Can Human Verb Associations help identify Salient Features for Semantic Verb Classification?

Sabine Schulte im Walde

Computational Linguistics

Saarland University

Saarbrücken, Germany

University of Sussex, May 2006

Overview

Assumption: *Associations model aspects of verb meaning. This knowledge is needed for semantic verb classes.*

1. Human verb associations - collection and analysis
2. Association-based verb classes and validation
3. Exploring semantic class features
4. Inducing verb classes with corpus-based features

Question: *Can human verb associations help identify salient features for semantic verb classification?*

Variety of Semantic Verb Classes

- Semantic verb classes with
  various instantiations of semantic similarity, e.g.
  - syntactic similarity / alternations (Levin, 1993):
    buy, catch, earn, find, steal, ... (obtaining:get verbs)
  - synonymy (WordNet):
    buy, purchase
  - situation-based agreement (FrameNet):
    buy, purchase (commerce_buy) inherits from
    acquire, gain, get, obtain, procure, secure (getting)

Creation of Semantic Verb Classes (1)

- Resource-intensive vs. automatic methods
- Examples of automatic methods:
  - » Merlo & Stevenson (CL Journal, 2001):

    classify 60 English verbs which alternate between an intransitive and a transitive usage into three classes;

    features model syntactic frame alternation proportions and heuristics for semantic role assignment
  - » Stevenson & Joanis (CoNNL, 2003):

    classify into 13 Levin classes with 20 verbs each in a two-/three-class distinction;

    general feature space and manual/seed subsets for syntactic slots, tense, voice, aspect, animacy

Creation of Semantic Verb Classes (2)

- Examples of automatic methods (cont'd):
  - » Korhonen, Krymolowski & Marx (ACL, 2003):
    48+26+57 polysemous Levin/Dorr/Korhonen classes;
    subcategorisation info from Briscoe/Carroll parser
  - » Schulte im Walde (PhD, 2003; CL Journal, 2006):
    classifies 168 verbs into 43 FrameNet-style classes;
    subcategorisation frames, PPs, selectional preferences

- Classification and clustering parameters:
  verbs, classes, algorithm, features, etc.

Semantic Verb Classes: Features

- Model semantic similarity of interest
- Similarity at the syntax-semantics interface: *behaviour*
- Potentially salient features:
  - » syntactic frames
  - » prepositional phrases
  - » argument role fillers
  - » adverbial adjuncts, etc.
- Granularity of features

Associations: Guide to Feature Selection

- Goal: human associations to identify salient features

- Assumptions:
  - » associations model verb meaning aspects
  - » theory-independent
  - » variety of semantic verb relations
  - » guidance to feature selection

- Empirical model for verb features (among others): window co-occurrence vs. syntactic frame fillers

Procedure

1. Collect human verb associations
2. Hierarchical clustering on experiment verbs; basis: verb associations (assoc-classes)
3. Validate clustering against GermaNet and FrameNet
4. Compare cluster features with corpus-based features
5. Hierarchical clustering on experiment verbs; basis: corpus-based features (corpus-classes)
6. Compare corpus-classes against assoc-classes
7. Evaluation of hypothesis

Hypothesis and Research Questions

- Hypothesis: The more associations are found as instantiations in a feature set, the better is a clustering as based on that feature type.

- Do the human associations help identify salient features to induce semantic verb classes?

  I.e., do the corpus-based results outperform previous results?

- Are the same types of features salient for different types of semantic verb classes?

Human Verb Associations:

Collection and Analysis

Web Experiment: Material

- 330 German verbs
- Variety of semantic verb classes, possible ambiguity:
  - » self-motion: *gehen* ‘walk’, *schwimmen* ‘swim’
  - » cause: *verbrennen* ‘burn’, *reduzieren* ‘reduce’
  - » experiencing: *lachen* ‘laugh’, *überraschen* ‘surprise’
  - » communication: *erzählen* ‘tell’, *klagen* ‘complain’
  - » body: *schlafen* ‘sleep’, *abnehmen* ‘lose weight’
- Variety of frequency ranges (1 < freq < 71,604)
- Random distribution: 6 data sets à 55 verbs, balanced for class affiliation and frequency ranges

Web Experiment: Procedure

schneien

kalt

rodeln

Schneemann

weiß

dämmern

Web Experiment: Data

- 299 accepted data files
- Participants per data set: between 44 and 54
- Number of trials: 16,445
- Number of associations per target verb:
  range 0-16, average: 5.16
- Responses: 81,373 tokens for 18,884 types

Quantification over Association Types

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

Linguistic Analysis of Experiment Data

- Preference for morpho-syntactic category of responses?

  → distinguish major parts-of-speech:
  nouns, verbs, adjectivs, adverbs

- Typical argument holders of verb valency?

  → investigate linguistic functions realised by nouns:
  empirical grammar model (Schulte im Walde, 2003)

Morpho-Syntactic Distribution

		V	N	ADJ	ADV
TOKEN	Freq	19.863	48.905	8.510	1.268
	Prob	25	62	11	2
TYPES	Freq	9.317	23.524	4.983	802
	Prob	24	61	13	2

Morpho-Syntactic Correlations/Tests

- Correlation **+**

  target verb frequency ⇔ verb/adverb responses

- Correlation **-**

  target verb frequency ⇔ noun responses

- Variation across verb classes

Syntax-Semantic Functions of Nouns

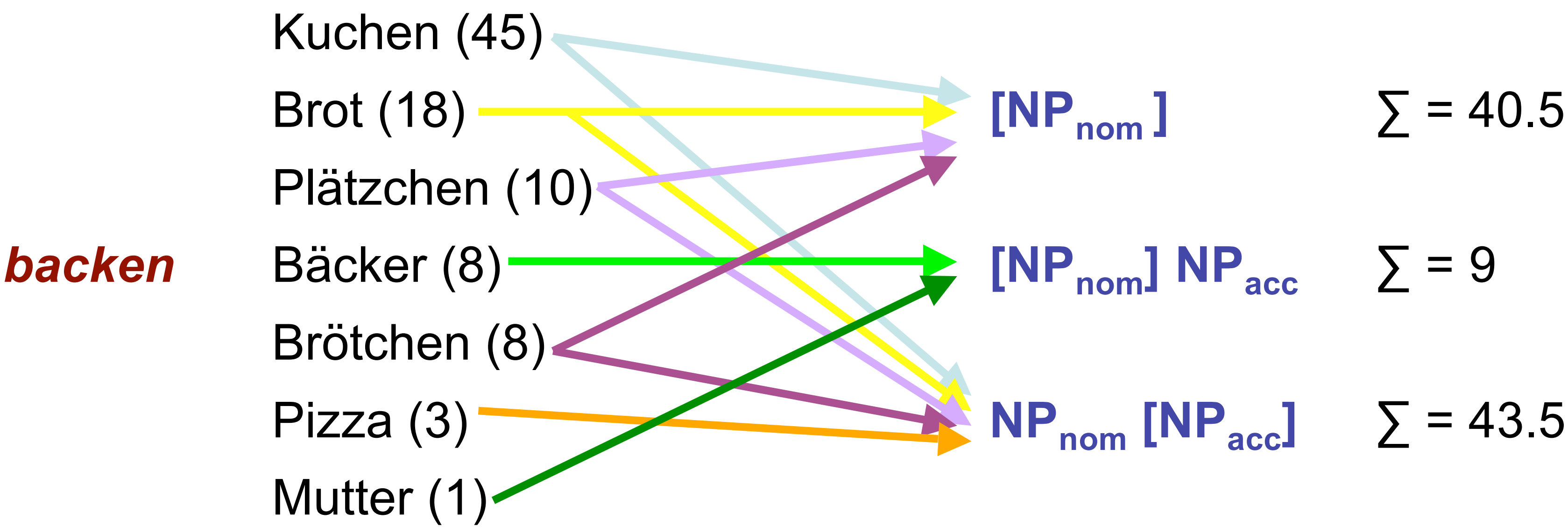
- Source: statistical grammar model
- Verb valency:
  - » 38 syntactic subcategorisation frames
  - » plus PP information (case+preposition) → 178 frames
  - » subcategorised nouns
- Example: *backen* 'bake'
  - » frames: **NP_{nom}**
    NP_{nom} NP_{acc} ...
  - » filler examples for **NP_{nom} [NP_{acc}]**: *Brot* 'bread'
    Kuchen 'cake' …

Excursus: Statistical Grammar Model

- Head-lexicalised probabilistic context-free grammar (Charniak, 1997; Carroll and Rooth, 1998)
- 35 million words of German newspaper corpora
- Unsupervised training by *EM-Algorithm* (Baum, 1972)
- Robust statistical parser *LoPar* (Schmid, 2000)
- Corpus-based quantitative lexical information: word frequencies, linguistic functions, head-head relations

Syntax-Semantic Functions: Analysis

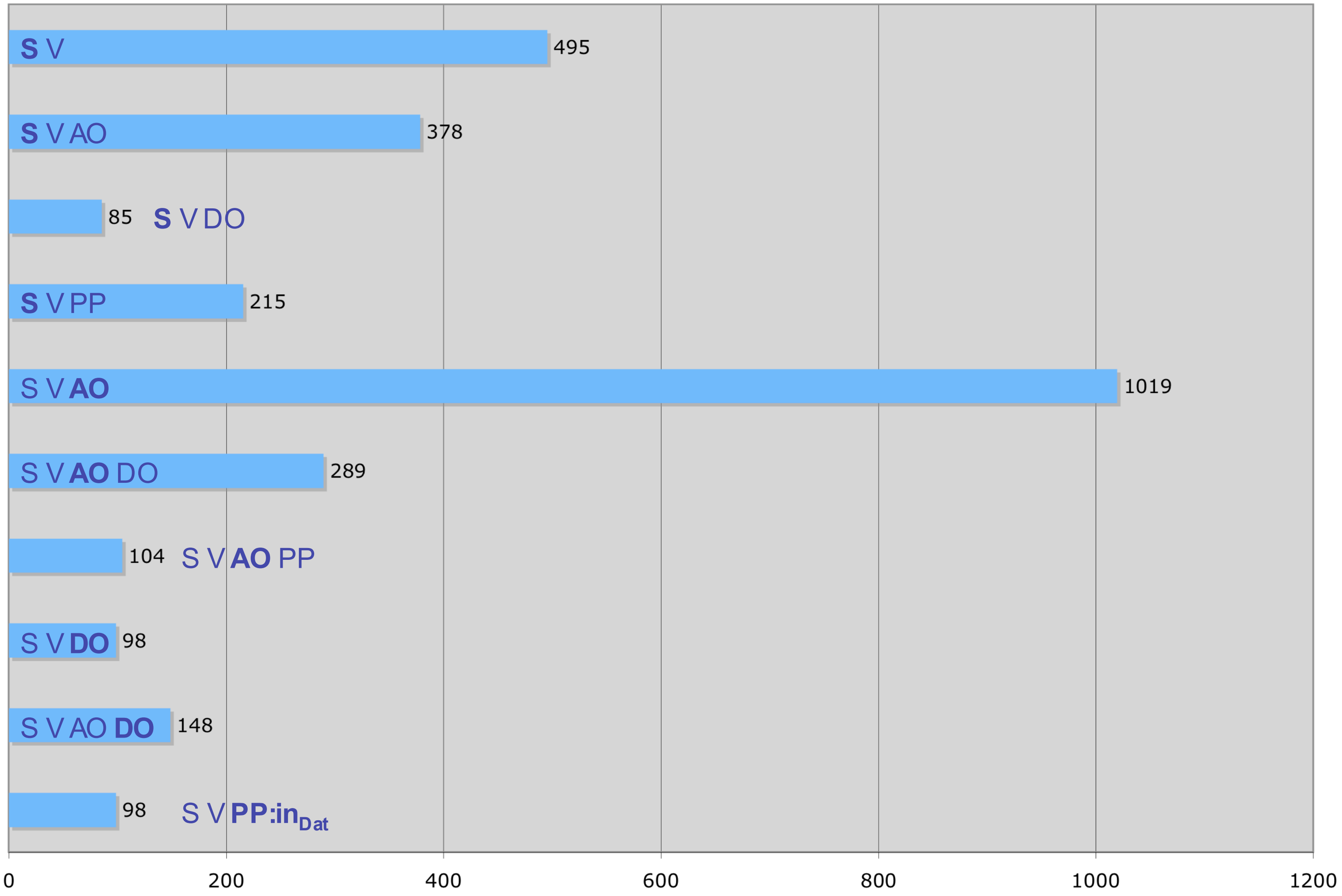
- Typical conceptual roles which speakers have in mind
- Look up syntactic relationships between verb and nouns
- Example:



Functions: Distributions

Function		TOKEN		TYPES	
S	**S** V	1,892	4	495	2
	S V AO	1,054	2	378	2
	S V DO	291	1	85	0
	S V PP	608	1	215	1
AO	S V **AO**	3,239	7	1,019	4
	S V **AO** DO	840	2	289	1
	S V **AO** PP	692	1	104	1
DO	S V **DO**	270	1	98	0
	S V AO **DO**	476	1	148	1
PP	S V **PP:in**$_{\mathbf{Dat}}$	487	1	98	0
Unknown noun		10,663	22	6,823	29
Unknown function		24,536	50	12,371	53

Syntax-Semantic Frame Inspection



No Linguistic Function in Grammar

- *backen* ‘bake’
  Ofen ‘oven’ (19), *Mehl* ‘flour’ (17), *Weihnachten* ‘Xmas’ (15)
- *fliegen* ‘fly’
  Urlaub ‘vacation’ (11), *Flügel* ‘wings’ (9)
- *anfangen* ‘begin’
  Start ‘start’ (14), *Motivation* ‘motivation’ (3)
- *enden* ‘end’
  Feierabend ‘leisure-time’ (4), *Rente* ‘retirement’ (2)

Window Co-Occurrence (1)

- Corpus data: 200 million word newspaper text
- Window (left+right): 5/20/50 words, excluding symbols
- Basis: association tokens

window	*pos (28%)*	*neg (72%)*	*all*
5	*99*	*55*	*68*
20	*100*	*69*	*78*
50	*100*	*75*	*82*

Window Co-Occurrence (2)

- Distinction with respect to window frequency

window	*all*						
	1	*2*	*3*	*5*	*10*	*20*	*50*
5	*68*	*59*	*53*	*45*	*36*	*25*	*15*
20	*78*	*72*	*68*	*61*	*52*	*42*	*28*
50	*82*	*78*	*74*	*69*	*61*	*52*	*38*

Association Analysis: Summary

- Morpho-syntactic distribution: nouns dominate
- Properties of nouns represent argument roles of verbs
- Scene information in addition to subcategorisation
- Co-occurrence counts to supplement argument counts
- Results depend on verb frequency and semantic class
- Usage of roles and window-based nouns for distributional verb descriptions

Association-based Verb Classes:
Creation and Validation

Association Overlap

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

Association-based Clustering

- Agglomerative (bottom-up) hierarchical clustering
- Similarity measure: *skew divergence*
- Merging criterion: *Ward's method* (sum-of-squares)
- Hierarchy cut: 100 classes
- Cluster analysis informs about
    - » classes
    - » verbs
    - » class features, i.e. associations

Association-based Example Classes

Class	Features
bedauern \`regret´, heulen \`cry´, jammern \`moan´, klagen \`complain, moan, sue´, verzweifeln \`become desperate´, weinen \`cry´	Trauer \`mourning´, weinen \`cry´, traurig \`sad´, Tränen \`tears´, jammern \`moan´, Angst \`fear´, Mitleid \`pity´, Schmerz \`pain´, etc.
abnehmen \`lose weight´, abspecken \`lose weight´, zunehmen \`gain weight´	Diät \`diet´, Gewicht \`weight´, dick \`fat´, abnehmen \`lose weight´, Waage \`scale´, Essen \`food´, essen \`eat´, Sport \`sports´, dünn \`thin´, Fett \`fat´, etc.

Validation: Procedure

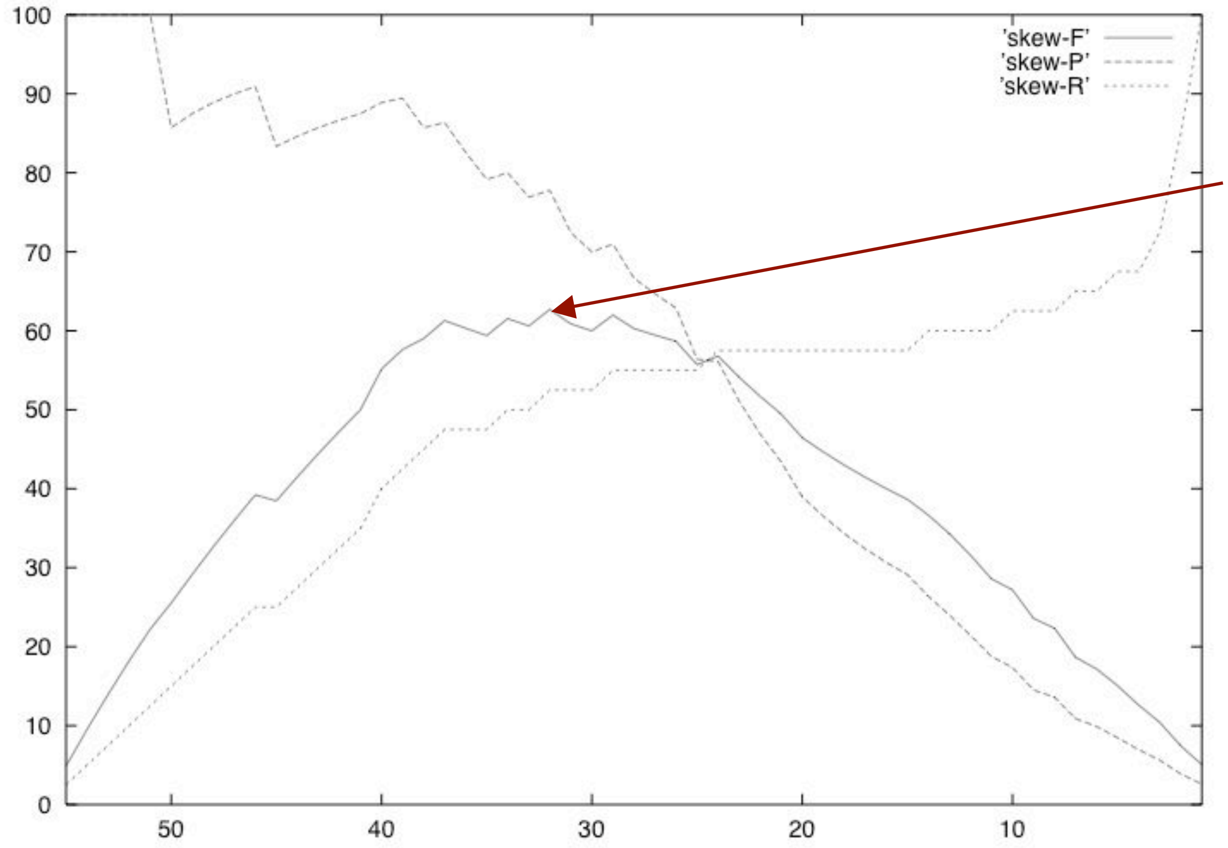
Claim: A clustering as based on verb associations and a standard clustering setting compares well with existing semantic classes.

1. Lexical resources:
   - » GermaNet (Kunze, 2000)
   - » Salsa / FrameNet (Erk *et al.*, 2003)
2. Extraction of sub-classifications of resources
3. Hierarchical clustering of verb subsets
4. Pair-wise evaluation (Hatzivassiloglou/McKeown, 1993)

Validation: Classes and Verbs

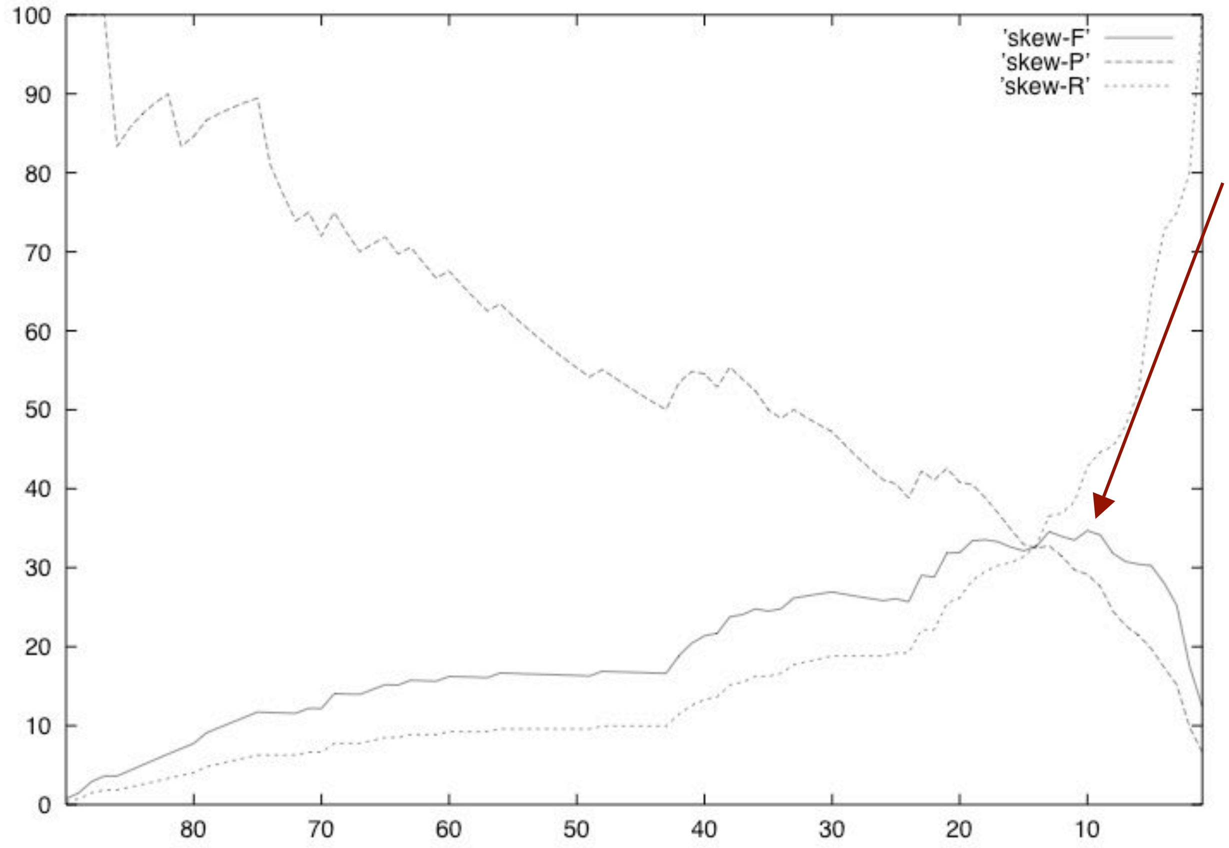
	classes	verb senses	verbs	amb
GermaNet	33	71	56	1.3
FrameNet	38	145	91	1.6

Validation Results: GermaNet



32 classes;
F = 62.69%
(UB: 82.35%)

Validation Results: FrameNet



10 classes;
F = 34.68%
(UB: 60.31%)

Association-based Classes: Summary

- Considerable overlap between association-based classes and the lexical resources GermaNet and FrameNet
- Differences in validation for GermaNet vs. FrameNet:
  - » types of semantic similarity
  - » degrees of ambiguity
  - » clustering parameters: number of verbs, etc.

→ Potential use of association-based classes as gold standard for clustering experiments

→ Associations provide guidance to feature selection

Exploring

Semantic Class Features

Exploring Semantic Class Features

- Grammar-based relations from statistical grammar:

  verb-noun pairs with nominal heads of NPs and PPs,
  verb-adverb pairs from adverbial modifiers

- Co-occurrence window:

  200-million word newspaper corpus,
  20-word window (left and right)

Exploring Semantic Class Features

features	grammar relations						
	n	na	na	NP	PP	NP&PP	ADV
cov. (%)	3.82	4.32	6.93	12.23	5.36	14.08	3.63

features	co-occurrence: window-20					
	all	cut	ADJ	ADV	N	V
cov. (%)	66.15	57.79	9.13	1.72	39.27	15.51

Corpus-based Clustering

- Experiment verbs:
  agglomerative hierarchical clustering,
  evaluation against assoc-classes: *accuracy*
- GermaNet:
  random selection of 100 synsets,
  random hard version with 233 verbs,
  clustering and evaluation as above
- FrameNet:
  pre-release version from May 2005,
  random hard version with 406 verbs in 77 classes,
  clustering and evaluation as above

Corpus-based Clustering: Questions

- Do the results of the clusterings with respect to the underlying feature types correspond to the overlap of associations and feature types?
- Do the corpus-based feature types which were identified on the basis of the associations outperform previous clustering results?
- Do the results generalise over the semantic class type?

Corpus-based Clustering: Results

	frames		grammar relations						
	f-pp	f-pref	<u>n</u>	<u>n</u>a	n<u>a</u>	NP	PP	NP&PP	ADV
Assoc	37.50	37.80	35.90	37.18	39.25	39.14	37.97	**41.28**	38.53
GN	46.98	49.14	**58.01**	53.37	51.90	53.10	54.21	51.77	51.82
FN	33.50	32.76	29.46	30.13	32.74	34.16	28.72	33.91	**35.24**

	co-occurrence: window-20					
	all	cut	ADJ	ADV	N	V
Assoc	39.33	**39.45**	37.31	36.89	39.33	38.84
GN	51.53	52.42	50.88	47.79	**52.86**	49.12
FN	missing	32.84	31.08	31.00	**34.24**	31.75

Summary of Results

- No correlation between overlap of associations / feature types and respective clustering results (Pearson's correlation, p>.1)
- Window-based features are not significantly worse than selected grammar-based functions;
  applying cut-offs has almost no impact
- Several cases of grammar-based and window-based features outperform frame-based features (i.e., previous work)
- Adverbs outperform frame-based features, even some nominals
- Most successful feature types vary for gold standards
- Significantly better results for GermaNet clusterings than for experiment-based and FrameNet clusterings

Outlook

- Which feature types are appropriate to model human associations?
- Which types of (semantic) verb classifications rely on which types of features?
- Which classification parameters (e.g., size of classes, ambiguity of verbs, empirical properties of verbs) influence the clustering result?
- How do the features and parameters differ with respect to a specific semantic verb class?