Universität Stuttgart

Institut für Maschinelle Sprachverarbeitung

Experiential Data and Distributional Models of German Particle Verbs

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Outline

Outline

Phenomenon

German Particle Verbs (PVs)

- Composition:
  - composition of base verbs (BVs) and prefix particles
  - PVs are separable: *kommt . . . an*
  - focus: preposition particles
- Examples:
  - *abholen* 'fetch': *ab* + *holen* 'fetch'
  - *anfangen* 'begin': *an* + *fangen* 'catch'
  - *einsetzen* 'insert'/'begin': *ein* + *setzen* 'put/sit (down)'
- References:
  - Stiebels (1996); Lüdeling (2001); Dehe et al. (2002)
  - Lechler & Roßdeutscher (2009); Haselbach (2011); Kliche (2011); Springorum (2011)

Syntax-Semantics Interface of German PVs

- Verb behaviour $\leftrightarrow$ verb meaning (Levin, 1993):
  distributional similarity with respect to subcategorisation (frames) corresponds to a large extent to semantic relatedness

- Particle verbs: behaviour $\leftrightarrow$ meaning:
  particle verbs change the subcategorisation behaviour in comparison to their base verbs; such changes are quite regular

  (1) Sie *lächelt*.
  'She smiles.'

  $*$Sie *lächelt* [$_{NP_{acc}}$ ihre Mutter].
  'She smiles her mother.'

  Sie *lächelt* [$_{NP_{acc}}$ ihre Mutter] *an*.
  'She smiles her mother at.'

Syntactic Transfer Types

- Argument extension:

(2) [$_{NP_{nom}}$ Die Lampe] *leuchtet*.
'The lamp shines.'

[$_{NP_{nom}}$ Peter] *leuchtet* [$_{NP_{acc}}$ das Bild] [$_{PP}$ mit der Lampe] *an*.
'Peter beams at the picture with the lamp.'

- Argument incorporation:

(3) [$_{NP_{nom}}$ Der Mechaniker] *schraubt* [$_{NP_{acc}}$ den Deckel] [$_{PP}$ auf die Öffnung].
'The mechanic screws the cover on the opening.'

[$_{NP_{nom}}$ Der Mechaniker] *schraubt* [$_{NP_{acc}}$ den Deckel] *an*.
'The mechanic screws the cover on.'

Past and Ongoing Research

- Models of Compositionality
  - Particle verb clusters: distributional clusters of particle verbs and base verbs (Kühner & Schulte im Walde, KONVENS 2010)
  - Window-based vector space models: optimising a lexical model of compositionality (Bott & Schulte im Walde, LREC 2014)
  - Empirical subcategorisation transfer patterns at the syntax-semantics interface (Hartmann et al., KONVENS Workshop 2008)
  - Compositionality models integrating syntactic transfer patterns (Bott & Schulte im Walde, IWCS 2015)
- Models of Particle Meaning
  - Particle clusters: distributional clusters of the German verb particle *an* (Springorum et al., LREC 2012)
  - Systematic neologisms of particle verbs: empirical identification of regularities and prototypicality of particle meaning (Springorum et al., QITL 2013; Springorum, CoGS 2014)
- Particle Verb Meaning Shifts
  - Metaphorical shifts of particle verbs: regularities at the syntax-semantics interface that indicate metaphorical uses of particles or particle verbs (Springorum et al., IWCS 2013)

Datasets

Particle Verbs: Datasets

1. GS-99:
   99 randomly selected particle verbs across 11 particles, balanced over 8 frequency ranges (Hartmann et al., KONVENS Workshop 2008)

2. GS-400:
   cleaned random selection of 400 particle verbs across 9 preposition particles and three particle-based frequency ranges obtained from the three corpora *DECOW12, SdeWaC, HGC* (Khvtisavrishvili et al., DGfS 2015)

3. neoPV-125:
   125 existing and neoPVs across 5 preposition particles and
   5 BVs from the 5 semantic verb classes *de-adjectival, state, physical process, mental process, achievement/accomplishment*
   (Springorum, QITL 2013 & CoGS 2014)

4. CI-300 (including 30 BVs):
   270 existing and neoPVs across 9 preposition particles and 10 BVs from the three classes *machines & tools, force, sound*

Compositionality Ratings

Experiment: Compositionality Ratings

Task: determine the degree of PV compositionality (range: 1–6)

Examples:

TRANSPARENT *aufnehmen* (5.91)
TRANSPARENT *auskratzen* (5.91)
TRANSPARENT *unterhaken* (4.75)

OPAQUE *auflehnen* (3.30)
OPAQUE *ausbilden* (3.08)
OPAQUE *unterjubeln* (2.50)

Collections:

- GS-99
- GS-400

Outline

Particle Verb Clusters

Particle Verb Clusters: Hypothesis

- Hypothesis: The more compositional a particle verb is, the more often it appears in the same cluster with its base verb.
  - Compositionality is restricted to the relationship between particle verbs and base verbs.
  - Contribution of particle is ignored.
- Dataset: 99 German particle verbs across 11 particles and 8 frequency ranges (GS-99)

Clustering

- Soft clustering:
  - Cluster membership is represented by a probability.
  - Probabilistic membership is turned into binary membership by establishing a membership cut-off.
- Clustering approaches:
  - Latent Semantic Classes (LSC) (Rooth, 1998):
    - two-dimensional soft clusters that generalise over hidden data
    - Expectation-Maximisation (EM) algorithm for unsupervised training on un-annotated data
    - model selectional dependencies between two sets of words participating in a grammatical relationship
  - Predicate-Argument Clustering (PAC) (Schulte im Walde et al., 2008):
    - extension of LSC to incorporate selectional preferences
    - combination of EM algorithm and Minimum Description Length (MDL) principle

LSC: Example Cluster

dimension 1: verbs		*dimension 2: direct object nouns*	
schicken	'send'	Artikel	'article'
verschicken	'send'	Nachricht	'message'
versenden	'send'	E-Mail	'email'
nachweisen	'prove'	Brief	'letter'
überbringen	'deliver'	Kind	'child'
abonnieren	'subscribe to'	Kommentar	'comment'
zusenden	'send'	Newsletter	'newsletter'
downloaden	'download'	Bild	'picture'
bescheinigen	'attest'	Gruß	'greeting'
zustellen	'send'	Soldat	'soldier'
abschicken	'send off'	Foto	'photo'
zuschicken	'send'	Information	'information'

PAC: Example Cluster

dimension 1: verbs		*dimension 2: WN concepts over PP arguments*	
steigen	'increase'	Maßeinheit	'measuring unit'
zurückgehen	'decrease'	e.g., Jahresende	'end of year'
geben	'give'	Geldeinheit	'monetary unit'
rechnen	'calculate'	e.g., Euro	'Euro'
wachsen	'grow'	Transportmittel	'means of transportation'
ansteigen	'increase'	e.g., Fahrzeug	'automobile'
belaufen	'amount to'	Gebäudeteil	'part of building'
gehen	'go'	e.g., Dach	'roof'
zulegen	'add'	materieller Besitz	'material property'
anheben	'increase'	e.g., Haushalt	'budget'
kürzen	'reduce'	Besitzwechsel	'transfer of property'
stehen	'stagnate'	e.g., Zuschuss	'subsidy'

Clustering Setup

- Corpus:
  - data: 880 million words from the German web corpus *SdeWaC* (Faaß et al., 2010; Faaß/Eckart, 2013); preprocessing: *Tree Tagger* (Schmid, 1994) and dependency parser *FSPar* (Schiehlen, 2003)
  - 2,152 verb types with $1,000 <$ verb freq $< 100,000$
- Distributional features:
  - nominal features
  - syntactic functions: subjects, objects, pp objects
  - incorporating vs. excluding the notion of syntax
- Clustering parameters:
  - number of clusters: 20, 50, 100, 200
  - probability thresholds: 0.01, 0.001, 0.0005, 0.0001
- Evaluation: proportion of PV–BV cluster co-occurrence against human ratings using Spearman's ρ

Results

LSC:

input	best result corr	cov	f-score	analysis clusters	iter	membership threshold
obj	.433	.59	**.499**	100	200	.0005
subj	.205	.76	.323	50	200	.0001
pp	.498	.40	.444	20	200	.0005
n+syntax	.303	.54	.388	50	200	.0005
n-syntax	.336	.56	.420	100	200	.001

PAC:

input	best result corr	cov	f-score	analysis clusters	iter	membership threshold
obj	.100	.53	.168	100	50	.0005
subj	.783	.05	.094	20	50	.01
pp	.275	.21	.238	200	100	.01
n+syntax	.213	.61	.316	20	100	.0001
n-syntax	.236	.53	**.327**	200	100	.001

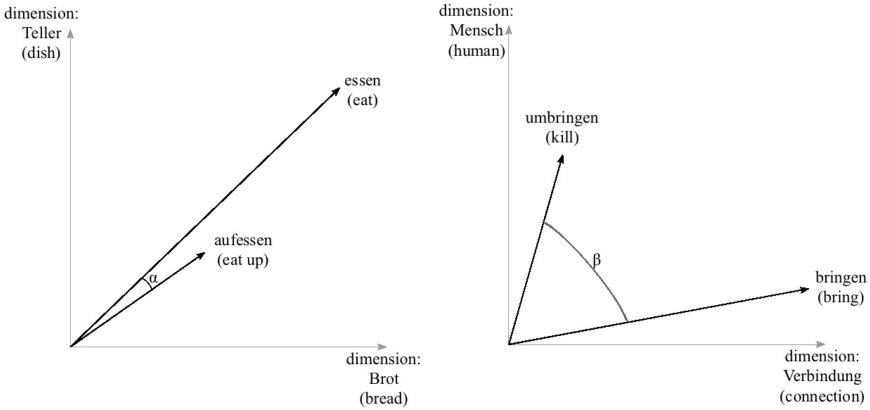
Results: Summary

- There is no clear tendency towards an optimal number of clusters.
- The optimal probability threshold for cluster membership depends on a preference for correlation vs. coverage.
- The unmarked *n-syntax* condition outperforms the marked *n+syntax* condition, but the difference is not impressive.
- The dependency of selectional preferences on the subcategorisation frames that represents a strength of PAC does not play an important role in our task.
- Best approach: LSC can predict the degree of compositionality for 59% of the particle verbs. The correlation with the gold standard judgements is $\rho = .433$.

Lexical Vector Space Models

Motivation

Verbs similar in meaning tend to occur in similar lexical contexts:



Lexical Parameters

- How good is window-based lexical distributional similarity ($\rightarrow$ cosine) as a predictor for compositionality?
- In how far do the following factors influence the predictability?
  - What is the ideal size of the context?
  - In how far does ambiguity of particle verbs influence?
  - In how far does a bad syntactic preprocessing and the resulting bad lemmatisation influence?
  - Are all POS equally predictive?
  - In how far does term weighting influence?

Setup of Vector Spaces

- *SdeWaC* corpus (Faaß and Eckart, 2013), dependency parsed (Bohnet, 2010), potential lemma correction
- Gold standard: 99 particle verbs, 11 particles, balanced over 8 frequency ranges (GS-99)
- Evaluation: Spearman's ρ

- Different window sizes (1, 2, 5, 10, 20 words to the left and right)
- Different frequency bands (from the gold standard)
- Ambiguous vs. non-ambiguous particle verbs
- Term weighting (LMI, Evert, 2004) vs. raw frequencies
- All context words vs. only content word POS categories
- Lemma correction (heuristics) applied/not applied

Heuristics for Lemma Correction

Dependencies:					
Surface:	Peter	ißt	das	Eis	auf
POS:	...	V	...	...	PRT
Lemma:	...	essen	...	...	auf
Corrected:			aufessen		

Results: Content Words & Weighting

The system performance **failed** to be statistically significant **unless**

- non-content words were filtered out and
- LMI (term-weighting) was applied.

This result is stronger than we expected.

Results: Restored Lemmatisation

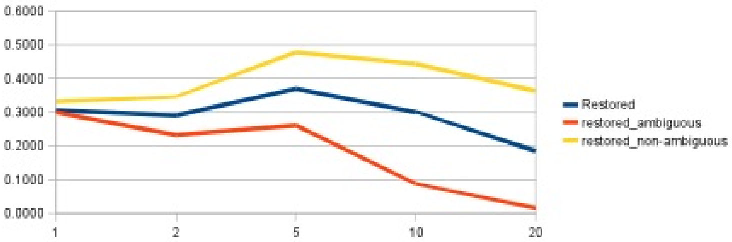
Comparison between baseline models vs. models with lemma correction (values given in Spearman ρ):

Window size	**1**	**2**	**5**	**10**	**20**
Original	0.2102*	0.2507*	0.2308*	0.2416*	0.2668**
Restored	0.3058**	0.2910**	**0.3696*** **	0.3008**	0.1859

Values which exceed the threshold for $p<0.025$, $p<0.005$ and $p<0.001$ are marked with *, ** and ***.

Results: Ambiguity

Performance of the models with lemma restoration for ambiguous vs. unambiguous particle verbs:



The x-axis represents the window size in the number of words, the y-axis represents values in Spearman's ρ.

Results: Frequency Bands

Spearman ρ values for different frequency ranges (models with restored lemma information, window size 5):

Frequency	**Spearman's ρ**
2-4	0.16
5-9	0.27
10-17	0.26
18-54	**0.59**
55-99	0.25
110-299	0.06
300-6000	0.13

Results: Summary

- Ideal window size in our experiments: 5 words (left and right).
- Content words are the most useful.
- Term-weighting is useful.
- Mid-frequency verbs are easier to model than low-frequency or high-frequency verbs.
- Ambiguous verbs are harder to model than non-ambiguous verbs.
- Lemma restoration is very helpful!

Compositionality Model integrating Syntactic Transfer

Motivation

Predictors for compositionality:

- Raw lexical distributional information (vector spaces relying on word windows)
- Lexical co-occurrence information filtered by syntax
- Syntactic subcategorisation frames
- Regular syntactic transfers: frame(BV_i) + $P_j \rightarrow$ frame(PV_{ij})

Method

- Use the degree of slot correspondence as a predictor for PV–BV compositionality:

  1. Select the 5 most common subcategorisation frames of each PV and each BV.
  2. Compare each PV slot against each BV slot, by measuring the cosine between the vectors containing the NP and PP complement heads as dimensions, and head counts within the slots as values.
  3. Take the best BV match for each PV subcategorisation slot.
  4. Calculate and average over the similarities of these best matches.
  5. Use Spearman's ρ to compare the cosine ranking to human ratings on compositionality.

- Use a threshold *t* on the cosine values to account for zero correspondence (incorporation and extension).

Generalisation over Head Nouns

- ***GermaNet (GN)*** is the German version of WordNet (Hamp & Feldweg, 1997). We use the n^{th} topmost taxonomy levels in the GermaNet hierarchy as generalisations of head nouns.
- ***LDA***: We use the MALLET tool (McCallum, 2002) to create LDA topic generalisations for the head nouns, in a similar way as Ó Séaghdha (2010). While LDA is usually applied over text documents, we consider as document the set of noun heads in the same subcategorisation slot.
- ***SVD***: We use the DISSECT tool (Dinu et al., 2013) to apply dimensionality reduction to the vectors of complement head nouns.

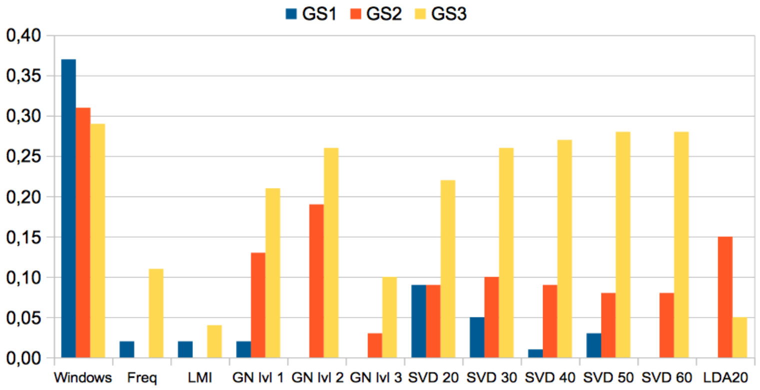
Gold Standards

- ***GS1 = GS-99***: A gold standard collected by Silvana Hartmann, consisting of 99 randomly selected PVs across 11 particles, balanced over 8 frequency ranges and judged by 4 experts.

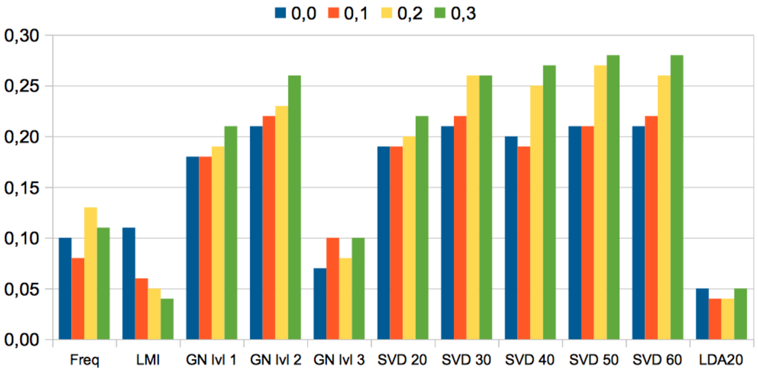
- ***GS2 = part of superset of GS-400***: A gold standard of 354 randomly selected PVs across the same 11 verb particles, balanced over 3 frequency ranges while taking the frequencies from three corpora into account. We collected ratings with Amazon Mechanical Turk.

- ***GS3 = subset of GS-400***: A subset of 150 PVs from GS2, after removing the most frequent and infrequent PVs as well as prefix verbs.

Results across Gold Standards



Results across Thresholds



Results: Summary

- The results improve with an increasing threshold.
  → Filtering out null-correspondences of subcategorisation slots in incorporation and extension cases has a positive effect.
- The approach works best for GS3.
  → It is thus not robust to very low and very high verb items.
- The syntactic transfer approach could not outperform the lexical window-based approach.
- Generalisation techniques improve the syntactic approach.
  → Data sparseness causes the main problems.
- A combination of the lexical and the syntactic approach does not improve the results. → No complementary strengths.

Outline

Classification of “an” Particle Verbs

Classification Setup

- Corpus and verbs:
  - data: 560 million words from the German web corpus *deWaC*; preprocessing: *Tree Tagger* (Schmid, 1994) and dependency parser *FSPar* (Schiehlen, 2003)
  - 40 *an* particle verbs (10 from each class)
- Distributional features:
  - prepositional heads of prepositional phrases
  - direct objects and their GermaNet generalisations
  - subjects (baseline)
- Classification approach:
  - WEKA J48 decision tree algorithm with pruned trees

Gold Standard Verb Classes

TOPOLOGICAL	EVENT INITIATION	DIRECTIONAL	PARTITIVE
anbauen (install)	anblicken (gaze at)	anheizen (heat up)	anbohren (drill part.)
anbinden (tie up)	angucken (look at)	ankurbeln (boost)	anbraten (roast part.)
anfassen (touch)	anlächeln (smile at)	anpfeifen (whistle)	anbrechen (broach)
anketten (chain)	anpeilen (locate)	anregen (instigate)	anknabbern (nibble)
anlehnen (lean on)	anreden (address)	anrichten (wreak)	anreißen (scribe)
anmalen (paint)	anschreiben (write to)	anspornen (cheer on)	anrösten (toast part.)
anschließen (affiliate)	anschreien (scream at)	anstiften (incite)	ansägen (saw part.)
anschnallen (belt on)	anstarren (stare at)	anstimmen (intone)	anschneiden (cut part.)
ansiedeln (settle)	anstreben (aspire)	antreiben (activate)	ansengen (scorch)
anstreichen (brush)	anvisieren (aim for)	anzetteln (plot)	anzahlen (deposit)

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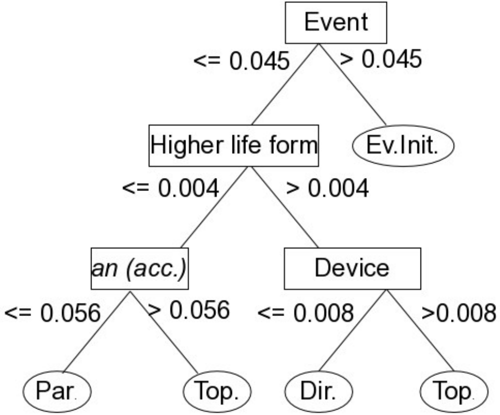
Results across Classes and Features

Experiment	Feature	Accuracy		TOP.	EV.I.	DIR.	PAR.
Baseline	Subject	13	32.50%	0	3	1	9
Judgements			79.06%				
Exp. 1	PPs	25	62.50%	6	5	5	9
Exp. 2	Objects	11	27.50%	0	0	2	9
Exp. 3	Object Classes	27	67.50%	1	8	8	10
Exp. 4	*an*+Object Classes	**28**	**70.00%**	4	7	7	10

Best Decision Tree



Results: Summary

- Replication of theoretical linguistic semantic classification by a machine learning approach to an extent of 70% (only 9% below the upper bound of human judgments).
- Best classification result is reached by a GermaNet-based generalisation of direct object nouns in combination with the most successful prepositional phrase (*PP-an*) feature.
  Semantic class *event* is identified as an effective feature for Event Initiation.
- The combination of features largely corresponds to the linguistic intuitions based on former linguistic studies.
- Computational analyses deepened our theoretical insights of the semantic properties of the particle verbs.
  Example: The verbs *anspornen* (cheer on) and *anstiften* (incite) were characterised as Event Initiation, but we found that this classification is not sufficient because they also have a directional component (i.e., communication) and therefore occur with an object with consciousness:
  Er stiftet den Bruder zu Unfug an. (He incites the brother to rag.)

Particle Verb Neologisms

Systematic Neologisms: Goals and Data

- Research questions:
  - Are German particle verbs compositional?
  - Are there any (prototypical) particle readings?
  - What is the meaning contribution of the base verbs?
- Dataset: 125 German particle verbs across 5 particles and 5 semantic base verb classes
  - particles: *ab, an, auf, aus, nach*
  - semantic verb classes:
    1. DE-ADJECTIVAL e.g. *kürzen* 'shorten'
    2. ACHIEVEMENT/ACCOMPLISHMENT e.g. *finden* 'find'
    3. PHYSICAL PROCESS e.g. *stricken* 'knit'
    4. MENTAL PROCESS e.g. *denken* 'think'
    5. STATE e.g. *lieben* 'love'

Experiment: Task and Example Sentences

- Task: generation of sentences with attested PVs and with systematic neologisms of German particle verbs

- Examples:

  Er hatte an der Wand angelauscht und wusste Bescheid.
  'He had listened at the wall and knew it all.'
  → `contact + partitive`

  Ich musste mich noch lange Zeit nachwundern.
  'I was wondering about it for a long time.'
  → `continuation`, cf. *nach-reifen*

  Ich werde den Zombie schon mal antöten, damit du ihn erledigen kannst.
  'I will kill at the Zombie, so that you can execute him.'
  → `partitive`, contradiction with absolute change of state of BV

Results: Summary

- Availability of particle verb meaning is relative and might be independent on the existence.
- Construction patterns become apparent.
- Analogies to existing verbs and/or concepts are detectable.
- People are able to use an unknown word in a non-literal way.
- Particle verbs are compositional. (?)

Outline

Phenomenon

Phenomenon

	Particle		Base Verb		Particle Verb	
LIT	literal		literal		literal	
	ab	removal	*nageln* *schminken*	put on	*abnageln* *abschminken*	NEO remove
	an	direction	*springen* *tanzen*	manner of motion	*anspringen* *antanzen*	directed manner of motion
(1)	literal		literal		meaning shifted	
	ab	removal	*nageln* *schminken*	put on	*abnageln* *abschminken*	forget about sth.
(2)	literal		meaning shifted		meaning shifted	
	an	direction	*springen* *tanzen*	motion	*anspringen* *antanzen*	negative force
(3)	meaning shifted		literal		meaning shifted	
	auf	social: direction (down)	*brummen* *donnern*	unpleasant sound	*aufbrummen* *aufdonnern*	negative social pressure

Hypothesis:
There are regular mechanisms in meaning shifts from one domain to another when a base verb is combined with a particle meaning.

Regular Metaphorical Shifts: Example

base verbs	frames	complements	connotations	properties
strahlen 'beam'	intrans	*Sonne* 'sun' *Auge* 'eye'	bright, warm	light emission
funkeln 'twinkle'	intrans	*Sternlein* 'little star' *Auge* 'eye'	pleasing, valuable	
lächeln 'smile'	intrans	*Mädchen* 'girl'	happy, friendly	positive emotion
grinsen 'grin'	intrans	*Freund* 'friend'	expression	

particle verbs	frames	complements	connotations	properties
anstrahlen 'beam at'	trans	*Decke* 'ceiling' *Muffel* 'grumpy person'	pleasing, positive communication	pos. directed communication
anfunkeln 'beam at'	trans	*Großmaul* 'loudmouth'		
anlächeln 'smile at'	trans	*Mädchen* 'girl'		
angrinsen 'grin at'	trans	*Mädchen* 'girl'		

Goals

Identify regular meaning shifts of German particle verbs (PVs) with prepositional particles.

1. Sense discrimination for PVs, particles and simplex verbs.
   - theoretical considerations about salient meaning components
   - empirical evidence from psycholinguistic experiments
   - computational distributional models: soft clustering
2. Identification of regular meaning shifts and their conditions.
   - incorporation of empirical sense properties into models
   - identification of regular polysemy regarding PV–BV meaning shifts
   - identification of shift conditions (subcat; abstractness; etc.)

Experiments

Experiment: PV Sentence Generation

Task: collect sentences with particle verbs

1. existing and neoPVs
2. literal and metaphorical senses

Examples:

LIT	*Kannst du das Bild von der Wand abnageln?*
NEO	*Den neuen Job kann ich mir abnageln.*
LIT	*Mir ist der Schlüssel abgebrochen.*
META	*Ich würde die Freundschaft zu ihm abbrechen.*
LIT	*Er ist mit dem Fahrrad nach rechts abgebogen.*
META	*Er ist in seinem Leben irgendwann auf die falsche Bahn abgebogen.*

Purposes:

1. identification of salient meaning components
2. gold standard data for classification and evaluation

Experiment: PV Metaphoricity Ratings

Task: classify sentences into literal vs. metaphorical readings

1. use generated sentences
2. use random selection of 50 sentences per PV from corpus

Examples:

LIT	*Die kleinen Augen werden abgeschminkt.*
LIT	*Nur Maria schminkt sich ab, nach der letzten Beichte.*
META	*Eine Familie zu gründen kann ich mir eigentlich abschminken.*
META	*Damit kann er sich seine Karriere als Tracksprinter abschminken.*

Purposes:

1. identification of salient meaning components
2. gold standard data for classification and evaluation

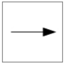
Experiment: Image Schema Ratings

Task: rate concept images for PV meaning

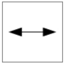
1. directional, shape and container images
2. existing and neoPVs
3. literal and metaphorical senses

Examples (directional):

aufschrauben (6/12)



vordrängen (6/23)



anschleifen (6/32)

anschleifen (6/32)

anschleifen (5/32)

Purpose: identification of embodiment features for particle readings

Experiment: Image Schema Ratings

Analyses:

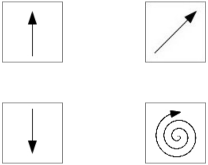
1. identification of distinctive patterns for particles over images
   (exclude PVs where particle distribution differs strongly)
2. PV–BV compositionality according to distributions over images
3. identification of prototypical particle reading(s) through neoPVs
   (neoPVs are expected to show some “prototypical” particle meaning)
4. justification/adjustment of concept images according to correlations between images across PVs

Experiment: Image Schema Eye-Tracking

Task: identify concept images for PV meaning

1. contrast multiple images at the same time
2. visual world paradigm

Example: *Und für wen sollte ich mich sonst noch aufdonnern?*



Purposes:

1. identification of embodiment features
2. identification of salient meaning components

Experiment: PV Antonyms and Synonyms

Task: generation/extraction of antonyms and synonyms

Sources: AMT; online dictionaries

Examples:

ANT	*aufschrauben–zuschrauben/zudrehen*
ANT	*aufklingen–abklingen*
ANT	*aufdrängen–abdrängen*
SYN	*aufschrauben–aufdrehen*
SYN	*aufdrängen–aufreden*
SYN	*aufbrausen–beruhigen*

Purposes:

1. extension of salient distributional PV features
2. identification of prototypical particle pairs

Experiment: Concreteness Ratings

Task: distinguish concrete vs. abstract words

1. use existing ratings (Kanske & Kotz, 2007; Lahl et al., 2009)
2. use translations of existing ratings (Brysbaert et al., 2014)
3. generate own ratings according to Turney et al. (2011)

Examples:

CONCRETE	*Tomatenkiste* (9.696)
CONCRETE	*Vampirgebiss* (9.591)
CONCRETE	*Dichtungsschaum* (9.484
ABSTRACT	*Bedeutsamkeit* (-8.604)
ABSTRACT	*Unerklärlichkeit* (-8.683)
ABSTRACT	*Rechtfertigungsbedürfnis* (-9.396)

Purpose: classify contexts into concrete vs. abstract

Experiment: Concreteness Ratings

Approach: Brysbaert et al. (2014)

Instructions:

Some words refer to things or actions in reality, which you can experience directly through one of the five senses. We call these words concrete words. Other words refer to meanings that cannot be experienced directly but which we know because the meanings can be defined by other words. These are abstract words. Still other words fall in-between the two extremes, because we can experience them to some extent and in addition we rely on language to understand them. We want you to indicate how concrete the meaning of each word is for you by using a 5-point rating scale going from abstract to concrete. . . .

Resource: concreteness ratings for 40,000 English words

Computational Models

Particle Verb Data: Preprocessing

- Distributional information from DECOW14 (approx. 20 billion tokens), cf. Schäfer and Bildhauer (2012)
- Morphology and parses for DECOW14 using the *D8 Pipeline* relying on SMOR, MarMoT and the MATE parser (Schmid et al., 2004; Bohnet, 2010; Müller et al., 2013)
- Refined extraction strategy for German PVs relying on separation vs. non-separation hypotheses (Khvtisavrishvili et al., DGfS 2015)
- PV syntactic transfer patterns from SemRel (Bott & Schulte im Walde, 2015)

Model: Concreteness Ratings and Contexts

Approach: Turney et al. (2011)

Steps:

1. create a window-based vector space for WordNet vocabulary
2. generate sets of concrete and abstract words:
   2.1 use existing concreteness ratings as training set
   2.2 start with an empty set of paradigm words
   2.3 add 20 words to each set by greedy forward search, alternating between concrete and abstract words
3. calculate abstractness for all words in vector space, by comparing similarity with 20 abstract paradigm words minus similarity with 20 concrete paradigm words
4. purpose: categorise contexts into concrete vs. abstract

Model: Binary Token Classification

Tasks:

- classify sentences into literal vs. metaphorical readings
- identify salient (distributional) features

Data for 174 gold-standard PVs:

1. use generated sentences
2. use random selection of 50 sentences per PV from corpus

Features (selection):

- particle type
- compositionality of PV
- text coherence of PV (antonyms/synonyms) and context
- generalisation of context: abstractness/concreteness; noun hypernyms
- adverbial verb modifiers

Past and Ongoing Research (repeated)

- Models of Compositionality
  - Particle verb clusters: distributional clusters of particle verbs and base verbs (Kühner & Schulte im Walde, KONVENS 2010)
  - Window-based vector space models: optimising a lexical model of compositionality (Bott & Schulte im Walde, LREC 2014)
  - Empirical subcategorisation transfer patterns at the syntax-semantics interface (Hartmann et al., KONVENS Workshop 2008)
  - Compositionality models integrating syntactic transfer patterns (Bott & Schulte im Walde, IWCS 2015)
- Models of Particle Meaning
  - Particle clusters: distributional clusters of the German verb particle *an* (Springorum et al., LREC 2012)
  - Systematic neologisms of particle verbs: empirical identification of regularities and prototypicality of particle meaning (Springorum et al., QITL 2013; Springorum, CoGS 2014)
- Particle Verb Meaning Shifts
  - Metaphorical shifts of particle verbs: regularities at the syntax-semantics interface that indicate metaphorical uses of particles or particle verbs (Springorum et al., IWCS 2013)