Automatic induction of German aspectual verb classes in a distributional framework

Jürgen Hermes
University of Cologne
Department of Linguistics
Linguistic Data Processing
hermesj@uni-koeln.de

Michael Richter
Radboud University
Nijmegen
Department of Linguistics
mprrichter@t-online.de

Claes Neuefeind
University of Cologne
Department of Linguistics
Linguistic Data Processing
c.neuefeind@uni-koeln.de

Abstract

The central question of this study is whether aspectual verb classes (Vendler, 1967) can be induced from corpus data in a fully automatic, distributionally motivated procedure. We propose an operationalization of 'aspectivity' utilizing distributional information about nominal fillers in the argument positions of verbs in combination with aspectual features automatically derived from dependency information. Using a support vector machine classifier and a classification into five aspectual classes (Richter and van Hout, 2015) as the gold standard, we observed excellent results that support our hypothesis.

1 Introduction

This study aims to empirically validate aspectual verb classes in German using corpus data. It is primarily motivated by a lack of studies on the induction of the complete Vendlerian typology. Vendler (1967) distinguished the four aspectual classes: *accomplishments, achievements, states* and *activities*, which are based on the temporal scheme of verbs and verb phrases. The grammatical verb category *aspect* (Klein, 2009) allows for a classification into *species of verb*[s] (Vendler, 1967), which Klein (2009: 22) defines by the five temporal features *qualitative change* ('non-stative' vs. 'stative'), *boundedness* (initial and final boundary, i.e. 'processes' vs. 'events'), *duration* ('punctual' vs. 'non-punctual' contents), *inner quantification*: ('iterative', 'frequentative', 'semelfactive'), *phase* ('inchoative', 'terminative', 'resultative', etc.), whereby the superior criterion is that of perfective vs. non-perfective aspect (Klein, 2009).

Research on aspectual verb classes is of particular relevance because the temporal and causal structure of events can be represented (Vendler, 1967; Fernando, 2004; Gründer, 2008); by aspect, which yields classificatory criteria for linguistic units such as verbs and documents (Siegel, 1997; Siegel and McKeown, 2000).

Based on previous work of Richter and Hermes (2015) we hypothesize, that aspectual verb classes can be automatically induced from the classified nominal fillers in the argument position of verbs. The nominal fillers were combined with aspectual features (co-occurences of specific words / phrases in dependent and governing positions relative to the verb), as we aimed to test whether, and what degree those features would improve the quality of the classification, an additional question being whether from single aspectual features satisfying classification results could be achieved. Our hypothesis refers to the *Distributional Hypothesis* (Rubenstein and Goodenough, 1965; Schütze and Pedersen, 1995; Landauer and Dumais, 1997; Pantel, 2005) which claims that semantically related linguistic elements appear in semantically related contexts. The present study in the framework of a vector space model is also driven by the *Statistical Semantics Hypothesis* (Weaver, 1955; Furnas et al., 1983; Turney and Pantel, 2010) which states that linguistic meaning can be derived from statistical linguistic patterns.

In order to test our hypothesis, we took a test set of 95 verbs from Schumacher (1986). Based on a dependency parse of the SdeWaC

Proceedings of the Int. Conference of the German Society for Computational Linguistics and Language Technology,
pages 122–129, University of Duisburg-Essen, Germany, Sep 30–Oct 2 2015.

corpus we determined the nominal fillers and their classes in argument positions (that is, in subject, direct object, and prepositional object positions) and additionally extracted aspectual features as defined by Vendler (1967) with regard to their structural positions. Both the nouns and the aspectual features were extracted from the respective sentences the 95 verbs occurred in. The indirect object was left out because there were few occurrences of verbs with indirect objects. In addition, Richter and Hermes (2015) brought to light, that indirect objects - contingent upon their sparsity - were weak predictors of verb classes. The aspect-based classification of Richter and van Hout (2015) was used as a gold standard in this study. This classification consists of five classes and extends the typology of Vendler (1967) by adding the class *accomplishments with an affected subject*.

In the present study we represent verbs as feature vectors that consist of nouns in argument positions separated into areas according to their noun classes which were induced by cluster analysis, accompained by aspectual features, the research questions being 1. to what extent the aspectual features will increase the predictive power of the nominal fillers in arguments positions, and 2. whether aspectual features as singletons would be sufficient to predict aspectual verb classes. The test set of verbs was classified in a supervised learning procedure using a support vector machine (SVM) classifier.

2 Related work

There are few studies which address the topic of automatic induction of aspectual verb classes. By focusing on tense forms, Klavans & Chodorow (1992) determined gradual *state*-properties of verbs. Siegel (1997) and Siegel & McKeown (2000) classified verbs using temporal and modal indicators such as temporal adverbs, tense forms and *manner*- and *evaluation*-adverbs into the two aspect classes *states* and *events*. No attempts have been made so far to induce the complete Vendlerian Typology.

Studies on the automatic induction of non-aspectual verb classes from Dorr & Jones (1996), Merlo & Stevenson (2001), Preiss, Briscoe & Korhonen (2007), Joanis, Stevenson & James (2008), Vlachos, Korhonen & Gahramani (2009) and Parisien & Stevenson (2011), amongst others, provide corpus based evidence that argument frames, syntactic subcategorization information and, in addition, aspect (Joanis, Stevenson & James, 2008) are reliable predictors. Merlo & Stevenson (2001), who induced a Levin-compatible classification from the argument structure of verbs, draw the conclusion that the semantics of the argument structure is decisive for the classification of verbs.

Classifications have been empirically induced which are compatible with the classifications of Levin (1993) and Schumacher (1986) but only for German. Examples are classes such as *verbs of existence*, *verbs of linguistic expression and verbs of vital needs*, see Schumacher, (1986) and *verbs of transfer of possession* und *verbs of communication*, see Levin (1993). Schulte im Walde & Brew (2002) induced 14 verb classes from a test corpus of 57 verbs focusing solely on the syntactic information of verbs. In a follow up study, Schulte im Walde (2003) induced 43 verb classes from a test corpus of 168 verbs considering both syntactic and semantic information, and in a replication of this study Schulte im Walde (2004) induced 100 verb classes from a test set of 883 verbs. Schulte im Walde (2003) concludes that in order to get linguistically plausible clusters, both idiosyncrasies and general, more abstract properties of verbs have to be taken into consideration.

3 Methodology

In this study, we classified a selection of 95 common German verbs taken from Schumacher (1986), who defines seven lexical semantic macrofields; *Verben der allgemeinen Existenz* ('verbs of general existence'), *Verben der speziellen Existenz* ('verbs of special existence'), *Verben des sprachlichen Ausdrucks* ('verbs of linguistic expression'), *Verben der Differenz* ('verbs of difference'), *Verben der Relation und des geistigen Handelns* ('verbs of relation and mental processing'), *Verben des Handlungsspielraums* ('verbs of freedom of action') and *Verben der vitalen Bedürfnisse* ('verbs of vital needs'). The macrofields are split into 30 subfields. We chose the verbs randomly from the thirty subfields, the only criterion being the inclusion of every subfield in order to cover the total semantic range of Schumacher's typology (1986).

Figure 1 presents the complete workflow of our analysis, from raw sentence data taken from the SdeWaC corpus (down left) to sets of classified verbs (up right). Below we describe the

main steps of the workflow as numbered in *figure 1*.

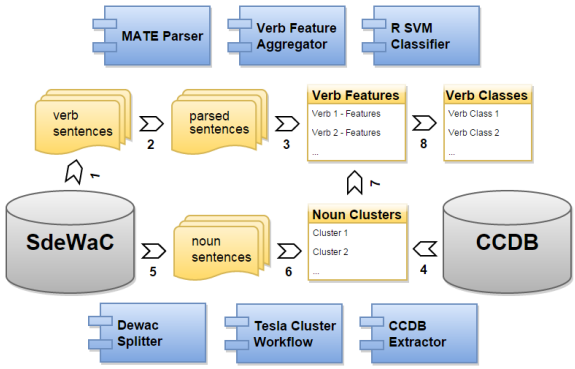

Figure 1 ***Synopsis of our processing workflow. Each processing step is realized as a largely independent, subordinated workflow, e.g. the description of the Tesla Cluster Workflow in figure 2 (see below).***

3.1 Determination of verb features

Initially, we extracted 3000 sentences for each verb in our list **(step 1)** and parsed them **(step 2)** with the *Mate Dependency Parser* from Bohnet (2010)[1] in order to determine subjects and objects (accusative, dative, and prepositional) for each verb **(step 3)** and in addition to determine aspectual features, which were suggested by Vendler (1967) to distinguish aspectual verb classes. The list of aspectual features is given below:

1. verb in imperative form,
2. verb complex with *aufhören / stoppen* ('to stop / to finish') as governing verbs,
3. verb complex with *überzeugen* ('to convince') as governing verb,
4. matrix verb with time adverbials for durations, like *minutenlang* ('for minutes'), *in einer Minute* ('in a minute'),
5. matrix verb with time units, like *minute* ('minute'), *jahrhundert* ('century'),
6. matrix verbs with *seit* ('since'), combined with a time unit,
7. matrix verb with adverbials *sorgfältig / mit Sorgfalt* ('careful / with care'),
8. matrix verb with adverbials *absichtlich / mit Absicht* ('on purpose'),
9. matrix verb with adverbials *fast / beinahe* ('almost').

[1] See \url: https://code.google.com/p/mate-tools/

To reduce the feature space and to increase the allocation density of the vectors, we clustered all nominal fillers that were identified to be verb arguments of relevant frequency. For comparative reasons, the cluster analysis was conducted in two independent subtasks.

3.1.1 Noun-clustering with the CCDB

First, the nouns were weighted by the TF-IDF measure and classified by a cluster analysis carried out on a matrix of similarity values taken from the co-occurrence data bank (CCDB) of the Institut für Deutsche Sprache Mannheim (IDS). On the matrix of the similarity values, a k-means cluster analysis was carried out. According to the *Bayesian Information Criterion* there are three optimal noun classes for subjects and prepositional objects and five for direct objects. This result was confirmed by inspecting the within variance of the resulting clusters.

$$\vec{v} = \begin{pmatrix} wn_1 c_1 \\ wn_2 c_1 \\ . \\ . \\ . \\ wn_n\ c_1 \\ wn_1\ c_2 \\ wn_2\ c_2 \\ . \\ . \\ . \\ wn_n v_n \end{pmatrix}$$

$(wn_i\, c_j\!: Weight\ of\ noun\ n_i\ in\ noun\ class\ \ c_j\ )$

Figure 2. ***Dimensions of verb vectors: Weighted verbs in noun class areas.***

The verbs' vectors consist of areas for each argument type that is, three areas for argument types in total and each area is split into areas for each noun class as depicted in *figure 2*.

3.1.2 Noun-clustering in Tesla

Additionally, we set up a workflow for noun clustering in Tesla[2]. Here, we computed co-

[2] Tesla (**T**ext **E**ngineering **S**oftware **LA**boratory, see \url: http://tesla.spinfo.uni-koeln.de) is an open source virtual research environment, integrating both a visual editor for conducting text-engineering experiments and a Java IDE for developing software components.

occurrence vectors based on a subset of the *SdeWaC* corpus, containing about 3000 sentences for each noun (**step 5**). For feature selection we used the simple frequency-based heuristics described in Levy & Bullinaria (2004), taking the *k* most frequent types of our corpus as vector features. The vectors were computed in three different configurations. As a baseline, we first took the 200 most frequently occurring elements (mostly closed class function words such as *und* 'and', *zu* 'to', *weil* 'because / since, etc.), and a context window of size 1, accepting only the direct neighbors as co-occurrences. In the second configuration, co-occurrences were computed against the 2000 most frequently occurring elements within a fixed context window of 5 items to both sides. In addition, we employed a positional weighting scheme using the HAL model (Hyperspace Analogue to Language, see Burgess & Lund 1996). In a third test, we took the 10.000 most frequently occurring words and a window size of 10 words, again using the HAL-weighting scheme. While the restriction to function words within a narrow window mainly reflects grammar-related distributional properties, the consideration of content words in combination with a broader window and position weighting emphasizes the more semantically oriented aspects of their distribution. The resulting vectors were weighted by the TF-IDF measure and passed to the cluster analysis **(step 6)**. The corresponding software component workflow as conducted in Tesla is shown in *figure 3*.

For cluster analysis we used three different clusterer implementations adopted from the *ELKI Data Mining API*,[3] namely KmeansLloyd, KmeansMacQueen, and KMedoidsEM, with cluster sizes of k=3 for subjects and prepositional objects and k=5 for direct objects, which we adopted from the CCDB cluster task (see above). For evaluation, we additionally processed all nouns with k=10, resulting in a total of 18 experiments (3 vector configurations for 3 clusterers with 2 different configurations). Finally, for each experiment the resulting word-cluster-pairs were transformed into verb vectors (see next section) and passed to the following processing steps.

[3] The open source framework ELKI (**E**nvironment for De-ve**L**oping **K**DD-Applications Supported by **I**ndex-Structures) was developed at the LMU Munich, see \url: http://elki.dbs.ifi.lmu.de.

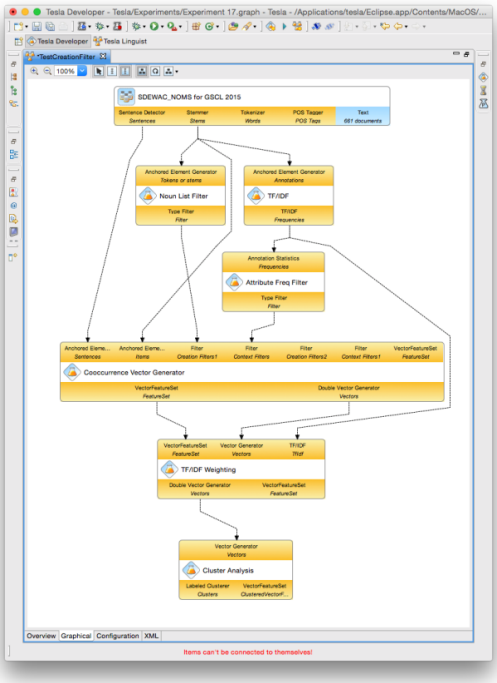

Figure 3. ***Cluster analysis workflow in Tesla. The Clusterers operate on TF-IDF-weighted co-occurrence vectors, computed on a subset of the SdeWaC corpus.***

3.1.3 Generating the Verb Vectors

Within step **(7)** the verb vectors resulting from step **(3)** were re-assembled using the generated noun classes from both steps **(4)** and **(6)**. Hereby the verb vectors could be reduced to 20 (nine aspectual features plus three features for each the subject and prepositional object clusters plus five direct object clusters), respective to 39 dimensions (nine aspectual features complemented by ten clusters for each argument position).

3.2 Classification

For the classification of the 95 verbs **(8)** we used a SVM classifier with a non-linear kernel. The identified arguments and the aspectual features were aggregated for each verb type and represented in feature vectors. For 35 verbs we adapted the classification to the five aspectual verb classes defined in Richter and van Hout (2015), the remaining verbs were manually classified into the five aspectual classes. We trained the SVM using this aspectual classification as training data and tested it with a 10-fold cross-validation. We give some examples of the verb classes of the aspectual gold standard classification below. Note that this classification uses Vendler's definitions (four verb classes), with

the addition of the separate sub-class of accomplishment verbs:

1. **accomplishments**: *aufbauen auf* ('to build on / to be based on'), *herstellen* ('to produce'), schneiden ('to cut'), *zersägen* ('to saw into pieces'), *verlängern* ('to extend'), *mitteilen* ('to tell / to inform'), *übermitteln* ('to communicate / to forward'), *verhindern* ('to prevent'), *abgrenzen* ('mark off / to define'), *verändern* ('to change')
2. **accomplishments with affected subject:** *untersuchen* ('to examine'), *bedenken* ('to consider'), *erörtern* ('to debate'), *nachprüfen* ('to ascertain / to check'), *aufessen* ('to eat up'), *essen* ('to eat'), *beachten* ('to note'), *kaufen* ('to buy')
3. **activities**: *laufen* ('to walk / to run'), *eingehen auf* ('to respond to so. / sth.'), *hämmern* ('to hammer'), *ansteigen* ('to increase'), *fallen* ('to fall'), *denken* ('to think'), *stattfinden* ('to take place'), *wachsen* ('to grow')
4. **achievements:** *einschlafen* ('to fall asleep'), *vergehen* ('to go (by) / to pass / to diasappear'), *übersehen* ('to overlook'), *verlieren* ('to lose'), *anfangen* ('to begin'), *abweichen* ('to deviate'), *sich orientieren an* ('to be geared to'), *richten auf* ('to direct towards / to focus')
5. **states**: *existieren* ('to exist'), *fehlen* ('to lack'), *müssen* ('to must'), *halten für* ('to take so. / sth. for so. / sth.'), *folgen aus* ('to follow from'), *angehören* ('to belong to'), *übereinstimmen* ('to agree'), *betreffen* ('to concern'), *abweichen* ('to deviate') , *verhindern* ('to prevent'), *sein* ('to be'), *vorherrschen* ('to predominate')

4 Results

In order to evaluate the consistency of the comparisons of the classifications against the gold standard we calculated both accuracy and Cohen's kappa. The latter measure considers the number of classes and gives the significance levels.

As a first step, we compared the results from the classifications based on different approaches of clustering arguments for the verb vectors (see *Table 1*). The noun cluster method in the first column specifies

1. the selected data source (CCDB vs. SdeWaC)
2. the number of noun clusters for each argument position
3. the cluster method (K-Medoids vs. K-Means Lloyd vs. K-Means MacQueen)
4. the number of features for each noun (l, 200 vs. 2000 vs. 10000)
5. the context window for co-occurences (win, 1 vs. 5 vs. 10)
6. the quantification of dimensions (count every token vs. count only one token per noun type)

Taking the classification with five aspectual verb classes as the gold standard, ten noun classes per argument position clearly outperform the approaches with fewer features. Additionally, counting every noun token leads to better results than counting only the noun types. Medium length vectors (2000 dimensions), constructed on the basis of a medium context width (window size of five elements) achieve the best outcomes. Specifically, the verb vectors of the 'SdeWaC 10 clusters kmeansLloyd l2k win5 tokens'-noun clustering show the best performance. *Figure 4* depicts the accuracy of combinations of features and is subject of the following result description.

Feature combinations exclusively comprising aspect yield high accuracy values. The combinations aspect-subject - direct-object and aspect-subject - direct-object - prepositional-object outperform the remaining feature combinations with .95 accuracy, **κ** = .93, and .94 accuracy, **κ** = .90, respectively. Kappa values above .81 are characterized as almost perfect agreement and therefore highly significant. The feature combinations aspect- direct object-prepositional object with .88 accuracy, **κ** = .84, and aspect-prepositional object with .86 accuracy, **κ** = .81, achieve also almost perfect agreements. Substantial agreements, that is, above .61, can be observed with the combinations aspect-subject-prepositional object, .84 accuracy, **κ** = .78, aspect-direct object, .92 accuracy, **κ** = .75, and aspect-subject, .82 accuracy**,** **κ** = .75. Considering the feature combinations without aspectual features, only the combination subject-prepositional

object achieves a satisfactory result with 62 accuracy, **κ** = .43, which is a moderate agreement.

The single features achieve only fair agreements: Aspect achieves .57 accuracy, **κ** = .34, subject achieves .52, **κ** = .27, and direct object and prepositional object achieve .51 accuracy and **κ** = .24 each,

Noun cluster method	acc	K
CCDB, 3-5-3 clusters, kmeans, tokens	.76	.71
CCDB, 3-5-3 clusters, kmeans, types	.64	.41
CCDB, 10 clusters, kmeans, tokens	**.93**	**.90**
CCDB, 10 clusters, kmeans, types	.60	.39
SdeWaC, 3-5-3 clusters, kmediods l2k, win5, tokens	.85	.80
SdeWaC, 10 cluster kmediods l10k win10 tokens	.85	.80
SdeWaC, 10 cluster kmediods l200 win1 tokens	.86	.83
SdeWaC, 10 cluster kmediods l2000 win5 tokens	**.93**	**.90**
SdeWaC, 10 cluster kmediods l2000 win5 types	.69	.48
SdeWaC, 3/5cluster kmediods l2000 win5 tokens	.85	.80
SdeWaC, 10 clusters, kmeansLloyd l10k win10 tokens	.88	.84
SdeWaC, 10 clusters kmeansLloyd l200 win1 tokens	.88	.84
SdeWaC, 10 clusters kmeansLloyd l2k win5 tokens	**.94**	**.93**
SdeWaC, 10 clusters kmeansMacQ l10k win10 tokens	.89	.86
SdeWaC, 10 cluster kmeansMacQ l200 win1 tokens	.92	.88
SdeWaC, 10 cluster kmeansMacQ l2k win5 tokens	.90	.90

Table 1. ***Evaluation of different approaches to construct the verb vectors of the verbs.***

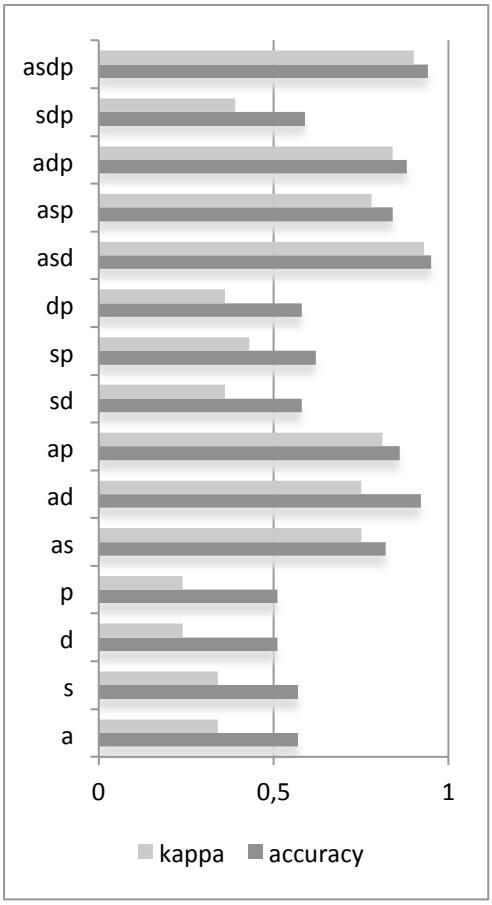

Figure 4 ***Accuracy of the argument and aspectual features from the best performing noun cluster method using five aspectual verb classes as gold standard.***

Legend: s: subject, d: direct object, p: prepositional object, a: aspectual features and combinations of predictors, for instance, da: direct object and aspect, sp: subject and prepositional object.

5 Conclusion

The study provides evidence for the hypothesis that the Vendlerian aspectual verb classes (plus a class of *accomplishments with an affected subject*) can be induced from classified nominal fillers in argument positions in combination with aspectual features in dependent or governing positions. In contrast to the study of Richter and Hermes (2015), which identified the subject as the feature with the highest predictive power, this study reveals that combinations of features comprising aspect features clearly outperform the remaining feature combinations which do not include aspect features, and also outperform the single features, that is, aspect, subject, direct object and prepositional object. This result could be observed in all clustering approaches, which, without exception, attest the high predictive

power of feature combinations comprising aspect. Aspectual features as singletons are not sufficient to predict aspectual verb classes.

In addition, it could be observed that a higher number of noun clusters in the argument features improves the quality of classifications. Compared to the 3-5-3 noun clustering (that is, 3 noun classes in the subject position, 5 noun classes in the object position and 3 noun classes in the prepositional object position), the 10-10-10 noun classes combinations achieve much better results. We draw the conclusion that the higher the number of noun classes, the greater the discriminating effect, presumably because a more finely grained distinction of semantic properties is achieved. This also holds for the comparison of the classification quality of verb vectors containing noun tokens with vectors containing noun types. The number of verb tokens is, by definition, considerably higher than that of the types, and we observed that with regard to the classification quality, verb vectors with noun tokens clearly outperform vectors with noun types. Finally we discovered that medium length vectors based on a medium context frame yield the best results.

All in all, the results of this study show that: 1. aspectual verb classes can be empirically validated, 2. classified nouns in argument positions in combination with aspectual features are reliable predictors of aspectual verb classes, i.e. the meaning of nouns (and noun classes, respectively) correlates with aspectual parts of the verbal meaning.

References

Judith Aissen. 2003. *Differential Object Marking: Iconicity vs. economy*. In: *Natural Language and Linguistic Theory*, 21:435–483.

Bernd Bohnet. 2010. *Very High Accuracy and Fast Dependency Parsing is not a Contradiction.* In: The 23rd International Conference on Computational Linguistics *(COLING 2010),* Beijing, China.

William Croft. 2003. *Typology and Universals*. Cambridge University Press (2nd edition).

Tim Fernando. 2004. *A finite-state Approach to Events in Natural Language Semantics*. Journal of Logic and Computation, 14(1):79-92.

Bonnie J. Dorr and Doug Jones. 1996. *Role of Word Sense Disambiguation in Lexical Acquisition: Predicting Semantics from Syntactic Cues*. In: *Proceedings of the 16th International Conference on Computational Linguistics*, 322–327. Copenhagen.

George W. Furnas, Thomas K. Landauer, Louis M. Gomez and Susan T. Dumais. 1983. *Statistical semantics: Analysis of the potential performance of keyword information systems.* Bell System Technical Journal, 62(6):1753–1806.

Sabine Gründer. 2008. *An Algorithm from Adverbial Aspect Shift.* In: *Proceedings of the 22nd International Conference on Computer Linguistics* (Coling08), 289–296.

Eric Joanis, Suzanne Stevenson and David James. 2008. *A General Feature Space for Automatic Verb Classification.* Natural Language Engineering 14(3):337-367.

Judith L. Klavans and Martin Chodorow. 1992. *Degrees of Stativity: The lexical representation of verb aspect.* In: *Proceedings of the 14th International Conference on Computational Linguistics.*

Wolfgang Klein. 2009. *How time is encoded*. In: Wolfgang Klein and Ping Li (eds.), *The expression of time*, 39–82. Mouton de Gruyter, Berlin.

Thomas K. Landauer and Susan T. Dumais. 1997. *A solution to Plato's problem: The Latent Semanctic Analysis theory of the acquisition, induction, and representation of knowledge*. Psychological Review, 104:211–140.

Joe P. Levy and John A. Bullinaria. 2001. *'Learing lexical properties from word usage patterns: Which context words should be used?' Connectionist models of learning, development and evolution,* 273-282. Springer, London.

Beth Levin. 1993. *English Verb Classes and Alternations*. The University of Chicago Press, Chicago.

Kevin Lund and Curt Burgess. 1996. *Hyperspace analogue to language (HAL): A general model semantic representation.* In: *Brain and Cognition 30*.

Paola Merlo and Suzanne Stevenson. 2001. Automatic verb classification based on statistical distributions of argument structure. In: *Computational Linguistics*, 27(3):373-408.

Patrick Pantel. 2005. Inducing ontological co-occurrence vectors. In *Proceedings of Association for Computational Linguistics* (ACL-05):125–132.

Christopher Parisien and Suzanne Stevenson. 2011. *Generalizing between form and meaning using learned verb classes*. In: *Proceed-*

ings of the 33rd Annual Conference of the Cognitive Science Society Boston, Massachusetts.

J. Preiss, T. Briscoe, and A. Korhonen. 2007. *A System for Large-Scale Acquisition of Verbal, Nominal and Adjectival Subcategorization Frames from Corpora*. In *Proceedings of the 45th Annual Meeting of the Association of Computational Linguistics,* 912–919, Prague.

Michael Richter and Jürgen Hermes. 2015. *Classification of German verbs using nouns in argument positions and aspectual features.* In: Vito Pirrelli, Claudia Marzi and Marcello Ferro (eds.) *Word Structure and Word Usage. Proceedings of the NetWordS Final Conference*, 177–181, Pisa.

Michael Richter and Roeland van Hout. 2015. *A classification of German verbs using empirical language data and concepts of Vendler and Dowty.* To appear in 2015. In: *Sprache und Datenverarbeitung – International Journal for Language Data Processing.*

Herbert Rubenstein and John B. Goodenough. 1965. *Contextual correlates of synonomy.* In: *Communications of the ACM,* Vol 8, (10):627–633.

Sabine Schulte im Walde and Chris Brew. 2002. *Inducing German Semantic Verb Classes from Purely Syntactic Subcategorisation Information.* In: *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics (ACL)*, 223–230. Philadelphia.

Sabine Schulte im Walde. 2003. *Experiments on the Choice of Features for Learning VerbClasses*. In: *Proceedings of the 10th Conference of the European Chapter of the Association for computational Linguistics*, 315–322. Budapest.

Sabine Schulte im Walde. 2004. *Automatic Induction of Semantic Classes for German Verbs*. In: Stefan Langer and Daniel Schnorbusch (eds.), *Semantik im Lexikon*. 59–86. Gunter Narr Verlag, Tübingen.

Eric V. Siegel. 1997. *Learning methods for combining linguistic indicators to classify verbs. Proceedings of the Second Conference on Empirical Methods in Natural Language Processing*.

Eric V. Siegel and Kathleen R. McKeown. 2000. *Learning Methods to Combine Linguistic Indicators: Improving Aspectual Classification and Revealing Linguistic Insights*. Computational Linguistics, 595–627.

Helmut Schumacher. 1986. *Verben in Feldern*. V*alenzwörterbuch zur Syntax und Semantik deutscher Verben.* De Gruyter, Berlin & New York.

Hinrich Schütze and Jan Pedersen. 1993. *A vector model for syntagmatic and paradigmatic relatedness.* In: *Making Sense of Words:* 104–113. Ninth Annual Conference of the UW Centre for the New OED and Text Research, Oxford.

Peter D. Turney and Patrick Pantel. 2010. From Frequency to Meaning: Vector Space Models of Semantics. *Journal of Artificial Intelligence Research*, 37:141–188.

Zeno Vendler. 1967. *Linguistics in Philosophy*. Ithaka / New York: Cornell University Press.

Andreas Vlachos, Anna Korhonen and Zoubin Ghahramani. 2009. *Unsupervised and constrained Dirichlet process mixture models for verb clustering'*. In: *Proceedings of the EACL Workshop on Geometrical Models of Natural Language Semantics*, 74–82. Athen.

Warren Weaver. 1955. *Translation*. In: William N. Locke and A. Donald Booth, *Machine Translation of Languages*: 15–23. MIT Press, Cambridge Mass.