Human Verb Associations as the Basis for Gold Standard Verb Classes: Validation against GermaNet and FrameNet

Sabine Schulte im Walde

Computational Linguistics
Saarland University
Saarbrücken, Germany
schulte@coli.uni-sb.de

Abstract

We describe a gold standard for semantic verb classes which is based on human associations to verbs. The associations were collected in a web experiment and then applied as verb features in a hierarchical cluster analysis. We claim that the resulting classes represent a theory-independent gold standard classification which covers a variety of semantic verb relations, and whose features can be used to guide the feature selection in automatic processes. To evaluate our claims, the association-based classification is validated against two standard approaches to semantic verb classes, GermaNet and FrameNet.

1. Introduction

This paper suggests a resource for gold standard semantic verb classes which is independent from manual definitions. We collected human associations of German verbs in a web experiment, and performed a simple hierarchical clustering on the verbs, as based on the human associations. We claim that the resulting verb classes and their underlying features (i.e. the verb associations) represent a valuable basis for a theory-independent semantic classification of the German verbs. To support this claim, we validate the association-based classes against existing verb classes.

Why are we interested in a gold standard semantic verb classification? There are a variety of manual semantic verb classifications; major frameworks are the Levin classes (Levin, 1993), *WordNet* (Fellbaum, 1998) with its German counterpart *GermaNet* (Kunze, 2000), and *FrameNet* (Fontenelle, 2003) with the Salsa project (Erk et al., 2003) creating its German counterpart. Different frameworks depend on different instantiations of semantic similarity, e.g. Levin relies on syntactic similarity and verb alternations, WordNet uses synonymy, and FrameNet relies on situation-based agreement as defined in Fillmore's frame semantics (Fillmore, 1982). As an alternative to the resource-intensive manual classifications, automatic methods such as classification and clustering techniques have been applied to induce verb classes from corpus data, e.g. (Schulte im Walde, 2000; Merlo and Stevenson, 2001; Joanis and Stevenson, 2003; Korhonen et al., 2003; Schulte im Walde, 2003; Ferrer, 2004). When evaluating such induced classifications, it is difficult to define a gold standard that is generally accepted and covers various aspects of semantic similarity.[1] Human associations should provide a useful source for such a gold standard, because (i) the induced classes are theory-independent and cover a variety of semantic verb relations (Schulte im Walde and Melinger, 2005), and (ii) we know which features (i.e. associations) underlie the classes and can use them to guide the feature selection in an automatic process.

In what follows, Section 2 introduces the association data which we obtained in a web experiment. Section 3 describes the cluster analysis which was performed on the experiment verbs and their associations, and Section 4 validates the clustering against GermaNet and FrameNet. In Section 5 we discuss details of the validation.

2. Web Experiment and Association Data

We obtained human associations to German verbs from native speakers in a web experiment (Schulte im Walde and Melinger, 2005). 330 verbs were selected for the experiment. They were drawn from a variety of semantic classes including verbs of self-motion (e.g. *gehen* 'walk', *schwimmen* 'swim'), transfer of possession (e.g. *kaufen* 'buy', *kriegen* 'receive'), cause (e.g. *verbrennen* 'burn', *reduzieren* 'reduce'), experiencing (e.g. *hassen* 'hate', *überraschen* 'surprise'), communication (e.g. *reden* 'talk', *beneiden* 'envy'), etc. The target verbs were divided randomly into 6 separate experimental lists of 55 verbs each. The lists were balanced for class affiliation and frequency ranges (0, 100, 500, 1000, 5000), such that each list contained verbs from each grossly defined semantic class, and had equivalent overall verb frequency distributions. The frequencies of the verbs were determined by a 35 million word newspaper corpus; the verbs showed corpus frequencies between 1 and 71,604.

The participants had 30 seconds per verb to type as many associations as they could. 299 native German speakers participated in the experiment, between 44 and 54 for each verb. In total, we collected 81,373 associations from 16,445 trials; each trial elicited an average of 5.16 associate responses with a range of 0-16. For the clustering to follow, we pre-processed all data sets in the following way: For

[1] Note that we refer to cases where it is desirable to have a generally accepted gold standard (e.g. to compare clustering results independent of a specific framework), in contrast to cases where a specific type of classification is the target (e.g. Merlo and Stevenson (2001) aim for a three-class distinction of English verbs that models three types of intransitive-transitive alternations).

each target verb, we quantified over all responses in the experiment, disregarding the order of the associates. Table 1 lists the 10 most frequent responses for the verb *klagen* 'complain, moan, sue'. The verb responses were not distinguished according to polysemic senses of the verbs.

klagen 'complain, moan, sue'		
Gericht	'court'	19
jammern	'moan'	18
weinen	'cry'	13
Anwalt	'lawyer'	11
Richter	'judge'	9
Klage	'complaint'	7
Leid	'suffering'	6
Trauer	'mourning'	6
Klagemauer	'Wailing Wall'	5
laut	'noisy'	5

Table 1: Association frequencies for target verb.

3. Association-based Clustering

The verb associations are considered as verb features that represent salient verb meaning aspects for semantic verb classes. The underlying assumption is that verbs which are semantically similar tend to have similar associations, and are therefore assigned to common classes. Table 2 illustrates the overlap of associations for the polysemous *klagen* with a near-synonym of one of its senses, *jammern* 'moan'. The table lists those associations which were given at least twice for each verb; the total overlap is 35 association types.

klagen/jammern 'moan'		
Frauen	'women'	2/3
Leid	'suffering'	6/3
Schmerz	'pain'	3/7
Trauer	'mourning'	6/2
bedauern	'regret'	2/2
beklagen	'bemoan'	4/3
heulen	'cry'	2/3
nervig	'annoying'	2/2
nölen	'moan'	2/3
traurig	'sad'	2/5
weinen	'cry'	13/9

Table 2: Association overlap for target verbs.

Considering the associations as verb features, we calculated probability distributions for the 330 experiment target verbs over the association types, and performed a standard clustering: The verbs and their features were taken as input to agglomerative (bottom-up) hierarchical clustering. As similarity measure in the clustering procedure (i.e. to determine the distance/similarity for two verbs), we used the standard measure *skew divergence*, cf. Equation (2), a smoothed variant of the *Kullback-Leibler divergence*, cf. Equation (1), which measures the difference between two probability distributions p and q. The weight w was set to 0.9. The measure has proven effective for distributional similarity in Natural Language Processing (Lee, 2001; Schulte im Walde, 2003). *Ward's method* (minimising the sum-of-squares) was used as criterion for merging clusters. The goal of the clustering was not to explore the optimal feature combination; thus, we relied on previous clustering experiments and parameter settings (Schulte im Walde, 2003). For details on the clustering method see e.g. Kaufman and Rousseeuw (1990).

$$KL(p \,||\, q) = \sum_i p_i \, log \, \frac{p_i}{q_i} \qquad (1)$$

$$skew(p, q) = KL(p \,||\, w * q + (1 - w) * p) \qquad (2)$$

The hierarchical clustering was cut at a hierarchy level with 100 verb classes, i.e. the classes contain an average of 3.3 verbs. This cut was not empirically verified; we argue that the exact level in the hierarchical clustering is not critical for the analyses to follow. The obtained classes are specified by a) the verbs in the classes, and b) the associations which underlie the respective classes. For example, the 100-class analysis contains a class with the verbs *bedauern* 'regret', *heulen* 'cry', *jammern* 'moan', *klagen* 'complain, moan, sue', *verzweifeln* 'become desperate', and *weinen* 'cry', with the most distinctive features[2] *Trauer* 'mourning', *weinen* 'cry', *traurig* 'sad', *Tränen* 'tears', *jammern* 'moan', *Angst* 'fear', *Mitleid* 'pity', *Schmerz* 'pain'. Another class contains the verbs *abnehmen*, *abspecken* (both: 'lose weight') and *zunehmen* 'gain weight', with the most distinctive features *Diät* 'diet', *Gewicht* 'weight', *dick* 'fat', *abnehmen* 'lose weight', *Waage* 'scale', *Essen* 'food', *essen* 'eat', *Sport* 'sports', *dünn* 'thin', *Fett* 'fat'. Intuitively, the classes in the hierarchical clustering are impressive and might therefore be useful as a gold standard semantic verb classification. The following section validates this intuition.

4. Validation against GermaNet and FrameNet

Our claim is that the hierarchical verb classes and their underlying features (i.e. the verb associations) represent a valuable basis for a theory-independent semantic classification of the German verbs. To support this claim, we validated the association-based classes against standard approaches to semantic verb classes, i.e. *GermaNet* (Kunze, 2000), and *Salsa* as the German counterpart to FrameNet (Erk et al., 2003), subsequently referred to as *FrameNet*. Since not all of our 330 experiments verbs were covered by the two resources, we performed a preparatory step where we extracted those classes from the resources which contain association verbs; non-association verbs, other classes as well as singletons were disregarded. We were left with 33 classes from GermaNet, and 49 classes from FrameNet. These remaining classifications are polysemous: The 33 GermaNet classes contain 71 verb senses which distribute over 56 verbs (ambiguity rate: 1.3), and the 49 FrameNet classes contain 220 verb senses which distribute over 104 verbs (ambiguity rate: 2.1). The resulting classes which

[2]The most distinctive features for a class were identified as those associations which accumulate most probability mass, summed over all verbs in the class.

each contain a subset of the experiment verbs were considered as the gold standards for the cluster analyses to follow. The appendix lists the selected classes.

Based on the 56/104 verbs in the two gold standard resources, we performed two cluster analyses, one for the GermaNet verbs, and one for the FrameNet verbs. As for the complete set of experiments verbs in Section 3, we performed a hierarchical clustering on the respective subsets of the experiment verbs, with their associations as verb features. The cluster experiments therefore replicated the original association-based clustering, but for a reduced number of verbs. The actual validation procedure then used the reduced classifications: The resulting analyses were evaluated against the resource classes on each level in the hierarchies, i.e. from 56/104 classes to 1 class. As evaluation measure, we used a pair-wise measure which calculates precision, recall and a harmonic f-score as follows: Each verb pair in the cluster analysis was compared to the verb pairs in the gold standard classes, and evaluated as true or false positive (Hatzivassiloglou and McKeown, 1993).

Figures 1 and 2 present the precision, recall and f-score values of the cluster analyses for the GermaNet and FrameNet verbs, respectively. The x-axis shows the number of clusters (ranging from 56/104 to 1), and the y-axis shows the percentage. Of course, the precision decreases with the bottom-up clustering, and the recall increases. For the FrameNet verbs, the decrease of the precision happens faster, and the increase of the recall happens slower than for the GermaNet verbs. This results in a lower maximum value for the f-scores (62.69% for GermaNet and 30.33% for FrameNet) and also in a smaller number of clusters in the optimal analyses (32 clusters for GermaNet and 5 clusters for FrameNet). Comparing the maximum f-scores with the corresponding upper bounds demonstrates that the overlap of the association-based GermaNet/FrameNet clusters with the respective gold standard resources is quite impressive: The upper bounds are only 82.35% for GermaNet and 49.90% for FrameNet. (They are below 100%, because the hierarchical clustering assigns a verb to only one cluster, but the lexical resources contain polysemy. We created a hard version of the lexical resource classes where we randomly chose one sense of each polysemous verb, and calculated the upper bounds by evaluating the hard versions against the soft versions.)

We were surprised that the f-score behaviour for the two resources was quite different, and decided to repeat the validation against FrameNet with a slightly changed version: We deleted those verbs and classes from the FrameNet gold standard where we found verbs that are mainly involved in multi-word expressions. I.e. for the verbs *gehen* ‘go’, *geben* ‘give’ and *sehen* ‘see’, we deleted all occurrences which referred to a multi-word expression; in addition we deleted a complete class that contained only verbs with respect to their support verb constructions. The reduced gold standard for FrameNet contained 38 classes with 145 verb senses for 91 verbs (ambiguity rate: 1.6). Figure 3 presents the precision, recall and f-score values of the cluster analyses for the FrameNet variant. The maximum f-score is 34.68% in a clustering with 10 classes; the upper bound is 60.31%.

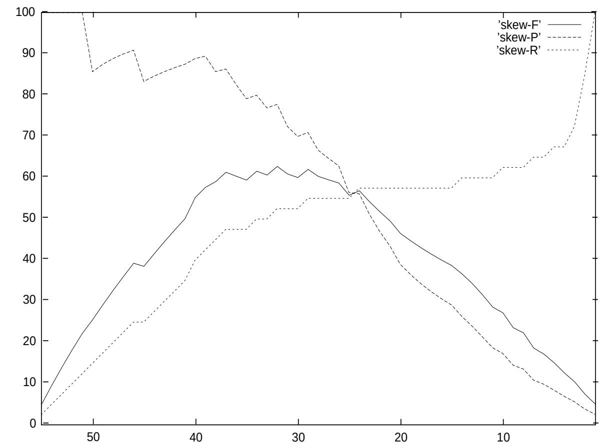

Figure 1: P/R/F for GermaNet clustering.

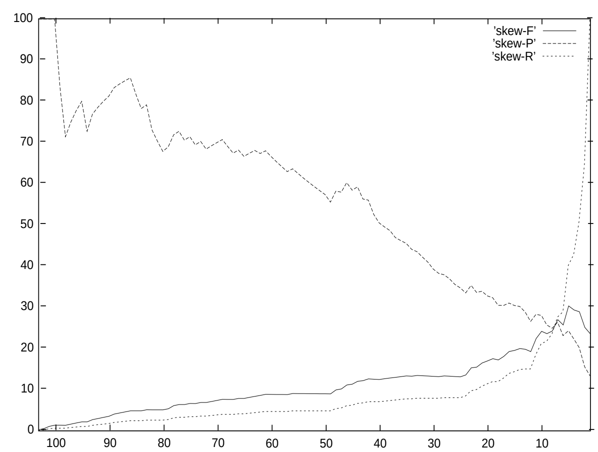

Figure 2: P/R/F for FrameNet clustering.

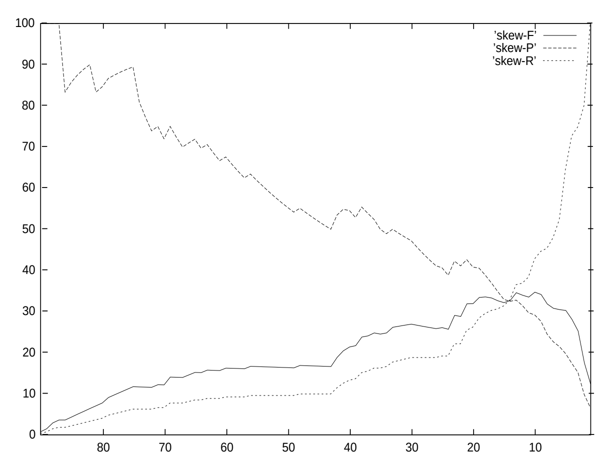

Figure 3: P/R/F for FrameNet clustering variant.

Resource	classes	f-score	upper bound
GermaNet	32	62.69%	82.35%
FrameNet	5	30.33%	49.90%
FrameNet (var)	10	34.68%	60.31%

Table 3: Validation results.

Table 3 summarises the f-score validation scores for the two lexical resources. The validation results demonstrate that when clustering the experiments verbs from Section 2 on the basis of their associations, the resulting classes show considerable overlap with the two lexical resources GermaNet and FrameNet. This finding suggests that human associations are a sensible choice when selecting verb features for semantic verb clustering.

5. Discussion

Even though the validation demonstrated considerable overlap between the association-based classes and GermaNet and FrameNet, we expected and found differences between the two lexical resources. This section discusses the differences. We concentrate on three aspects, (i) the notion of *semantic similarity* in GermaNet vs. FrameNet, (ii) the association features which underlie the cluster analyses, and (iii) the parameters which influence the clustering results, i.e. the number of classes and verbs, and the ambiguity of the verbs.

5.1. Semantic Similarity in GermaNet vs. FrameNet

As mentioned in Section 1, different frameworks for semantic verb classes depend on different instantiations of semantic similarity: WordNet uses synonymy, and FrameNet relies on situation-based agreement as defined in Fillmore's frame semantics (Fillmore, 1982). This difference in semantic similarity is reflected in our cluster analyses: In our best GermaNet clustering with a total of 32 classes, 15 out of 21 non-singleton classes are completely correct classes, according to the gold standard, and therefore model near-synonymy among verbs. For example, we find {*amüsieren, vergnügen*} 'amuse', {*aufregen, ärgern*} 'upset, annoy', {*erkennen, feststellen*} 'realise, notice', and {*heulen, weinen*} 'cry'. Classes which would be judged correct according to the FrameNet idea, such as {*ausgeben* 'spend money', *kosten* 'cost'} are not correct with respect to GermaNet. In our best FrameNet clustering, we find verbs that are related by a common situation. For example, the verbs *ausgeben* 'spend money', *kaufen* 'buy', *mieten* 'rent' and *pachten* 'lease' are in the same cluster and all belong to the frame *Commerce*; the verbs *gleiten* 'glide', *fahren* 'ride, drive', *rollen* 'roll', *fliegen* 'fly' and *gehen* 'go' all belong to the frame *Motion*; and the verbs *ahnen* 'guess', *vermuten* 'assume', *glauben* 'believe', *denken* 'think', *verstehen* 'understand' and *wissen* 'know' all belong to the frame *Awareness*. The examples show that the association-based clustering realises synonymous relations between verbs as well as various situation-based relations including temporal order, script-based relations, and co-troponymy.

5.2. Association Features

The associations which underlie the induced classes provide guidance to the feature selection for automatic classification methods: Knowing which features were relevant (i.e. most probable) for the resulting clusters in the cluster analyses helps to choose appropriate features for semantic class induction. The knowledge about features can refer to the words themselves, or to some generalisation of the words. For example, the most probable associations in the above mentioned GermaNet cluster {*amüsieren, vergnügen*} 'amuse' are *Spaß* 'fun', *Freunde* 'friends', *lachen* 'laugh', *Freude* 'joy', and *Freizeit* 'leisure time'; the most probable associations in the also mentioned FrameNet *Motion* cluster are *laufen* 'walk', *schnell* 'fast', *Flugzeug* 'plane', *rennen* 'run', and *Auto* 'car'. Naturally, the associations in the two clusters are different, because they refer to different semantic classes and verbs. What is more interesting is that – when referring to a more general level of association types – the GermaNet cluster is dominated by abstract nouns, but the FrameNet cluster is dominated by concrete nouns. In addition, the distribution over the part-of-speech types is different: Among the 10 most probable associations in the four GermaNet clusters described in the previous subsection we find 60% nouns, 27.5% verbs, and 12.5% adjectives and adverbs; in the three FrameNet clusters we find 57% nouns, 40% verbs, and 3% adjectives and adverbs. These simple insights in the associations types demonstrate that we might detect systematic differences in association types with respect to semantic classes and with respect to the kind of semantic similarity, as based on the clusterings.

5.3. Clustering Parameters for GermaNet vs. FrameNet

One should be aware that the clustering results were influenced by the clustering parameters. As mentioned in Section 3, the technical parameters such as the clustering algorithm and the similarity measure were based on experience from previous experiments. In addition, however, the clustering results were influenced by the number of classes, the number of verbs, and the verb properties. Validating against the FrameNet classes was a more difficult task than validating against the GermaNet classes because (i) there were almost twice as many verbs to cluster in the original clustering setup, and (ii) the ambiguity rate was much larger. In addition, most of the gold standard classes in GermaNet contain few (i.e. 2-3) verbs per class, whereas the FrameNet classes contain an average of 4.9 verbs per class. Finally, the ambiguity rate has a rather strong impact on the clustering, because our pre-release version of FrameNet[3] contains verb senses which rely on support verb constructions or metaphorical or idiomatic expressions. For example, the verb *sehen* 'see' is in 11 out of the 49 classes: The frame *Categorisation* applies to cases such as *Man sieht es als ein Problem* 'One sees something as a problem'; the frame *Existence* applies to cases such as *Die Stadt hat schon bessere Zeiten gesehen* 'The city had seen better times'; the

[3] Our FrameNet version dates from May 2005; the first release is announced for May 2006.

frame *Statement* applies to cases such as *So sah es auch der Chef* 'The chef was in agreement'; and the frame *Expectation* applies to cases such as *Ich sehe mich unglücklich werden* 'I see myself becoming unhappy'. Clustering on the FrameNet variant demonstrated that by removing the verbs with the largest number of senses from the gold standard, both the upper bound and the optimal clustering results improved; the difference is significant ($\chi^2, df = 1, \alpha = 0.05$).

6. Conclusions

This paper presented a hierarchical clustering of German verbs, as based on human associations to the verbs. The cluster analysis was validated against the two standard semantic classifications GermaNet and FrameNet. The results demonstrated considerable overlap between the association-based verb classes and the existing verb classes, and the association-based classes capture different types of semantic similarity: The clustering realises synonymous relations between verbs as well as various situation-based relations including temporal order, script-based relations, and co-troponymy.

The validation results justify the potential use of the association-based classes as a gold standard resource in verb clustering experiments. In addition to providing knowledge about the verbs and their classes, the associations which underlie the induced classes provide guidance to the feature selection for automatic classification methods. This does not mean that we intend to rely on human associations in order to cover an extensive number of verb features. Rather, the associations in relation to the verbs in a certain class inform us about relevant class features, with respect to their semantic concepts, their part-of-speech types, their functions, etc. Future work will elaborate on the idea to use the associations as guidelines in feature selection.

7. References

Katrin Erk, Andrea Kowalski, Sebastian Padó, and Manfred Pinkal. 2003. Towards a Resource for Lexical Semantics: A Large German Corpus with Extensive Semantic Annotation. In *Proceedings of the 41st Annual Metting of the Association for Computational Linguistics*, Sapporo, Japan.

Christiane Fellbaum, editor. 1998. *WordNet – An Electronic Lexical Database*. Language, Speech, and Communication. MIT Press, Cambridge, MA.

Eva Esteve Ferrer. 2004. Towards a Semantic Classification of Spanish Verbs based on Subcategorisation Information. In *Proceedings of the 42nd Annual Meeting of the Association for Computational Linguistics*, Barcelona, Spain.

Charles J. Fillmore. 1982. Frame Semantics. *Linguistics in the Morning Calm*, pages 111–137.

Thierry Fontenelle, editor. 2003. *FrameNet and Frame Semantics*, volume 16(3) of *International Journal of Lexicography*. Oxford University Press. Special issue devoted to FrameNet.

Vasileios Hatzivassiloglou and Kathleen R. McKeown. 1993. Towards the Automatic Identification of Adjectival Scales: Clustering Adjectives According to Meaning. In *Proceedings of the 31st Annual Meeting of the Association for Computational Linguistics*, pages 172–182, Columbus, Ohio.

Eric Joanis and Suzanne Stevenson. 2003. A General Feature Space for Automatic Verb Classification. In *Proceedings of the 10th Conference of the European Chapter of the Association for Computational Linguistics*, Budapest, Hungary.

Leonard Kaufman and Peter J. Rousseeuw. 1990. *Finding Groups in Data – An Introduction to Cluster Analysis*. Probability and Mathematical Statistics. John Wiley & Sons, Inc., New York.

Anna Korhonen, Yuval Krymolowski, and Zvika Marx. 2003. Clustering Polysemic Subcategorization Frame Distributions Semantically. In *Proceedings of the 41st Annual Meeting of the Association for Computational Linguistics*, pages 64–71, Sapporo, Japan.

Claudia Kunze. 2000. Extension and Use of GermaNet, a Lexical-Semantic Database. In *Proceedings of the 2nd International Conference on Language Resources and Evaluation*, pages 999–1002, Athens, Greece.

Lillian Lee. 2001. On the Effectiveness of the Skew Divergence for Statistical Language Analysis. *Artificial Intelligence and Statistics*, pages 65–72.

Paola Merlo and Suzanne Stevenson. 2001. Automatic Verb Classification Based on Statistical Distributions of Argument Structure. *Computational Linguistics*, 27(3):373–408.

Sabine Schulte im Walde and Alissa Melinger. 2005. Identifying Semantic Relations and Functional Properties of Human Verb Associations. In *Proceedings of the joint Conference on Human Language Technology and Empirial Methods in Natural Language Processing*, pages 612–619, Vancouver, Canada.

Sabine Schulte im Walde. 2000. Clustering Verbs Semantically According to their Alternation Behaviour. In *Proceedings of the 18th International Conference on Computational Linguistics*, pages 747–753, Saarbrücken, Germany.

Sabine Schulte im Walde. 2003. *Experiments on the Automatic Induction of German Semantic Verb Classes*. Ph.D. thesis, Institut für Maschinelle Sprachverarbeitung, Universität Stuttgart. Published as AIMS Report 9(2).

Appendix. GermaNet and FrameNet Classes

Tables 4 and 5 list the GermaNet and FrameNet classes which were used as lexical resource standards for validating the association-based clustering. For the FrameNet resource we restrict the classes to example classes, because we worked on a pre-release version; the first release is announced for May 2006.

The verbs in the classes represent a subset of the German verbs in the association web experiment. All German verbs are translated into English, referring to the verb sense in the respective class.

Synset	Verbs
00008824	*bilden* ‘form’, *formen* ‘form’
00034646	*arbeiten* ‘function’, *gehen* ‘function’, *laufen* ‘function’
00044386	*gefallen* ‘like’, *mögen* ‘like’
00143506	*fließen* ‘float’, *laufen* ‘go, float’
00151748	*gehen* ‘go’, *laufen* ‘walk’
00159548	*laufen* ‘walk’, *rennen* ‘run’
00225732	*beugen* ‘bend’, *lehnen* ‘lean’
00285607	*entwickeln* ‘develop’, *laufen* ‘run’
00392330	*ermorden* ‘kill’, *umbringen* ‘kill’
00437053	*beladen* ‘load’, *laden* ‘load’
00495701	*erkennen* ‘recognise’, *feststellen* ‘notice’
00537327	*ausgeben* ‘spend’, *verteilen* ‘distribute’
00569120	*bekommen* ‘receive’, *erfahren* ‘experience’, *erhalten* ‘get’
00569557	*bekommen* ‘receive’, *erhalten* ‘get’, *kriegen* ‘get’
00569716	*bekommen* ‘receive’, *kriegen* ‘get’
00618219	*bekommen* ‘receive’, *erwarten* ‘expect’
00620610	*töten* ‘kill’, *umbringen* ‘kill’
00637652	*heulen* ‘cry’, *weinen* ‘cry’
00774549	*reden* ‘talk’, *sprechen* ‘speak’
00864958	*essen* ‘eat’, *futtern* ‘guzzle’, *nehmen* ‘take’
00881991	*schlucken* ‘swallow’, *trinken* ‘drink’
00983725	*schätzen* ‘estimate’, *vermuten* ‘guess’
00991131	*wollen* ‘want’, *wünschen* ‘wish’
00995163	*erhoffen* ‘hope’, *wünschen* ‘wish’
01002907	*brauchen* ‘need’, *kosten* ‘cost’
01213787	*entwickeln* ‘develop’, *zeigen* ‘show’
01242032	*schlucken* ‘swallow’, *verdauen* ‘digest’
01248488	*amüsieren* ‘amuse’, *vergnügen* ‘amuse’
01263398	*aufregen* ‘upset’, *ärgern* ‘annoy’
01341455	*knattern* ‘crackle’, *röhren* ‘roar’
01372575	*trauen* ‘marry’, *verheiraten* ‘marry’
01382942	*bitten* ‘ask’, *einladen* ‘invite’, *laden* ‘ask’
01449147	*lehren* ‘teach’, *unterrichten* ‘teach’

Table 4: GermaNet classes.

Frame	Verbs
Awareness	*ahnen* ‘guess’, *denken* ‘think’, *glauben* ‘believe’, *sehen* ‘see’, *vermuten* ‘assume’, *verstehen* ‘understand’, *wissen* ‘know’
Change position on a scale	*abstürzen* ‘crash’, *klettern* ‘climb’, *reduzieren* ‘reduce’, *rollen* ‘roll’, *sinken* ‘sink’, *zunehmen* ‘increase’
Commerce	*ausgeben* ‘spend money’, *geben* ‘give’, *gehen* ‘go’, *kaufen* ‘buy’, *mieten* ‘rent’, *pachten* ‘lease’
Evidence	*erkennen* ‘realise’, *feststellen* ‘notice’, *nahelegen* ‘suggest’, *sagen* ‘say’, *sprechen* ‘speak’, *zeigen* ‘show’
Killing	*ermorden* ‘kill’, *erschlagen* ‘strike dead’, *töten* ‘kill’, *umbringen* ‘kill’, *verbrennen* ‘burn’
Motion	*fahren* ‘ride, drive’, *fliegen* ‘fly’, *gehen* ‘go’, *gleiten* ‘glide’, *legen* ‘lay’, *rollen* ‘roll’, *schlagen* ‘beat’, *treten* ‘kick’

Table 5: Example FrameNet classes.