *Pos_score* and *Neg_score* trade places (same procedure for weights) in case of a *Reversing* affix. If the affix belongs to the *Intensifying* or *Weakening* type, the original scores are multiplied by empirically defined coefficients (2.0 or 0.5, respectively).

In order to properly treat attachment of suffixes to base lexemes, we apply the following rules:

1. Replace lexeme ending *"f"* (except the case of *"ff"*) by *"v"* if suffix starts with *"a/e/i/o/u/y."*

TABLE 8
Examples of Morphologically Modified Words

POS	Lemma	*Pos_score* / *Neg_score*	*Pos_weight* / *Neg_weight*
adjective	*lovable*	0.85 / 0.0	1.0 / 0.0
	reproachful	0.0 / 0.625	0.0 / 1.0
adverb	*proficiently*	0.3 / 0.0	1.0 /0.0
noun	*spoilage*	0.133 / 0.3	0.167 / 0.833
verb	*beautify*	0.45 / 0.0	1.0 / 0.0

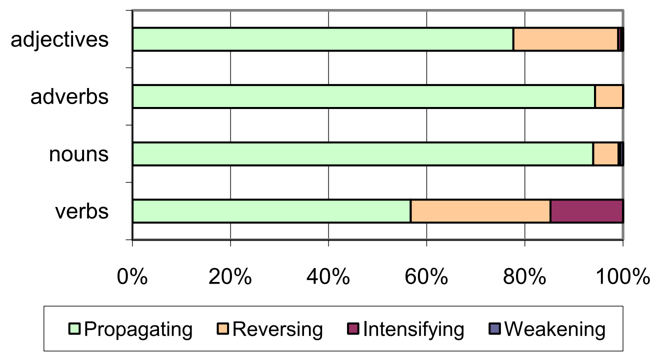

Fig. 3. Percentage distribution of words derived by means of different affix types.

2. Replace lexeme ending *"fe"* (except the case of *"ffe"*) by *"v"* if suffix starts with *"a/e/i/o/u/y."*
3. Remove lexeme ending *"y"* if suffix starts with *"i."*
4. Replace lexeme ending *"y"* which follows the consonant by *"i."*
5. Remove (noun or adjective) lexeme ending *"t"* or *"te"* before suffix *"cy."*
6. Remove lexeme ending *"e"* if suffix starts with *"a/e/i/o/u/y."*
7. Double lexeme ending *"b/d/f/g/l/m/n/p/r/s/t/v/z,"* which follows the vowel preceded by consonant, if suffix starts with *"a/e/i/o/u/y."*

For example, while attaching the suffix *"-fy"* to the base lexeme *"beauty"* (noun), we replace the lexeme ending *"y"* by *"i"* to correctly derive verb *"beautify"* (rule 4); or in the case of base lexeme *"love"* (verb) and suffix *"able,"* we remove lexeme ending *"e"* to derive adjective *"lovable"* (rule 6).

Using this morphologically inspired method, we automatically derived and scored 4,029 new words (see examples in Table 8): 1,405 adjectives, 484 adverbs, 1,800 nouns, and 340 verbs.

The *Propagating* type of affixes proved to be the most frequent and efficient in building words of all content parts of speech (Fig. 3). The *Reversing* type of affixes also played a significant role in the derivation process for adjectives and verbs, while *Intensifying* affixes brought a noticeable effect only in building new verbs.

The block diagram shown in Fig. 4 indicates that adjectives, adverbs, and nouns were mainly derived by means of suffixes, whereas prefixes dominated in the case of verbs. The most productive affixes to form new words are listed in Table 9.

5.5 Compounding Using Known Sentiment-Carrying Base Components

Besides derivation, we considered compounding, which is a highly productive process, especially in the case of nouns and adjectives. Compounds are words that contain at least two roots. In other words, independently existing bases are combined to form new lexemes. Compounding functions as a linguistic economy-mechanism that allows expressing in a concise way something which would otherwise have to be rendered by means of a phrase [28].

A number of different compounding patterns are attested in English. We analyzed major patters of formation

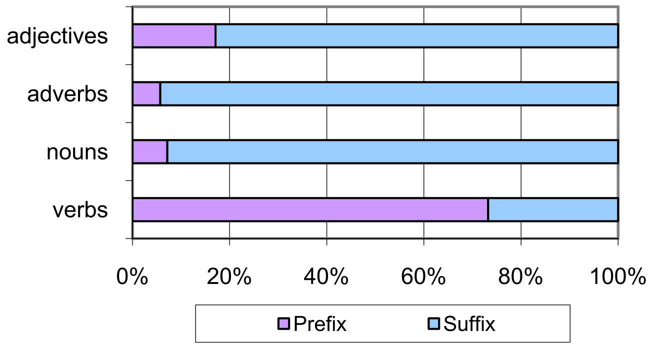

Fig. 4. Percentage distribution of words derived by means of prefixes and suffixes.

TABLE 9
Top 10 Most Productive Affixes to Form Adjectives, Adverbs, Nouns, and Verbs

POS	Affixes and counts									
adj.	-ed 492	-ing 226	un- 148	-able 97	-less 80	-ive 64	-y 64	-ful 50	-al 31	in- 29
adv.	-ly 458	un- 14	a- 7	in- 3	im- 2	dis- 2	-wise 2	-wards 1	- -	- -
noun	-er 607	-ing 367	-ness 340	-or 79	-ion 75	-ation 53	-ment 45	-ist 37	-ery 34	-ity 32
verb	re- 56	over- 34	-en 30	dis- 26	un- 22	de- 21	out- 18	mis- 18	-ize 16	-ise 16

of noun compounds and adjectival compounds described in [26], [27], [28]. The patterns, which are our main interest, are summarized in Table 10, along with the examples illustrating sentiment-conveying compounds.

Although some compounds have idiosyncratic meanings which are different from the sum of the meanings of their parts, the meanings of many compounds may be systematically related to the meanings of their components via a number of different rules [29]. We assume that if a compound contains at least one base component that conveys sentiment features, we can predict the valence of this compound. Based on this assumption, we elaborated the algorithm for automatic extraction of new sentiment-related terms (particularly, compounds) from WordNet using words from SentiFul as seeds for sentiment-carrying base components and patterns for the formation of compounds (Table 10). It is important to note here that we restricted the algorithm to forming compounds written with a hyphen. The rules for estimation of sentiment features (*Pos_score*, *Neg_ score*, *Pos_weight*, and *Neg_weight*) of newly retrieved words are described below. The examples of compound words, the valence-based interpretations of their constituent parts, and the corresponding rules are also given in Table 10.

Rule 1. If one of the constituent elements of a compound conveys sentiment features, and another element, which is not a "negation" or "valence shifter" word, is neutral, then sentiment-features are propagated to the whole compound. For example (here and below, we use *Pos* and *Neg* instead of *Pos_score* and *Neg_score*, respectively):

$$\begin{aligned}&\text{`}\mathit{good}\text{'} \quad \& \quad \text{`}\mathit{neighborliness}\text{'}\\&[Pos = 0.3, Neg = 0.0] \quad \& \quad [\text{neutral}]\\&\quad => \text{`}\mathit{good\text{-}neighborliness}\text{'}\ [Pos = 0.3, Neg = 0.0].\end{aligned}$$

Rule 2. If one of the constituent elements of a compound conveys sentiment features and another element is a "negation" word, then sentiment features of the sentiment-conveying component are reversed and assigned to the whole compound. For example:

$$\begin{aligned}&\text{`}\mathit{no}\text{'} \quad \& \quad \text{`}\mathit{nonsense}\text{'}\\&[\text{negation}] \quad \& \quad [Pos = 0.0, Neg = 0.5]\\&\quad => \text{`}\mathit{no\text{-}nonsense}\text{'}\ [Pos = 0.5, Neg = 0.0];\\&\text{`}\mathit{good}\text{'} \quad \& \quad \text{`}\mathit{nothing}\text{'}\\&[Pos = 0.3, Neg = 0.0] \quad \& \quad [\text{negation}]\\&\quad => \text{`}\mathit{good\text{-}for\text{-}nothing}\text{'}\ [Pos = 0.0, Neg = 0.3].\end{aligned}$$

Rule 3. If the left-hand member of a compound conveys sentiment features and the right-hand member is a "valence shifter" (e.g., "*safe*," "*free*," "*proof*," etc.) or its derivative, then the sentiment features of the sentiment-conveying component are reversed and assigned to the whole compound. For example:

$$\begin{aligned}&\text{`}\mathit{fail}\text{'} \quad \& \quad \text{`}\mathit{safe}\text{'}\\&[Pos = 0.0, Neg = 0.9] \quad \& \quad [\text{valence shifter}]\\&\quad => \text{`}\mathit{fail\text{-}safe}\text{'}\ [Pos = 0.9, Neg = 0.0];\\&\text{`}\mathit{risk}\text{'} \quad \& \quad \text{`}\mathit{free}\text{'}\\&[Pos = 0.0, Neg = 0.567] \quad \& \quad [\text{valence shifter}]\\&\quad => \text{`}\mathit{risk\text{-}free}\text{'}\ [Pos = 0.567, Neg = 0.0].\end{aligned}$$

Rule 4. If a compound is interpreted in such a way that one member modifies another member (so-called "modifier-head" structure), and both the "modifier" and the "head" are sentiment-conveying terms, then:

Rule 4a. If both components are predominantly positive (or negative), then their sentiment features (scores and weights) are averaged and the result is assigned to the whole word. For example:

$$\begin{aligned}&\text{`}\mathit{loving}\text{'} \quad \& \quad \text{`}\mathit{kindness}\text{'}\\&[Pos = 0.9, Neg = 0.0] \quad \& \quad [Pos = 0.6, Neg = 0.0]\\&\quad => \text{`}\mathit{loving\text{-}kindness}\text{'}\ [Pos = 0.75, Neg = 0.0];\\&\text{`}\mathit{death}\text{'} \quad \& \quad \text{`}\mathit{feud}\text{'}\\&[Pos = 0.0, Neg = 0.65] \quad \& \quad [Pos = 0.0, Neg = 0.4]\\&\quad => \text{`}\mathit{death}\text{'-`}\mathit{feud}\text{'}\ [Pos = 0.0, Neg = 0.525].\end{aligned}$$

Rule 4b. If both components have contrasting sentiment features, then the sentiment features of the "modifying" member are considered as dominant and are propagated to the whole word. For example:

TABLE 10
Patterns of Formation of Noun Compounds and Adjectival Compounds

Patterns	Structure in terms of paraphrasing	Examples of compound words	Valence-based interpretation	Rule
		Formation of noun compounds		
noun + noun	'modifier-head'	*love-affair*	pos-neutral => pos	Rule 1
		death-feud	neg-neg => neg	Rule 4a
noun + noun/verb-er	'verb-object'	*life-saver*	neutral-pos => pos	Rule 1
		peace-lover	pos-pos => pos	Rule 5a
		pain-killer	neg-neg => pos	Rule 5b
noun + verb-ing	'verb-object'	*law-breaking*	neutral-neg => neg	Rule 1
		peace-keeping	pos-neutral => pos	Rule 1
adjective + noun	'modifier-head'	*poor-quality*	neg-neutral =>neg	Rule 1
		good-neighborliness	pos-neutral => pos	Rule 1
		no-nonsense	'negation'-neg=> pos	Rule 2
verb + noun	'modifier-head'	*cry-baby*	neg-neutral => neg	Rule 1
verb-ing + noun	'modifier-head'	*loving-kindness*	pos-pos => pos	Rule 4a
pronoun + noun	'modifier-head'	*self-pity*	neutral-neg => neg	Rule 1
noun + preposition + noun	'modifier-head'	*wall-of-death*	neutral-neg => neg	Rule 1
		Formation of adjectival compounds		
noun + verb-ing	'verb-object'	*eye-gladdening*	neutral-pos => pos	Rule 1
		fight-eliciting	neg-neutral => neg	Rule 1
		award-winning	pos-pos => pos	Rule 5a
		health-destroying	pos-neg => neg	Rule 5c
		quarrel-loving	neg-pos => neg	Rule 5d
pronoun +verb-ing	'verb-object'	*self-destructing*	neutral-neg => neg	Rule 1
adjective + verb-ing	'modifier-head'	*pleasant-testing*	pos-neutral => pos	Rule 1
		evil-smelling	neg-neutral => neg	Rule 1
adverb + verb-ing	'modifier-head'	*equally-damaging*	neutral-neg => neg	Rule 1
		ever-loving	neutral-pos => pos	Rule 1
		badly-fitting	neg-neutral => neg	Rule 1
noun + verb-en	'verb-PP'	*poverty-stricken*	neg-neutral => neg	Rule 1
		fortune-favored	pos-pos => pos	Rule 6a
		snob-despised	neg-neg => neg	Rule 6a
		war-torn	neg-neg => neg	Rule 6a
		love-agonized	pos-neg => neg	Rule 6b
pronoun + verb-en	'verb-PP'	*self-convicted*	neutral-neg => neg	Rule 1
adjective + verb-en	'modifier-head'	*kind-hearted*	pos-neutral => pos	Rule 1
adverb + verb-en	'modifier-head'	*poorly-adapted*	neg-neutral => neg	Rule 1
		well-merited	pos-pos => pos	Rule 4a
		ill-famed	neg-pos =>neg	Rule 4b
verb-en + preposition	'verb-preposion'	*broken-down*	neg-neutral => neg	Rule 1
adjective + verb	'modifier-head'	*easy-follow*	pos-neutral => pos	Rule 1
		difficult-to-master	neg-pos => neg	Rule 4b
noun + adjective	'modifier-head'	*user-friendly*	neutral-pos => pos	Rule 1
		money-mad	neutral-neg => neg	Rule 1
		crash-proof	neg-'valence shifter' => pos	Rule 3
		error-free	neg-'valence shifter' => pos	Rule 3
pronoun + adjective	'modifier-head'	*self-conscious*	neutral-pos => pos	Rule 1
adjective + preposition + pronoun	'adjective-PP'	*spurious-to-me*	neg-neutral => neg	Rule 1
		good-for-nothing	pos-'negation' => neg	Rule 2
adjective + noun	'modifier-head'	*no-win*	'negation'-pos=> neg	Rule 2
adjective + adjective	'modifier-head'	*manic-depressive*	neg-neg => neg	Rule 4a
adverb + adjective	'modifier-head'	*highly-respectable*	neutral-pos => pos	Rule 1
		critically-ill	neg-neg => neg	Rule 4a
		not-too-pleasant	'negation'-pos => neg	Rule 2
verb + noun	'verb-object'	*cut-throat*	(indirect)neg-neutral => neg	Rule 1
		ban-the-bomb	neg-neg => pos	Rule 5b
verb + adjective	'verb-adjective'	*get-rich-quick*	neutral-pos => pos	Rule 1
verb + adverb	'modifier-head'	*die-hard*	neg-(indirect)pos => pos	Rule 4b

$$`ill' \quad \& \quad `famed'$$
$$[Pos = 0.0, Neg = 0.467] \quad \& \quad [Pos = 0.475, Neg = 0.0]$$
$$=> `ill\text{-}famed' \; [Pos = 0.0, Neg = 0.467].$$

Rule 5. If a compound corresponds to one of the patterns, which can be paraphrased as "verb+direct object" (so-called "verb-object" structure), and both components are sentiment-conveying terms, then:

Rule 5a. If both "noun" and "verb/verbal" members are predominantly positive, then their sentiment features (scores and weights) are averaged and the result is assigned to the whole word. For example:

$$`award' \quad \& \quad `winning'$$
$$[Pos = 0.55, Neg = 0.0] \quad \& \quad [Pos = 0.8, Neg = 0.0]$$
$$=> `award\text{-}winning' \; [Pos = 0.675, Neg = 0.0].$$

Rule 5b. If both "noun" and "verb/verbal" members are predominantly negative, then their sentiment features (scores and weights) are averaged, and the inverted result is assigned to the whole word. For example:

$$`pain' \quad \& \quad `killer'$$
$$[Pos = 0.0, Neg = 0.8] \quad \& \quad [Pos = 0.0, Neg = 0.35]$$
$$=> `pain\text{-}killer' \; [Pos = 0.575, Neg = 0.0].$$

Rule 5c. If the "noun" member is predominantly positive and the "verb/verbal" member is predominantly negative, then sentiment features of the "verb/verbal" member are considered as dominant and are propagated to the whole word. For example:

$$`health' \quad \& \quad `destroying'$$
$$[Pos = 0.25, Neg = 0.0] \quad \& \quad [Pos = 0.0, Neg = 0.65]$$
$$=> `health\text{-}destroying' \; [Pos = 0.575, Neg = 0.0].$$

Rule 5d. If the "noun" member is predominantly negative and the "verb/verbal" member is predominantly positive, then sentiment features of the "noun" member are considered as dominant and are propagated to the whole word. For example:

$$`quarrel' \quad \& \quad `loving'$$
$$[Pos = 0.0, Neg = 0.35] \quad \& \quad [Pos = 0.9, Neg = 0.0]$$
$$=> `quarrel\text{-}loving' \; [Pos = 0.0, Neg = 0.35].$$

Rule 6. If a compound corresponds to the pattern which can be paraphrased as "verb-en by/with/in/from noun" (so-called "verb-PP" structure), where "noun" member represents an agent, instrument, location, etc., and both components are sentiment-conveying terms, then:

Rule 6a. If both components are predominantly positive (or negative), then their sentiment features (scores and weights) are averaged, and the result is assigned to the whole word. For example:

$$`fortune' \quad \& \quad `favored'$$
$$[Pos = 0.7, Neg = 0.0] \quad \& \quad [Pos = 0.6, Neg = 0.0]$$
$$=> `fortune\text{-}favored' \; [Pos = 0.65, Neg = 0.0],$$

which is paraphrased as "*favored by fortune*";

$$`war' \quad \& \quad `torn'$$
$$[Pos = 0.0, Neg = 0.85] \quad \& \quad [Pos = 0.0, Neg = 0.1]$$
$$=> `war\text{-}torn' \; [Pos = 0.0, Neg = 0.475].$$

Rule 6b. If both components have contrasting sentiment features, then the sentiment features of the "verbal" member (verb-en) are considered as dominant and are propagated to the whole word. For example:

$$`love' \quad \& \quad `agonized'$$
$$[Pos = 0.9, Neg = 0.0] \quad \& \quad [Pos = 0.0, Neg = 0.85]$$
$$=> `love\text{-}agonized' \; [Pos = 0.0, Neg = 0.85],$$

which is paraphrased as "*agonized by love*."

Based on the sentiment-conveying words from SentiFul and the above rules, we could automatically extract and annotate not only new noun compounds and adjectival compounds from WordNet, but also some adverbs (e.g., "*light-heartedly*") and verbs (e.g., "*goof-proof*," "*atom-bomb*"). During evaluation of newly derived compounds, we found out that few words were assigned incorrect sentiment features (e.g., negative adjective "*half-truth*" was given dominant *Pos_score* due to positive noun "*truth*"; positive verb "*trouble-shoot*" was given dominant *Neg_score* due to negative noun "*trouble*," etc.).

We also decided to add some neoclassical compounds automatically retrieved from WordNet to our SentiFul database. Neoclassical compounds are defined as forms in which lexemes of Latin or Greek origin are combined to form new combinations that are not attested in the original languages [26]. Key ending elements that have strongly affective content, such as "*-cide*" (meaning: "*murder*"), "*-itis*" (meaning: "*disease*"), and "*-phobe*" (meaning: "*fear*"), were considered. Compounds having these endings were automatically retrieved from WordNet. Sentiment features of the meaning word representing particular key ending element were assigned to the compounds derived by means of this element. For example:

"*genocide*," "*suicide*," etc. were given sentiment features of word "*murder*" (*Pos_score* $= 0.0$, *Neg_score* $= 0.8$, *Pos_weight* $= 0.0$, *Neg_weight* $= 1.0$); exceptions are "*viricide*" and "*virucide*";

"*appendicitis*," "*radiculitis*," etc. are characterized by sentiment features of word "*disease*" (*Pos_score* $= 0.0$, *Neg_score* $= 0.3$, *Pos_weight* $= 0.0$, *Neg_weight* $= 1.0$);"*claurtrophobe*," "*technophobe*" were assigned sentiment features of word "*fear*" (*Pos_score* $= 0.0$, *Neg_score* $= 0.9$, *Pos_weight* $= 0.0$, *Neg_weight* $= 1.0$).

Compounding using known sentiment-carrying key elements allowed us to expand our SentiFul lexicon by 853 new words: 377 adjectives, 15 adverbs, 445 nouns (including 184 common compounds and 261 neoclassical compounds), and 16 verbs.

6 Evaluation

6.1 Evaluation Based on Human Annotations

In order to evaluate the accuracy of the methods described in the previous section, we randomly extracted 1,000 terms from SentiFul, particularly, 200 terms from each of the five lists created by different methods, including techniques

TABLE 11
Results of Evaluation of Polarity Assignments

Method	Inter-rater agreement (Cohen's Kappa)	GS* with complete agreement (GS-1)	Distribution of labels in GS-1, %			Results on GS-1 Accuracy, %	GS* w/o neutral words (GS-2)	Results on GS-2						
								Accuracy, %	Precision, %		Recall, %		F-score, %	
			pos	neg	neutral				pos	neg	pos	neg	pos	neg
Synonymy	0.78	179	27.9	69.8	2.2	93.3	175	95.4	86.2	100	100	93.6	92.6	96.7
Antonymy	0.66	156	44.2	26.3	29.5	66.7	110	94.5	97.0	90.7	94.2	95.1	95.6	92.9
Hyponymy	0.87	187	31.6	67.4	1.1	97.9	185	98.9	96.7	100	100	98.4	98.3	99.2
Derivation	0.91	191	35.6	60.7	3.7	94.2	184	97.8	95.7	99.1	98.5	97.4	97.1	98.3
Compounding	0.93	193	45.6	53.9	0.5	99.0	192	99.5	98.9	100	100	99.0	99.4	99.5

* GS stands for gold standard.

based on synonymy, antonymy, and hyponymy relations, derivation process, and compounding. We asked two human annotators (nonnative fluent English speakers) to assign the dominant polarity label (positive, negative, or neutral) and polarity score to each of the randomly retrieved word. As the first gold standard (GS-1) we considered words where both annotators agreed on the polarity labels. In the second gold standard (GS-2), we excluded words with a neutral label, as our methods were not designed to distinguish between neutral and sentiment-conveying terms. For the comparison with the gold standard annotations, the dominant polarity of each word was extracted from SentiFul.

The results of the evaluation of polarity assignments are shown in Table 11. As seen from the data, the method relying on antonymy relations yielded noisy results (for instance, 29.5 percent of words, on which both annotators agreed, are neutral). On GS-1 and GS-2, the method based on compounding performed with the highest accuracy (99.0 percent, 99.5 percent) in assigning dominant positive or negative labels, followed by the methods considering hyponymy relations (97.9 percent, 98.9 percent), derivation process (94.2 percent, 97.8 percent), synonymy relations (93.3 percent, 95.4 percent), and antonymy relations (66.7 percent, 94.5 percent). With regard to positive and negative labels, the F-score of assigning negative label is greater than the F-score of assigning positive label in the case of four out of five methods, except for the method based on antonymy relations. A possible explanation might be in the proportions of positive and negative labels in the gold standard. The accuracy of the methods concerning different content words (adjectives, adverbs, nouns, and verbs) is given in Table 12.

TABLE 12
Accuracy with Regard to Different Parts-of-Speech

Method	Accuracy, % [GS-1/GS-2]			
	adjectives	adverbs	nouns	verbs
Synonymy	93.8/95.7	88.4/90.5	93.6/97.8	97.6/97.6
Antonymy	68.8/91.7	60.0/75.0	85.1/100	49.0/96.2
Hyponymy	-	-	97.9/98.9	-
Derivation	93.8/93.8	97.9/97.9	91.5/100	93.8/100
Compounding	98.8/100	100/100	98.8/98.8	100/100

TABLE 13
Results of Evaluations of the Polarity Scores

Method	Pearson correlation coefficient (r)	
	Scores of Annotator 1	Scores of Annotator 2
Synonymy	0.576	0.626
Antonymy	0.112	0.599
Hyponymy	0.498	0.618
Derivation	0.520	0.603
Compounding	0.617	0.757

The evaluations of the polarity scores were based on Pearson correlation between the polarity scores automatically assigned by each of the methods and the gold standard scores manually assigned by human annotators. We considered only those words, on the dominant polarity label of which our methods agreed with both annotators. Table 13 contains the values of Pearson correlation between scores provided by each method and scores given by each annotator individually, showing mainly strong positive relationships ($r > 0.5$).

The obtained results indicate that methods based on compounding and synonymy relations achieved high accuracy in assigning appropriate polarity scores to sentiment-conveying terms; the method relying on antonymy relations was the least accurate (for instance, there is negligible relationship with polarity scores of Annotator 1).

We analyzed the erroneous outcomes of the derivation process. We found that, for example, the derivation algorithm assigned positive scores to the verb "*reprise*" ("*re-*"+"*prise*") and nouns "*lovage*" ("*love*"+"*-age*") and "*truster*" ("*trust*"+"*-er*"), which were labeled as neutral by both human raters. The examples of mislabeled words include the adjectives "*chanceful*," "*fanciful*," and "*oddish*" (positive in SentiFul, while negative in the gold standard), and the adverb "*modestly*" (negative in SentiFul, while positive in the gold standard).

6.2 Evaluation Based on General Inquirer

Next, we evaluated our SentiFul entries based on the polarity lexicon from General Inquirer[3] (GI). In particular, we collected 4,002 GI terms (distinct adjectives, adverbs,

3. General Inquirer. http://www.wjh.harvard.edu/~inquirer/.

TABLE 14
Results of Evaluation Based on General Inquirer

Lexicon (intersection with GI)	Accuracy, %	Precision, %		Recall, %		F-score, %	
		pos	neg	pos	neg	pos	neg
SentiFul core (812 words)	94.1	91.0	96.5	95.3	93.2	93.1	94.8
SentiFul (2223 words)	86.3	81.8	90.1	87.6	85.3	84.6	87.6

nouns, and verbs) labeled as "Positiv" (1,813) and "Negativ" (2,189). The value of expansion of SentiFul was investigated by comparing the preexpansion (SentiFul core) and postexpansion (SentiFul) statistics (see Table 14). The gold standards for evaluation were based on the intersection of polarity-based GI and SentiFul core (338 positive and 474 negative, in total 812 words) and GI and SentiFul (957 positive and 1,266 negative, in total 2,223 words).

The calculated agreement (Cohen's Kappa coefficient) between SentiFul annotations and the GI gold standard was substantial ($k = 0.72$) for all content words. The highest agreement was obtained on adverbs (0.81), followed by adjectives (0.79), nouns (0.7), and verbs (0.67).

The measured precision, recall, and F-score are 81.8, 87.6, and 84.6 percent for positive labels and 90.1, 85.3, and 87.6 percent for negative labels, respectively. As seen from Table 14, SentiFul expansion yielded a drop in accuracy of about 8 percent (94.1 percent vs 86.3 percent).

7 Modifiers and Intensifying/Reversing Words

A robust sentiment analysis method should rely not only on sentiment terms, but also on modifiers and contextual valence shifters (this term was introduced by Polanyi and Zaenen [30]), which are integral parts of SentiFul.

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

1. Adverbs of degree (e.g., "*significantly*," "*slightly*," etc.) that influence 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 neighboring 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*") $= 0.2$). The Pearson correlation coefficient calculated between human annotations ($r = 0.98$) showed a very strong positive relationship. In total, currently, we have collected 138 modifiers.

In addition, we distinguish two types of words that can influence the contextual sentiment:

1. *Intensifying* type of adjectives (e.g., "*resurgent*" and "*rapidly-growing*"), nouns (e.g., "*increase*" and "*uptick*"), and verbs (e.g., "*to grow*" and "*to rocket*"), which increase the strength of sentiment of the related words.
2. *Reversing* type of adjectives (e.g., "*reduced*"), nouns (e.g., "*termination*" and "*reduction*"), and verbs (e.g., "*to decrease*," "*to limit*," and "*to diminish*"), which reverse the prior polarity of related words.

Using the list of seed functional words, we analyzed their basic semantic relations (synonymy and antonymy relations) in WordNet, and thus collected 240 relevant terms.

8 Modal Operators

Modality could, that is to say, be defined as the grammaticalization of speaker's (subjective) attitudes and opinions. Palmer [31, p. 16]

Modality is related to assertions of probability, possibility, permission, intention, obligation, and the like [32]. Consideration of the modals in the tasks of opinion mining and sentiment analysis is very important as they indicate the degree of a person's belief in the truth of the proposition, which is subjective in nature. In contrast to sentiment words, which can be characterized by the degrees of positivity or negativity, modals are distinguished by the *confidence level*. Hoye [32, p. 80] argues that "*inference and confidence go "hand-in-hand" and are directly tied to the status of the speaker's "knowledge"; the stronger the evidence, the more forceful can be the expression of the speaker's resolve*."

We collected modal operators of two categories:

1. Modal verbs (in total, 13 verbs).
2. Modal adverb satellites (in total, 61 adverbs).

Table 15 includes the classification of the collected modal operators and their examples. Since modals are considered as indicators of the *confidence level* of expressed sentiment or opinion, we asked three human annotators to assign the *confidence level*, which ranges from 0.0 to 1.0, to each modal verb and adverb, based on the corresponding predefined range of *confidence level*, displayed in the last column of Table 15. The Pearson correlation coefficients calculated between human annotations pairwise ($r_1 = 0.98$, $r_2 = 0.99$, and $r_3 = 0.99$) showed very strong positive correlations. Three ratings of each modal operator were averaged.

The percentage distributions of modal verbs and adverbs according to the ranges of *confidence level* are given in Table 16. The set of modal operators as well as their *confidence levels* were added to the SentiFul lexicon to assist in analysis of sentiment expressed through written language.

9 Conclusions

This paper focuses on the development of the SentiFul database that is comprised of a reliable lexicon of sentiment-conveying terms, modifiers, functional words, and modal

TABLE 15
Classification of Modal Operators

Type	Example (*confidence level*)	Range of *conf. level*
	Modal verbs	
central modal auxiliaries of possibility	*may* (0.27), *can* (0.5)	[0.2-0.5]
central modal auxiliaries of probability	*should* (0.6), *would* (0.8), *will* (0.9)	(0.5-1.0)
central modal auxiliaries of certainty	*must* (1.0)	1.0
modal 'marginals'	*dare* (0.5), *ought* (0.7)	[0.2-1.0]
	Modal adverb satellites	
adverbs of doubt	*doubtfully* (0.1), *vaguely* (0.17)	[0.0-0.3)
adverbs of possibility	*conceivably* (0.37)	[0.3-0.5]
adverbs of probability	*arguably* (0.63), *likely* (0.7)	(0.5-0.9)
adverbs of certainty	*ultimately* (0.97), *indeed* (1.0)	[0.9-1.0]
adverbs of trueness	*truthfully* (0.97), *veritably* (1.0)	[0.9-1.0]
adverbs of falseness	*falsely* (1.0)	[0.9-1.0]

TABLE 16
Percentage Distributions of Modal Operators

Category	Ranges of *confidence level* [0.0-0.2)	[0.2-0.4)	[0.4-0.6)	[0.6-0.8)	[0.8-1.0)	1.0
Modal verbs	0.0	23.1	15.4	23.1	15.4	23.1
Modal adverbs	9.8	8.2	4.9	4.9	26.2	45.9

operators which are necessary for robust analysis of orientation, strength, and confidence level of the sentiment reflected in text. In the paper, we described techniques for finding new sentiment-conveying words, particularly through synonymy, antonymy, hyponymy relations, derivation, and compounding. We believe that the proposed methods for derivation of new sentiment-related English terms can be applicable to other languages, especially fusional languages that use bound morphemes and are characterized by a rich inflectional system. The evaluations of the proposed methods showed that they achieved high accuracy in assigning dominant polarity labels and polarity scores to the words. Using these methods, it is possible to expand a sentiment lexicon and improve coverage of sentiment analysis systems. Currently, SentiFul contains about 12,900 sentiment-related terms, 137 modifiers, 240 intensifying/reversing words, and 74 modal operators. Our primary objectives for the future are to evaluate the validity of our rules in a machine learning setting and to evaluate SentiFul on real tasks of sentiment analysis.

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Alena Neviarouskaya received the BS degree from the Belarusian State University of Informatics and Radioelectronics, Minsk, and the MS degree in information and communication engineering from the University of Tokyo, Japan. She is now a PhD candidate in the Department of Information and Communication Engineering, Graduate School of Information Science and Technology, The University of Tokyo. She is partially employed as a research assistant in the Digital Content and Media Sciences Research Division, National Institute of Informatics, Tokyo. Her research interests include artificial intelligence, affective computing, intelligent user interfaces, and natural language processing.

Helmut Prendinger received the MA and PhD degrees from the University of Salzburg, Austria. He is an associate professor at the National Institute of Informatics, Tokyo, Japan. Previously, he was a research associate and a JSPS postdoctoral fellow at the University of Tokyo. Earlier, he was a junior specialist at the University of California, Irvine. He is a coeditor (with Mitsuru Ishizuka) of a book on lifelike characters that appeared in the Cognitive Technologies series of Springer. His research interests include artificial intelligence, online virtual worlds, affective computing, and human-computer interaction, in which areas he has published more than 170 papers in international journals and conference proceedings.

Mitsuru Ishizuka received the BS, MS, and PhD degrees in electronic engineering from the University of Tokyo, Japan. He is a vice dean and professor in the Graduate School of Information Science and Technology, The University of Tokyo. Previously, he was with the NTT Yokosuka Laboratory and the Institute of Industrial Science, The University of Tokyo. During 1980-1981, he was a visiting associate professor at Purdue University. His research interests include artificial intelligence, multimodal media with life-like agents, and semantic computing for the Web. He is a member of the IEEE, AAAI, JSAI, IPSJ, IEICE, etc., and was the president of the Japanese Society for Artificial Intelligence (JSAI) during 2004-2006.