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

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Semantic

Verb Classifications

Examples: Semantic Verb Classifications

- Various instantiations of semantic similarity, e.g.
  - » syntax-semantics alternation behaviour (Levin, 1993):
    buy, catch, earn, find, steal, ...
    (obtaining:get verbs with benefactive alternation)
  - » synonymy (WordNet):
    buy, purchase (sub-class of get/acquire verbs)
  - » situation-based agreement (FrameNet):
    buy, purchase (commerce_buy) inherits from
    acquire, gain, get, obtain, procure, secure (getting);
    commercial transaction with *buyer, goods,* etc.

Creation of Semantic Verb Classes

- Resource-intensive vs. automatic methods
- Classification and clustering parameters:
  verbs, classes, algorithm, features, etc.
- Features model semantic similarity of interest
- Example of automatic method:
  - » Merlo & Stevenson (CL Journal, 2001):
    classify 60 English verbs which alternate between intransitive and transitive usage into three classes;
    features model syntactic frame alternation proportions and heuristics for semantic role assignment

Semantic Verb Classes: Features

- Features for larger-scale classifications with similarity at the syntax-semantics interface: *behaviour*
- Potentially salient features:
  - » syntactic frames
  - » prepositional phrases
  - » argument role fillers
  - » adverbial adjuncts, etc.
- Granularity of features

Human Associations and Semantic Verb Classifications

Associations: Guide to Feature Selection

- Basis: semantic associates, concepts spontaneously called to mind by a stimulus word
- Idea: human associations to identify salient features
- Assumptions:
  - » associations reflect linguistic and conceptual features and therefore model verb meaning aspects
  - » theory-independent
  - » variety of semantic verb relations
  - » guidance to feature selection

Goals

- Insights into the usefulness of standard feature types in verb clustering (e.g., direct object)
- Exploring additional feature types, e.g., assessment of low-level window co-occurrence vs. higher-order syntactic frame fillers
- Variation of corpus-based features by corpus frequency
- Are the same types of features salient for different types of semantic verb classes?

Procedure

1. Collection of human verb associations
2. Association-based verb classes (assoc-classes)
3. Validation against GermaNet and FrameNet
4. Analysis of empirical properties of verb associations and transfer of insights to the selection of features types
5. Hierarchical clustering with corpus-based features (corpus-classes)
6. Comparison of corpus-classes against assoc-classes
7. Evaluation of goals

Human Verb Associations: Collection and Analysis

Joint work with Alissa Melinger and Katrin Erk.

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: 79,480 tokens for 39,254 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 Analyses 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

- Common appearance in corpus data?
  → determine co-occurrence of target and reponse:
  German newspaper corpus, 200 million words

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

Morpho-Syntactic Distribution

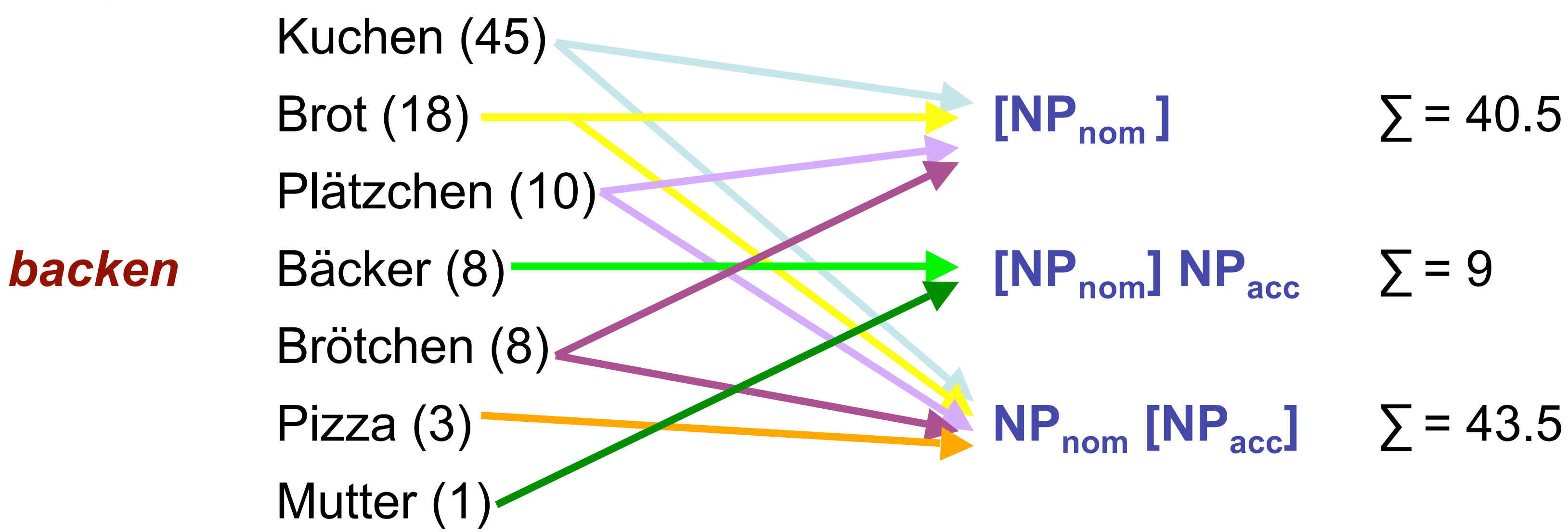
	V	N	ADJ	ADV	
Freq	19.863	48.905	8.510	1.268	TOKEN
Prob	25	62	11	2	
Freq	9.317	23.524	4.983	802	TYPES
Prob	24	61	13	2	

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: $\mathbf{NP_{nom}}$
    $\mathbf{NP_{nom}}$ $\mathbf{NP_{acc}}$ …
  - » filler examples for $\mathbf{NP_{nom}}$ $\mathbf{[NP_{acc}]}$: *Brot* ‘bread’
    Kuchen ‘cake’ …

Syntax-Semantic Functions: Analysis

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



Functions: Distributions

Function		TOKEN	
S	**S** V	1,892	4
	S V AO	1,054	2
	S V DO	291	1
	S V PP	608	1
AO	S V **AO**	3,239	7
	S V **AO** DO	840	2
	S V **AO** PP	692	1
DO	S V **DO**	270	1
	S V AO **DO**	476	1
PP	S V **PP:in$_{Dat}$**	487	1
Unknown noun		10,663	22
Unknown function		24,536	50

Window Co-Occurrence across POS

- Corpus data: 200 million word newspaper text
- Window (left+right): 5/20 words, excluding symbols
- Basis: association tokens
- Distinction with respect to window frequency

window	*1*	*2*	*3*	*5*	*10*	*20*	*50*
5	*66*	*56*	*50*	*42*	*33*	*23*	*14*
20	*77*	*70*	*66*	*59*	*50*	*40*	*27*

Window Co-Occurrence Verb-Noun

- Corpus data: 200 million word newspaper text
- Window (left+right): 5/20 words, excluding symbols
- Basis: association tokens
- Distinction with respect to window frequency

window	*1*	*2*	*3*	*5*	*10*	*20*	*50*
5	*66*	*56*	*50*	*43*	*34*	*24*	*14*
20	*76*	*69*	*66*	*59*	*50*	*40*	*27*

Window Co-Occurrence Verb-Adverb

- Corpus data: 200 million word newspaper text
- Window (left+right): 5/20 words, excluding symbols
- Basis: association tokens
- Distinction with respect to window frequency

window	*1*	*2*	*3*	*5*	*10*	*20*	*50*
5	*84*	*78*	*73*	*67*	*55*	*43*	*30*
20	*91*	*88*	*85*	*80*	*72*	*62*	*50*

Association Analysis: Summary

- Morpho-syntactic distribution: nouns dominate
- Nouns represent (prominent) argument roles of verbs
- Scene information in addition to subcategorisation; co-occurrence counts to supplement argument counts
- Strong co-occurrence of verbs and adverb responses
- 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'

overlap:
35 types

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

- Claim: A clustering based on verb associations and a standard setup compares well with existing semantic classes.
- Lexical semantic resources:
  » GermaNet (Kunze, 2000)
  » Salsa / FrameNet (Erk *et al.*, 2003)
- Extraction of sub-classifications of resources:
  » GermaNet 33 classes with 56 verbs (71 senses)
  » FrameNet 49 classes with 104 verbs (220 senses)
- Hierarchical clustering of verb subsets;
  pair-wise evaluation (Hatzivassiloglou/McKeown, 1993):
  $\langle v1, v2 \rangle \in$ cluster $\rightarrow$ $\langle v1, v2 \rangle \in$ gold standard ?
  » GermaNet 62.69% (upper bound: 82.35%)
  » FrameNet 34.68% (upper bound: 49.90%)

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:

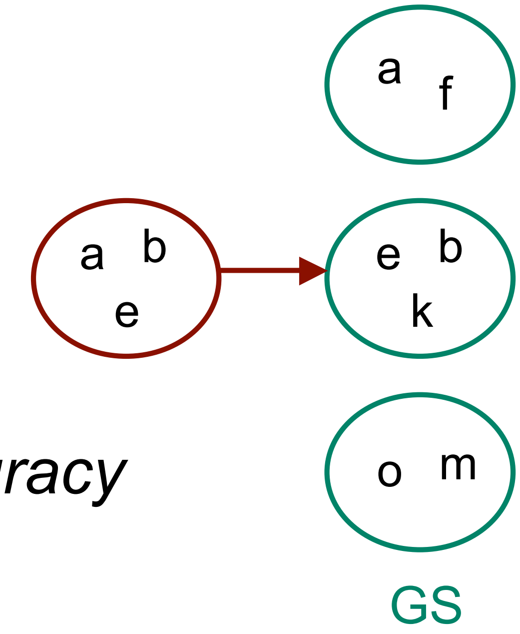
  200-million word newspaper corpus,
  20-word window (left and right)

Exploring Semantic Class Features

features	grammar relations						
	n	na	na	NP	PP	NP&PP	ADV
	12,635	14,458	13,416	20,792	14,513	22,366	10,080
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
	934,783	100,305	96,178	5,688	660,403	34,095
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: Results

	frames		grammar relations						
	f-pp	f-pref	n	na	na	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	32.01	32.84	31.08	31.00	**34.24**	31.75

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no correlation!

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Corpus-based Clustering: Results

no significant difference!

	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
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significant difference!

Properties of Gold Standard Verb Classes

	verbs	average verb freq	no. of verbs with freq < 50/20/10		
Assoc	330	2,465	41	16	8
GN	233	1,040	98	65	40
FN	406	1,876	54	16	11

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?