

# Experiments with a Differential Semantics Annotation for WordNet 3.0

**Dan Tufiş**

Research Institute for Artificial Intelligence  
Romanian Academy  
Calea "13 Septembrie", no.13  
Bucharest 5, 050711, Romania  
tufis@racai.ro

**Dan Ştefănescu**

Research Institute for Artificial Intelligence  
Romanian Academy  
Calea "13 Septembrie", no.13  
Bucharest 5, 050711, Romania  
danstef@racai.ro

## Abstract

This article reports on the methodology and the development of a complementary information source for the meaning of the synsets of Princeton WordNet 3.0. This encoded information was built following the principles of the Osgoodian differential semantics theory and consists of numerical values which represent the scaling of the connotative meanings along the multiple dimensions defined by pairs of antonyms (factors). Depending on the selected factors, various facets of connotative meanings come under scrutiny and different types of textual subjective analysis may be conducted (opinion mining, sentiment analysis).

## 1 Introduction

According to "Semantic Differential" theory (Osgood et al., 1957), the connotative meaning of most adjectives can be, both qualitatively and quantitatively, differentiated along a scale, the ends of which are antonymic adjectives. Such a pair of antonymic adjectives is called a factor. The intensive experiments Osgood and his colleagues made with their students<sup>1</sup> outlined that most of the variance in the text judgment was explained by only three major factors: the evaluative factor (e.g., good-bad), the potency factor (e.g., strong-weak), and the activity factor (e.g., active-passive).

<sup>1</sup> The students were asked to rate the meaning of words, phrases, or texts on different scales defined in terms of pairs of bipolar adjectives such as *good-bad*, *active-passive*, *strong-weak*, *optimistic-pessimistic*, *beautiful-ugly*, etc.)

Kamps and Marx (2002) implemented a WordNet-based method in the spirit of the theory of semantic differentials and proposed a method to assess the "attitude" of arbitrary texts. In their approach, a text unit is regarded as a bag of words and the overall scoring of the sentence is obtained by combining the scores for the individual words of the text. Depending on the selected factor, various facets of subjective meanings come under scrutiny.

The inspiring work of Kamps and Marx still has several limitations. The majority of researchers working on subjectivity agree that the subjectivity load of a given word is dependent on the senses of the respective word (Andreevskaja and Bergler, 2006), (Bentivogli et al., 2004), (Mihalcea et al., 2007), (Valiutti et al., 2004) and many others.; yet, in Kamps and Marx's model (KMM, henceforth), because they work with words and not word-senses, the sense distinctions are lost, making it impossible to assign different scores to different senses of the word in case. Going up from the level of word to the level of sentence, paragraph or entire text, the bag of words approach can easily be fooled in the presence of valence shifters (Polanyi and Zaenen, 2006). In order to cope with this problem, the text under investigation needs a minimal level of sentence processing, required for the identification of the structures that could get under the scope of a valence shifter (Tufiş, 2008). For dealing with irony or sarcasm, processing requirements go beyond sentence level, and discourse structure of the text might be necessary.

On the other hand, although the adjectives make up the obvious class of subjectivity words, the other open class categories have significant potential for expressing subjective meanings.

In our models, unlike KMM, the building block is the word sense, thus making possible to assign different connotation values to different senses of a word. This was possible by using an additional source of information besides the WordNet itself, namely the SUMO/MILO ontology. Moreover, we considered all the word classes contained in WordNet, not only adjectives.

From this point of view, our work, although through a different approach, shares objectives with other wordnet-based methods such as SentiWordNet (Esuli and Sebastiani, 2006) (Baccianella et al., 2010) and WordNet Affect (Valiuttti et al. 2004).

## 2 Base Definitions

Let us begin with some definitions, slightly modified, from KMM. We will progressively introduce new definitions to serve our extended approach.

**Definition 1:** Two words  $w_\alpha$  and  $w_\beta$  are *related* if there exists a sequence of words ( $w_\alpha w_1 w_2 \dots w_i \dots w_\beta$ ) so that each pair of adjacent words in the sequence belong to the same synset. If the length of such a sequence is  $n+1$  one says that  $w_\alpha$  and  $w_\beta$  are *n-related*.

Two words may not be related at all or may be related by many different sequences, of various lengths. In the latter case, one would be interested in their minimal path-length.

**Definition 2:** Let  $MPL(w_i, w_j)$  be the partial function:

$$MPL(w_i, w_j) = \begin{cases} n & \text{the smallest } n \text{ when } w_i \text{ and } w_j \text{ are } n\text{-related} \\ \text{undefined} & \text{otherwise} \end{cases}$$

Kamps and Marx (2002) showed that MPL is a distance measure that can be used as a metric for the semantic relatedness of two words. Observing the properties of the MPL partial function, one can quantify the relatedness of an arbitrary word  $w_i$  to one or the other word of a bipolar pair. To this end, KMM introduced another partial function as in Definition 3.

**Definition 3:** Let  $TRI(w_i, w_\alpha, w_\beta)$ , with  $w_\alpha \neq w_\beta$  be:

$$TRI(w_i, w_\alpha, w_\beta) = \begin{cases} \frac{MPL(w_i, w_\alpha) - MPL(w_i, w_\beta)}{MPL(w_\alpha, w_\beta)} & \text{if MPLs defined} \\ \text{undefined} & \text{otherwise} \end{cases}$$

When defined,  $TRI(w_i, w_\alpha, w_\beta)$  is a real number in the interval  $[-1, 1]$ . The words  $w_\alpha$  and  $w_\beta$  are the

antonymic words of a factor, while  $w_i$  is the word of interest for which TRI is computed. If one takes the negative values returned by the partial function  $TRI(w_i, w_\alpha, w_\beta)$  as an indication of  $w_i$  being more similar to  $w_\alpha$  than to  $w_\beta$  and the positive values as an indication of  $w_i$  being more similar to  $w_\beta$  than to  $w_\alpha$ , then a zero value could be interpreted as  $w_i$  being neutrally related with respect to  $w_\alpha$  and  $w_\beta$ . This is different from being unrelated.

**Definition 4:** If  $\alpha\beta$  is a factor used for the computation of relatedness of  $w_i$  to  $\alpha$  and  $\beta$ , the proper function  $TRI_{\alpha\beta}^*(w_i)$  returns a value outside the interval  $[-1, 1]$  when  $w_i$  is unrelated to the  $\alpha\beta$  factor:

$$TRI_{\alpha\beta}^*(w_i) = \begin{cases} TRI(w_i, \alpha, \beta) & \text{iff } TRI(w_i, \alpha, \beta) \text{ defined} \\ 2 & \text{otherwise} \end{cases}$$

Given a factor  $\alpha\beta$ , for each word  $w_i$  in WordNet that *can be reached on a path* from  $\alpha$  to  $\beta$ , the function  $TRI_{\alpha\beta}^*(w_i)$  computes a score number, which is a proportional to the distances from  $w_i$  to  $\alpha$  and to  $\beta$ . The set of these words defines the coverage of the factor –  $COV(\alpha, \beta)$ .

Our experiments show that the coverage of the vast majority of the factors, corresponding to the same POS category, is the same. From now on, we will use LUC (Literal Unrestricted<sup>2</sup> Coverage) to designate this common coverage. The table below gives coverage figures for each of the POS categories in Princeton WordNet 3.0 (PWN 3.0).

Class	Factors	LUC
Adjectives	199	4,402 (20.43%)
Nouns	106	11,964 (10.05%)
Verbs	223	6,534 (56.66%)
Adverbs	199	1,291 (28.81%)

Table 1: LUC Statistics According to the POS of the Literals in PWN 3.0

The PWN structuring does not allow us to compute  $TRI^*$  scores for adverbs using this approach, but, more than half of the total number of adverbs (63.11%) are derived from adjectives. For those adverbs, we transferred the score values from their correspondent adjectives in the LUC set and we used the adjectival factors.

<sup>2</sup> In the following we will gradually introduce several restrictions, thus justifying the acronym used here.

The results reported for adjectives by Kamps and Marx<sup>3</sup> are consistent with our findings. The difference in numbers might be explained by the fact that the two compared experiments used different versions of the Princeton WordNet.

### 3 Introducing Word-Sense Distinctions

KMM defines a factor as a pair of words with antonymic senses. We generalize the notion of a factor to a pair of synsets. In the following, we will use the colon notation to specify the sense number of a literal that licenses the synonymy relation within a synset. Synonymy is a lexical relation that holds not between a pair of words but between specific senses of those words. That is, the notation  $\{\text{literal}_1:n_1 \text{ literal}_2:n_2 \dots \text{literal}_k:n_k\}$  will mean that the meaning given by the sense number  $n_1$  of the literal<sub>1</sub>, the meaning given by sense number  $n_2$  of the literal<sub>2</sub> and so on are all pair-wise synonymous. The term *literal* is used to denote the dictionary entry form of a word (lemma).

The antonymy is also a lexical relation that holds between specific senses of a pair of words. The synonyms of the antonymic senses, taken pairwise, definitely express a semantic opposition. Take for instance the antonymic pair  $\langle \text{rise:1} \text{ fall:2} \rangle$ . These two words belong to the synsets  $\{\text{rise:1, lift:4, arise:5, move up:2, go up:1, come up:6, uprise:6}\}$  and  $\{\text{descend:1, fall:2, go down:1, come down:1}\}$ . The pair  $\langle \text{rise:1} \text{ fall:2} \rangle$  is explicitly encoded as antonymic. However, there is a conceptual opposition between the synsets to which the two word senses belong, that is between any pair of the Cartesian product:  $\{\text{rise:1, lift:4, arise:5, move up:2, go up:1, come up:6, uprise:6}\} \otimes \{\text{descend:1, fall:2, go down:1, come down:1}\}$ . This conceptual opposition is even more obvious in this example, as the pairs  $\langle \text{go up:1} \text{ go down:1} \rangle$  and  $\langle \text{come up:1} \text{ come down:1} \rangle$  are also explicitly marked as antonymic.

**Definition 5:** An **S-factor** is a pair of synsets  $(S_\alpha, S_\beta)$  for which there exist  $w_i^\alpha:s_i^\alpha \in S_\alpha$  and  $w_j^\beta:s_j^\beta \in S_\beta$  so that  $w_i^\alpha:s_i^\alpha$  and  $w_j^\beta:s_j^\beta$  are antonyms and  $MPL(w_i^\alpha, w_j^\beta)$  is defined.  $S_\alpha$  and  $S_\beta$

have opposite meanings, and we consider that  $MPL(S_\alpha, S_\beta) = MPL(w_i^\alpha, w_j^\beta)$ .

The previous example shows that the semantic opposition of two synsets may be reinforced by multiple antonymic pairs. Because of how MPL is defined, choosing different antonymic pairs might produce different values for  $MPL(S_\alpha, S_\beta)$ . That is why, wherever is the case, we need to specify the antonymic pair which defines the S-factor.

Based on the definition of the coverage of a factor  $\langle w_i^\alpha, w_i^\beta \rangle$ , one may naturally introduce the notion of coverage of a S-factor -  $\langle S_\alpha, S_\beta \rangle$ : the set of synsets containing the words in  $COV\langle w_i^\alpha, w_i^\beta \rangle$ . The coverage of an S-factor  $\langle S_\alpha, S_\beta \rangle$  will be onward denoted by  $SCOV\langle S_\alpha, S_\beta \rangle$ .

Since the word-relatedness and MPL definitions ignore the word senses, it might happen that the meaning of some synsets in the coverage of an S-factor have little (if anything) in common with the semantic field defined by the respective S-factor. More often than not, these outliers must be filtered out and, to this end, we further introduce the notions of *semantic type of a synset*, *typed S-factor*, and *scoped synset with respect to a typed S-factor*, which represent major deviations from KMM.

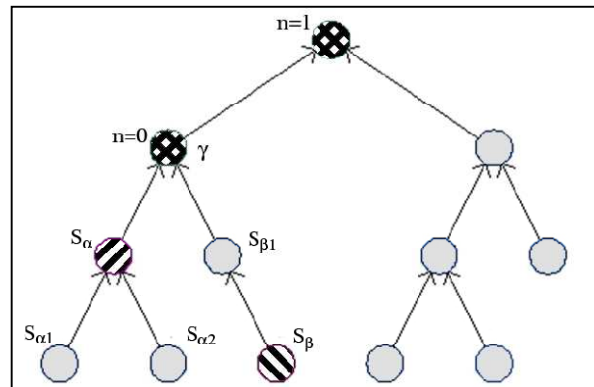


Figure 1. Different levels of coverage (marked with cross hatching) for the S-factor  $\langle S_\alpha, S_\beta \rangle$

Before that, we need to introduce the mapping between the WordNet synsets and the SUMO/MILO concepts. The Suggested Upper Merged Ontology (SUMO), Mid-Level Ontology (MILO) and its domain ontologies form the largest formal public<sup>4</sup> ontology in existence today, containing roughly 20,000 terms and 70,000 axioms (when

<sup>3</sup> They found 5410 adjectives that were in the coverage of the factors they investigated (WordNet 1.7). For PWN 2.0, the total number of covered adjectives is 5307.

<sup>4</sup> <http://www.ontologyportal.org/>

SUMO, MILO, and domain ontologies are combined). One of the major attractions of this ontology (Niles and Pease, 2003) is that it has been mapped to the WordNet lexicon. Using this mapping, synsets are labeled with a SUMO/MILO concept which we will refer to as the synset’s *semantic type*. The hierarchical structure of SUMO/MILO induces a partial ordering of the S-factors.

**Definition 6:** An S-factor  $\langle S_\alpha, S_\beta \rangle$  is said to be a *typed S-factor* if the types of the synsets  $S_\alpha$  and  $S_\beta$  are identical or they have a common ancestor. If this ancestor is the lowest common ancestor, it is called the *0-semantic type* of the S-factor. The direct parent of the *n-semantic type* of an S-factor is the *n+1-semantic type* of the S-factor (Fig. 1).

A typed S-factor is represented by indexing the S-factor with its type as in the examples below:

$\langle \{\text{unfairness:2...}\}, \{\text{fairness:1...}\} \rangle_{\text{NormativeAttribute}}$   
 $\langle \{\text{discomfort:1...}\}, \{\text{comfort:1...}\} \rangle_{\text{StateOfMind}}$   
 $\langle \{\text{distrust:2...}\}, \{\text{trust:3...}\} \rangle_{\text{TraitAttribute}}$   
 $\langle \{\text{decrease:2...}\}, \{\text{increase:3...}\} \rangle_{\text{QuantityChange}}$

In the following, if not otherwise specified, by S-factors we mean typed S-factors. Unless there is ambiguity, the type of an S-factor will be omitted.

**Definition 7:** A synset  $S_i$  with the type L is *n-scoped* relative to a typed S-factor  $\langle S_\alpha, S_\beta \rangle$  if L is a node in a sub-tree of the SUMO/MILO hierarchy having as root the n-semantic type of the S-factor  $\langle S_\alpha, S_\beta \rangle$ . We say that **n** defines the **level of the scope coverage of the S-factor**  $\langle S_\alpha, S_\beta \rangle$  and that every synset in this coverage is **n-scoped**.

We use the notation  $SCOV_n \langle S_\alpha, S_\beta \rangle$  for the scope coverage of level n of an S-factor  $\langle S_\alpha, S_\beta \rangle$ . If the root of the tree has the semantic type  $\gamma$ , we will use also use the notation  $SCOV_n \langle S_\alpha, S_\beta \rangle_\gamma$  or simply  $SCOV \langle S_\alpha, S_\beta \rangle_\gamma$ . In other words,  $SCOV \langle S_\alpha, S_\beta \rangle_\gamma$  is the set of synsets the semantic types of which are subsumed by  $\gamma$ . For the example in Fig. 1, only the synsets  $S_{\alpha 1}$ ,  $S_{\alpha 2}$  and  $S_{\beta 1}$  are in the  $SCOV_0 \langle S_\alpha, S_\beta \rangle$ . All depicted synsets are in  $SCOV_1 \langle S_\alpha, S_\beta \rangle$ .

It is easy to see that when the value of the scope coverage level is increased so as to reach the top of the ontology,  $SCOV_n \langle S_\alpha, S_\beta \rangle_\gamma$  will be equal to the set of synsets containing the literals in *LUC* (see Table 1). Let us call this set *SUC* (Synset Unrestricted Coverage).

Class	S-Factors	SUC
Adjectives	264	4,240 (23.35%)
Nouns	118	11,704 (14.25%)
Verbs	246	8,640 (62.75%)
Adverbs	264	1,284 (35.45%)

Table 2: SUC Statistics According to the POS of the Synsets in PWN 3.0

From the differential semantics point of view, the S-factor  $\langle S_\alpha, S_\beta \rangle$  quantitatively characterizes each synset in  $SCOV_n \langle S_\alpha, S_\beta \rangle$  by a TRI\*-like score (Definition 4). The synsets in  $SCOV_0 \langle S_\alpha, S_\beta \rangle$  are best discriminated, meaning that their scores for the  $\langle S_\alpha, S_\beta \rangle$  factor are the highest. For the synsets in  $SCOV_n \langle S_\alpha, S_\beta \rangle$  but not in  $SCOV_{n-1} \langle S_\alpha, S_\beta \rangle$ , the scores are smaller and we say that the characterization of these synsets in terms of the  $\langle S_\alpha, S_\beta \rangle$  factor is weaker. Our model captures this through a slight modification of the TRI function in Definition 3, where  $w_\alpha$  and  $w_\beta$  are the antonyms belonging to  $S_\alpha$  and  $S_\beta$  respectively, and  $w_i$  is a literal of a synset  $S_j$  in  $SCOV_n \langle S_\alpha, S_\beta \rangle$  but not in  $SCOV_{n-1} \langle S_\alpha, S_\beta \rangle$ :

**Definition 8:** The *differential score for a literal*  $w_i$  occurring in a synset  $S_j$  in  $SCOV_n \langle S_\alpha, S_\beta \rangle$  but not in  $SCOV_{n-1} \langle S_\alpha, S_\beta \rangle$  is computed by the function  $TRI^+$ :

$$TRI^+(w_i, S_\alpha, S_\beta) = \frac{MPL(w_i, w_\alpha) - MPL(w_i, w_\beta)}{MPL(w_\alpha, w_\beta) + n}$$

Since we imposed the requirement that  $S_j$  be in  $SCOV_n \langle S_\alpha, S_\beta \rangle$ ,  $TRI^+(w_i, S_\alpha, S_\beta)$  is defined for all literals in  $S_j$ , thus for any  $w_i \in S_j$  the value of  $TRI^+(w_i, S_\alpha, S_\beta)$  is in the [-1,1] interval. The scores computed for the synsets in  $SCOV_n \langle S_\alpha, S_\beta \rangle$  remained unchanged in  $SCOV_{n+k} \langle S_\alpha, S_\beta \rangle$  for any  $k \geq 0$ . The above modification of the TRI function insures that the score of a synset gets closer to zero (neutrality) with the increase of  $n$ .

It is worth mentioning that using different antonymic literal pairs from the same opposed synsets does not have any impact on the sign of  $TRI^+$  scores, but their absolute values may differ.

If one associates a semantic field with  $\gamma$ , the type of an S-factor  $\langle S_\alpha, S_\beta \rangle$ , then all the synsets in  $SCOV_n \langle S_\alpha, S_\beta \rangle_\gamma$  are supposed to belong to the semantic field associated with  $\gamma$ . This observation should clarify why different senses of a given word

may belong to different semantic coverages and thus, may have different scores for the S-factor in case.

**Definition 9:** The differential score of a synset  $S_i$  in  $SCOV_n \langle S_\alpha, S_\beta \rangle$  with respect to the S-factor  $\langle S_\alpha, S_\beta \rangle$  is given by the function  $TRIS(S_i, S_\alpha, S_\beta)$ , defined as the average of the  $TRI^+$  values associated with the  $m$  literals in the synset  $S_i$ .

$$TRIS(S_i, S_\alpha, S_\beta) = \frac{\sum_{j=1}^m TRI^+(w_j, S_\alpha, S_\beta)}{m}$$

#### 4 Computing the S-Factors and the Differential Scores for Synsets

In accordance with the equations in the previous definitions, we associated each synset  $S_k$  of WordNet 3.0 with an ordered vector  $\langle F_1, F_2, \dots, F_n \rangle$  where  $F_i$  is a pair (*score; level*) with *score* and *level* representing the value of the  $i^{\text{th}}$  S-factor and, respectively, the minimal S-factor coverage level in which  $S_k$  was found.

For instance, let us assume that the first S-factor in the description of the adjectival synsets is:

$\langle \{nice:3\}, \{nasty:2 \dots\} \rangle_{\text{SubjectiveAssesmentAttribute}}$   
then for the synset  $\{fussy:1, crabby:1, grumpy:1, cross:2, grouchy:1, crabbed:1, bad-tempered:1, ill-tempered:1\}_{\text{SubjectiveAssesmentAttribute}}$  the vector  $\langle F_1, \dots \rangle$  is  $\langle (0,66;0) \dots \rangle$  while for the synset  $\{unplayful:1, serious:5, sober:4\}_{\text{SubjectiveAssesmentAttribute}}$  the vector  $\langle F_1, \dots \rangle$  is  $\langle (-0,166;0) \dots \rangle$ .

The values signify that the synset  $\{fussy:1, crabby:1, grumpy:1, cross:2, \dots\}_{\text{SubjectiveAssesmentAttribute}}$  is 0-scoped with respect to the S-factor  $\langle \{nice:3\}, \{nasty:2 \dots\} \rangle$  and its connotative meaning is significantly closer to the meaning of *nasty:2* (0,66). Similarly, the synset  $\{unplayful:1, serious:5, sober:4\}$  is 0-scoped with respect to the considered S-factor and its connotative meaning is closer to the meaning of *nice:3* (-0,166).

Our experiments showed that in order to ensure the same sets of synsets for all factors of a given part-of-speech we had to set the level of the semantic coverages to 7 (corresponding to the SUC). For each of the typed S-factors  $\langle S_\alpha, S_\beta \rangle$  and for each synset  $S_i$  in their respective semantic coverage  $SCOV \langle S_\alpha, S_\beta \rangle_\gamma$  we computed the  $TRIS(S_i, S_\alpha, S_\beta)$  score. Each synset from the coverage of each POS category was associated with a vector of scores, as described above. Since

the number of S-factors depends on the POS category the lengths of each of the four type vectors is different. The cell values in a synset vector have uneven values, showing that factors have different discriminative power for a given meaning. Because we considered SUC, all S-factors are relevant and the cells in any synset vector are filled with pairs (*score; level*).

For the noun part of the PW3.0 we identified 118 typed S-factors, all of them covering the same set of 11,898 noun literals (9.99%) with their senses clustered into 11,704 synsets (14.25%).

For the verb part of the PWN 3.0, we identified 246 typed S-factors, all of them covering the same set of 6,524 verb literals (56.57%) with their senses clustered into 8,640 synsets (62.75%).

For the adjective part of the PWN 3.0, we identified 264 typed S-factors, all of them covering the same set of 4,383 literals (20.35%) with their senses clustered into 4,240 synsets (23.35%)<sup>5</sup>. As previously mentioned, the same factors were used for the adverbs derived from adjectives. In this way, a total of 1,287 adverbs (28.72%) clustered into 1,284 synsets (35.45%) were successfully annotated (see Table 2).

Apparently, the cardinals of the factor sets in Table 2 should be identical with those in Table 1. The differences are due to the fact that a pair of opposed synsets may contain more than a single pair of antonymic senses each of them specifying a distinct S-factor.

In case the user restricted the coverages to lower levels, the original maximal semantic coverages are split into different subsets for which several S-factors become irrelevant. The cell values corresponding to these factors are filled in with a conventional value outside the interval  $[-1, 1]$ .

Thus, we have the following annotation cases:

A synset of a certain POS is not in the corresponding SUC. This case signifies that the synset cannot be characterized in terms of the differential semantics methodology and we conventionally say that such a synset is “objective” (insensitive to any S-factor). Since this situation would require a factor vector with each cell having the same value (outside the  $[-1, 1]$  interval) and as

<sup>5</sup> In PWN 2.0 the number of covered literals (and synsets) is with almost 20% higher (Tufiş and Ştefănescu, 2010). This difference is explained by the fact that 1081 adjectives (5%), mostly participial, from PWN 2.0 are not any more listed as adjectives in PWN 3.0.

such a vector would be completely uninformative, we decided to leave the “objective” synsets unannotated. As one can deduce from Table 2, the majority of the synsets in PWN3.0 are in this category (89,556 synsets, i.e. 77.58%).

Any synset of a certain POS in the corresponding SUC will have an associated factor vector. There are 25,868 such synsets. The  $i^{\text{th}}$  cell of such a vector will correspond to the  $i^{\text{th}}$  S-factor  $\langle S_{\alpha}, S_{\beta} \rangle$ . We may have the following sub-cases:

(a) All cell scores are in the  $[-1, 1]$  interval, and in this case all S-factors are relevant, that is, from any word in the synset one could construct a path to both words prompting an S-factor, irrespective of the S-factor itself. A negative score in the  $i^{\text{th}}$  cell of the S-factor vector signifies that the current synset is more semantically related to  $S_{\alpha}$  than to  $S_{\beta}$ , while a positive score in the  $i^{\text{th}}$  cell of the factor vector signifies that the synset is more semantically related to  $S_{\beta}$  than to  $S_{\alpha}$ . A zero score in the  $i^{\text{th}}$  cell of the factor vector signifies that the synset is neutral with respect to the  $\langle S_{\alpha}, S_{\beta} \rangle$  S-factor.

(b) Several cell scores are not in the interval  $[-1, 1]$ , say  $FV[i_1]=FV[i_2] \dots =FV[i_k]=2$ . This signifies that the S-factors corresponding to those cells  $\langle S_{\alpha_1}, S_{\beta_1} \rangle, \langle S_{\alpha_2}, S_{\beta_2} \rangle, \dots, \langle S_{\alpha_k}, S_{\beta_k} \rangle$  are irrelevant for the respective synset and that the current synset is not included in the scope of the above-mentioned S-factors, owing to the selected scope level of the coverage<sup>6</sup>. We say that, at the given scope level, the synset became “objective” with respect to the S-factors  $FV[i_1], FV[i_2] \dots FV[i_k]$ .

There are various ways to select, for a given POS coverage, those S-factors which are most informative or more interesting from a specific point of view. The simplest criterion is based on the coverage level: for a specified coverage level, select only those S-factors the coverage of which contains the analyzed synsets. In general, the most restrictive condition is choosing the 0-level coverage. This condition is equivalent to saying that the S-factors and the analyzed synsets should be in the same semantic class as defined by the SUMO/MILO labeling. For instance, assume that the synset under investigation is {good:1} with the

definition “*having desirable or positive qualities especially those suitable for a thing specified*” and the semantic type *SubjectiveAssessmentAttribute*. Imposing the restriction that the semantic type of the selected factors should be the same with the semantic type of good:1, some relevant factors for estimating the various connotations of “good” from different perspectives are given below. In the shown factors, the words in bold face are those the meaning of which is closer to “good”.

good 01123148-a (SubjectiveAssessmentAttribute)

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effective ineffective#00834198-a_00835609-a (SubjectiveAssessmentAttribute)	-0,78
reasonable unreasonable#01943406-a_01944660-a (SubjectiveAssessmentAttribute)	-0,71
rich lean#02026785-a_02027003-a (SubjectiveAssessmentAttribute)	-0,63
ample meager#00105746-a_00106456-a (SubjectiveAssessmentAttribute)	-0,5
safe dangerous#02057829-a_02058794-a (SubjectiveAssessmentAttribute)	-0,33
brave cowardly#00262792-a_00264776-a (SubjectiveAssessmentAttribute)	-0,14
distant close#00450606-a_00451510-a (SubjectiveAssessmentAttribute)	0,64
busy idle#00292937-a_00294175-a (SubjectiveAssessmentAttribute)	0,63
cursed blessed#00669478-a_00670741-a (SubjectiveAssessmentAttribute)	0,5
old new#01638438-a_01640850-a (SubjectiveAssessmentAttribute)	0,45
formal informal#01041916-a_01044240-a (SubjectiveAssessmentAttribute)	0,38

These factors’ values should be clearer in the context of adequate examples:

A *good* tool is an **effective** tool;  
A *good* excuse is a **reasonable** excuse;  
A *good* vein of copper is a **reach** vein of copper;  
A *good* resource is an **ample** resource;  
A *good* position is a **safe** position;  
A *good* attitude is a **close** attitude;  
A *good* soldier is a **brave** soldier  
A *good* time is an **idle** time;  
A *good* life is a **blessed** life;  
A *good* car is a **new** car;  
A *good* party is an **informal** party.

From the definitions in the previous sections, one can easily see that the sign of a S-factor score depends on the order in which the semantically opposite pairs are considered. If one wishes to have a consistent interpretation of the factor scores (e.g. negative scores are “bad” and positive scores are “good”) the synset ordering in the S-factors is

<sup>6</sup> Remember that for the highest level (7) that corresponds to SUC, all factors are relevant. When the user selects coverages of lower levels some factors might become irrelevant for various synsets.

significant. We used a default ordering of antonyms in all factors, yet a text analyst could modify this ordering. For each POS, we selected a representative factor for which the synset order, from a subjective point of view, was very intuitive. For instance, for the adjective factors we selected the factor <good:1, bad:1>, for noun factors we selected the factor <order:5, disorder:2>, and for verb factors we selected the factor <succeed:1, fail:2>, the first word sense in each of the representative factors having a clear positive connotation. Then for each POS factor  $\langle S_\alpha, S_\beta \rangle$  we computed the distance of its constituents to the synsets of the representative factor of the same POS. The one that was closer to the “positive” side of the reference factor was also considered “positive” and the order of the synsets was established accordingly. This empirical approach proved to be successful for most of the factors, except for a couple of them, which were manually ordered.

We developed an application that allows text analysts to choose the S-factors they would like to work with. The interface allows the user to both select/deselect factors and to switch the order of the poles in any given factor. Once the user decided on the relevant S-factors, the synsets are marked up according to the selected S-factors. This version of the WordNet can be saved and used as needed in the planned application.

## 5 Extending the LUCs and SUCs

Although the maximum semantic coverage of the S-factors for the adjectives contains more than 28% of the PWN3.0 adjectival synsets, many adjectives with connotative potential are not in this coverage. This happens because the definition of the *relatedness* (Definition 1) implicitly assumes the existence of synonyms for one or more senses of a given word. Therefore from mono-semantic words in mono-literal synsets a path towards other synsets cannot be constructed anymore. Because of this, there are isolated “bubbles” of *related* synsets that are not connected with synsets in maximum semantic coverage. In order to assign values to at least a part of these synsets, we experimented with various strategies out of which the one described herein was considered the easiest to implement and, to some extent motivated, from a conceptual point of view. The approach is similar for all the

synsets which are not in the SUCs, but the algorithms for extending these coverages slightly differ depending on the part of speech under consideration.

Class	E-LUCs	E-SUCs
Adjectives	7,124 (33.07%)	6,216 (34.23%)
Nouns	27,614 (23.19%)	22,897 (27.88%)
Verbs	8,910 (77.26%)	10,798 (78.43%)
<i>Adverbs</i>	1,838 (41.01%)	1,787 (49.35%)

Table 3: Extended LUCs and SUCs

The basic idea is to transfer the vectors of the synsets in SUC to those in the complementary set  $\overline{SUC}$ , provided they have “similar meanings”. We say that  $S_i^{POS} \in SUC_{POS}$  and  $S_j^{POS} \in \overline{SUC}_{POS}$  have “similar meanings” if  $SUMO/MILO(S_i^{POS}) = SUMO/MILO(S_j^{POS})$  and  $S_i^{POS}$  and  $S_j^{POS}$  are directly linked by a semantic WordNet relation of a certain type. For adjectival synsets we consider the relations *similar\_to* and *also\_see*, for verbal synsets we consider the relations *hyponym* and *also\_see*, and for the nominal synsets we take into account only the *hyponymy*. Consequently, the S-factors coverage increased as shown in Table 3.

## 6 A Preliminary Comparison with SentiWordnet 3.0

SentiWordNet 3.0 (Baccianella, et al. 2010) is the only public resource we are aware of, which considers sense distinctions and covers all synsets in Princeton WordNet 3.0. Although in SentiWordNet (henceforth SWN3.0) only the Subjective-Objective dichotomy is marked-up, with a further distinction between Positive-Subjectivity and Negative-Subjectivity, using it for the comparison with our annotations is meaningful and relevant for both approaches. First, the connotative meanings are subjective meanings. Then, while the SWN3.0 mark-up is based on ML techniques and various heuristics exploiting the structure of PWN3.0 and some other external resources, the differential semantics approach, as implemented here, is a deterministic one, considering only the content and structural information in PWN3.0 + SUMO/MILO. Identifying contradictions in the two annotations might reveal limitations in the ML techniques and heuristics used by SWN3.0 on one hand, and, on

the other hand, flaws in our method, possible incompleteness or inconsistencies in PWN3.0+SUMO/MILO. It has to be noted that the possible incompleteness or inconsistencies in PWN3.0 would also affect the accuracy of the SWN3.0 values.

Synset	SWN	DSA	Definition
dangerous, grave, grievous, serious, severe ...	-0,63	0,42	causing fear or anxiety by threatening great harm
live	0,5	-0,5	exerting force or containing energy
bastardly, mean	-0,5	0,5	of no value or worth
dangerous, unsafe	-0,75	0,5	involving or causing danger or risk; liable to hurt or harm
delirious, excited, unrestrained, mad, frantic	0,5	-0,5	marked by uncontrolled excitement or emotion
haunted	0,5	-0,43	showing emotional affliction or disquiet
impeccable	-0,63	0,8	not capable of sin
evil, vicious	0,5	-0,75	having the nature of vice
delectable, sexually attractive	<u>0,63</u>	<u>-0,5</u>	capable of arousing desire
ordinary	<u>-0,5</u>	<u>0,75</u>	not exceptional in any way especially in quality or ability or size or degree
serious	<u>-0,75</u>	<u>0,75</u>	requiring effort or concentration; complex and not easy to answer or solve
excusable	<u>0,63</u>	<u>-0,4</u>	capable of being overlooked

Table 4: Examples of divergent scores among the SWN3.0 and DSA

For the partial comparison we selected the adjectives in SWN3.0 with Positive-Subjectivity or Negative-Subjectivity greater than or equal to 0.5. From our differential semantic (DSA) annotation we extracted all the adjectives which along the good-bad differential dimension had an absolute value greater than 0.4. Those adjectives closer to good were considered to be Subjective-Positive while the others were considered to be Subjective-Negative. The threshold value was empirically selected, by observing that beyond the 0.4 and -0.4 values the factorial annotation was closer to our

intuition concerning the connotative load of the analyzed words. We computed the intersection of the two adjectival synsets extracted this way and retained only the synsets contradictorily annotated. We found only 150 differences, which by itself is a small difference, showing that, at least with respect to the good-bad factor, SWN3.0 and DSA annotations are to a large extent consistent.

We manually checked-out the 150 synsets marked-up with contradictory scores and the authors and 6 MSc students negotiated the scores towards reaching the consensus. For 142 of these synsets the consensus was easily reached with 76 considered to be correct in the DSA annotation and 65 correct in the SWN3.0 annotation. Table 4 shows some examples of synsets, the scores of which were correctly judged (in bold) either by SWN3.0 or DSA as well as some examples of non-consensual annotations (in underlined italics).

## 7 Conclusions

Differential semantics annotation addresses the connotative meanings of the lexical stock, the denotative meanings of which are recorded in WordNet 3.0. We revised and improved our previous method (Tufiş and Ştefănescu, 2010). It generalizes the SWN3.0 subjectivity mark-up, according to a user-based multi-criteria differential semantics model.

The partial comparison with SWN3.0 revealed specific limitations of our approach. The major one is due to the definitions of n-relatedness and the TRI relation. The problem resides in indiscriminate treatment of literals which have senses with different polarities with respect to a factor. If one of these senses is significantly closer to one of the poles of the factor, that sense might impose the sign for the rest of the senses. This risk is amplified when literals with high degrees of polysemy and/or high degrees of synonymy are reached on the way from the synset of interest to the synsets defining the S-factor (higher the polysemy/synonymy, higher the number of paths to the constituents of the S-factor). Most of the erroneous scores we noticed were explained by this drawback. We say that the words affected by this limitation of the current algorithm have a significant *connotation shift* potential (Tufiş, 2009), (Ştefănescu, 2010). As such words could generate undesired implicatures, they should be



avoided in formal texts and replaced by synonyms with less connotation shift potential.

We also observed some inconsistencies regarding the association of SUMO/MILO (and the additional domain ontologies) concepts to PWN 3.0 synsets. The semantic types of two opposable synsets (in the same semantic field) should be closely related, if not the same. However, for some S-factors, such as <agreement:3, disagreement:1> this does not happen. The semantic type of the synset {agreement:3...} is “Cooperation”, while the semantic type of {disagreement:1...} is “SubjectiveAssessmentAttribute”. “Cooperation” is a “Process” (subsumed by “Physical”) but, “SubjectiveAssessmentAttribute” is an “Attribute” (subsumed by “Abstract”). There are 9 such cases for nouns, 30 for verbs and 16 for adjectives.

The current multi-factored annotation vectors for nominal, verbal, and adjectival synsets for PWN3.0, as well as an application to manage these annotations, can be freely downloaded from <http://www.racai.ro/differentialemantics/>.

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