Semantic Verb Classification: Task, Experiments, Choice of Features

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Overview

1. Semantic verb classification
2. Clustering and classification
3. Clustering of German verbs
4. Human associations as source for feature selection

Semantic Verb Classification

Semantic Verb Classifications (SVCs)

- Groupings of verbs according to semantic properties
- Classes refer to general semantic level; idiosyncratic lexical semantic properties are underspecified
- Intuitive examples:
  - » motion with a vehicle: *drive, fly, row,* etc.
  - » break a solid surface with an instrument: *break, crush, fracture, smash,* etc.

SVCs: Variety

- Manual definitions for several languages (examples):
  English (Levin 1993; Fellbaum 1998; Fillmore et al. 2003),
  Spanish (Vázquez et al. 2000),
  German (Ballmer&Brennenstuhl 1986, Schumacher 1986)
- Semantic similarity:
  - » synonymy (WordNet/GermaNet; Kunze 2000):
    buy, purchase, take
  - » situations (FrameNet/Salsa; Erk et al. 2003):
    buy, purchase
  - » alternation behaviour (Levin 1993):
    buy, catch, earn, find, steal, ...

SVCs: Interest & Applications

- Theoretical linguistics: organise verbs with respect to common properties, such as meaning components (Koenig & Davis 2001), or shared argument structure (Levin 1993)
- Computational Linguistics:
  underspecification / generalisation over shared properties
  → data sparseness in processing natural language
  → applications: word sense disambiguation (Dorr & Jones 1996; Kohomban & Lee 2005), machine translation (Prescher et al. 2000; Koehn & Joang 2007), document classification (Klavans & Kan 1998), etc.

Clustering and Classification

Illustration (1)

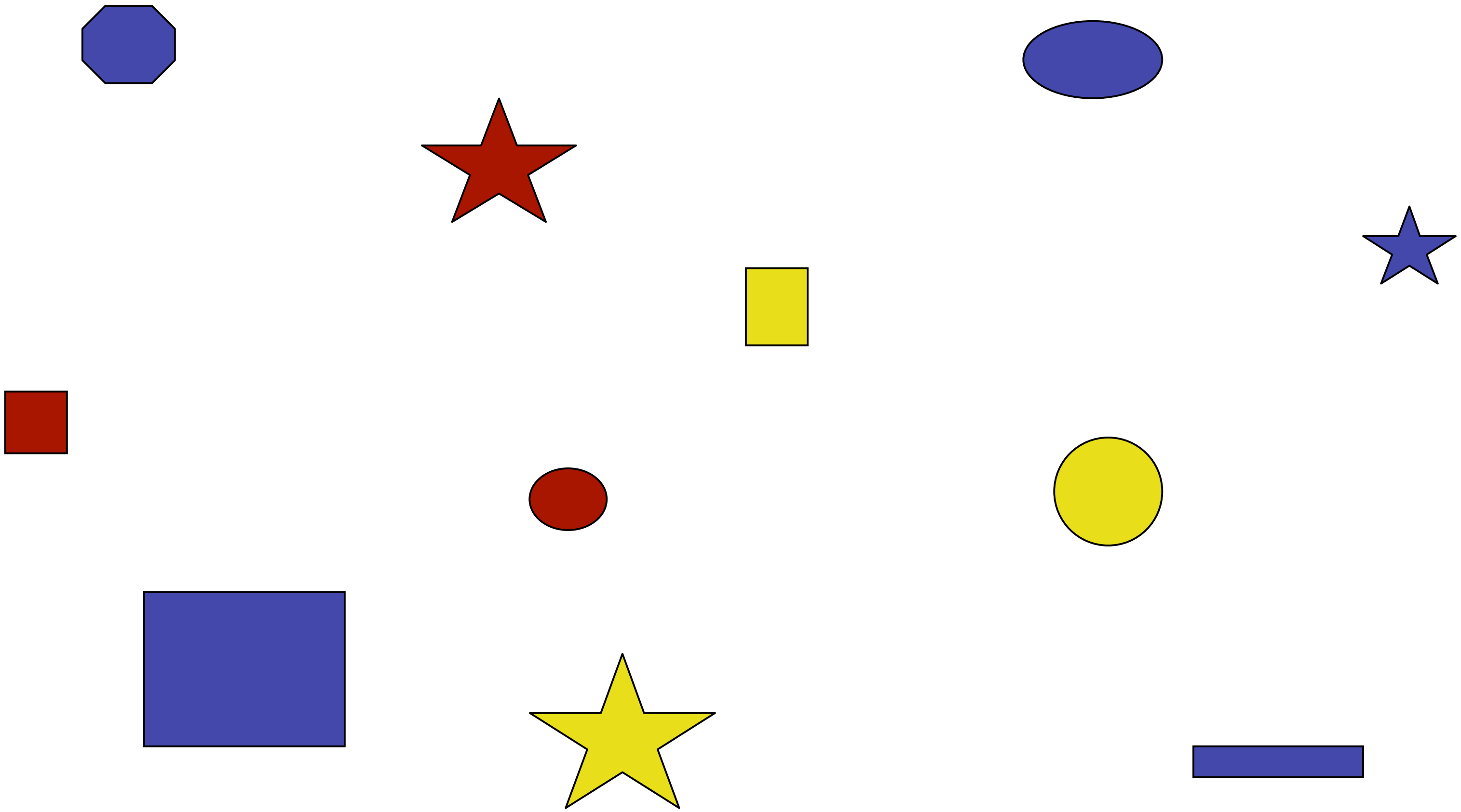


Illustration (2)

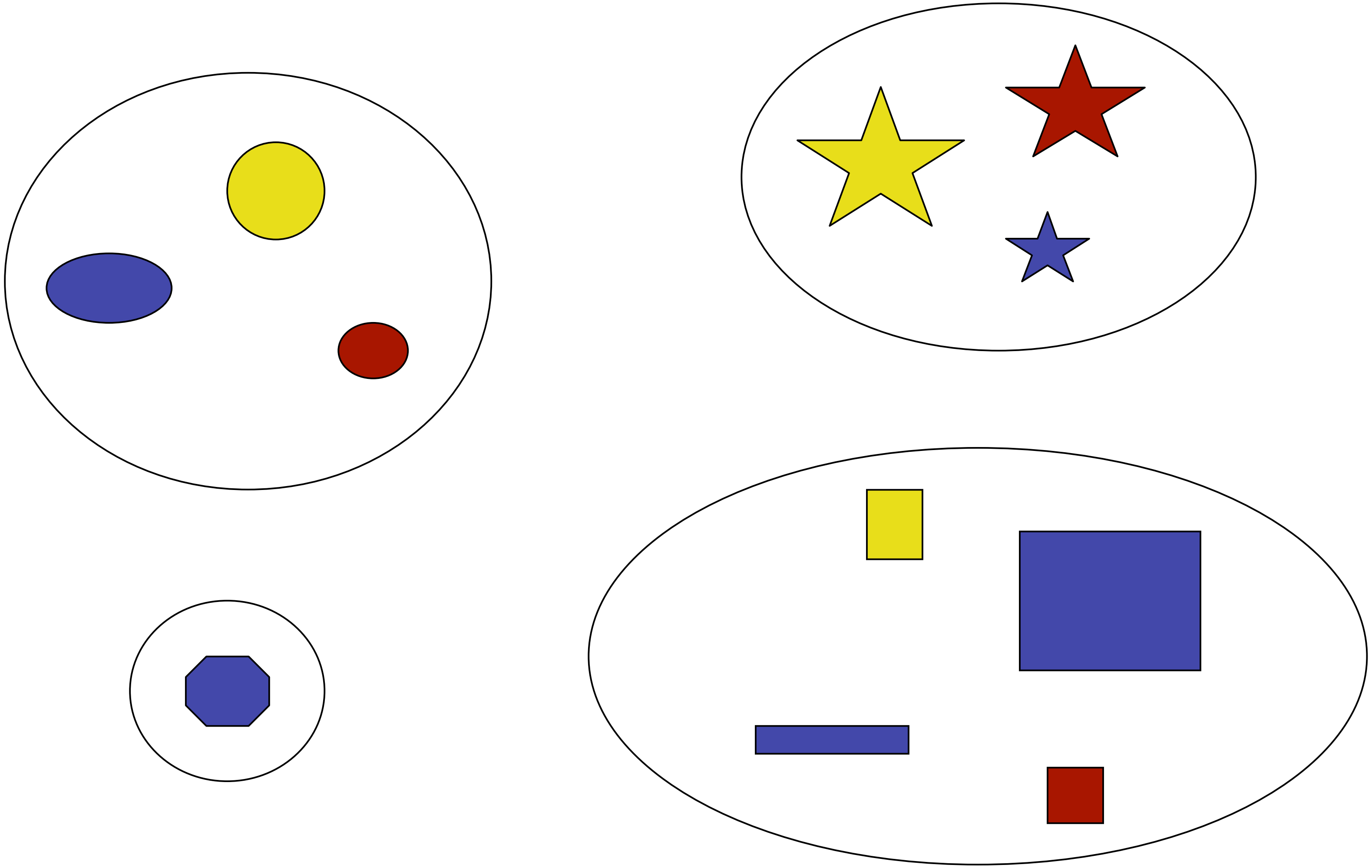
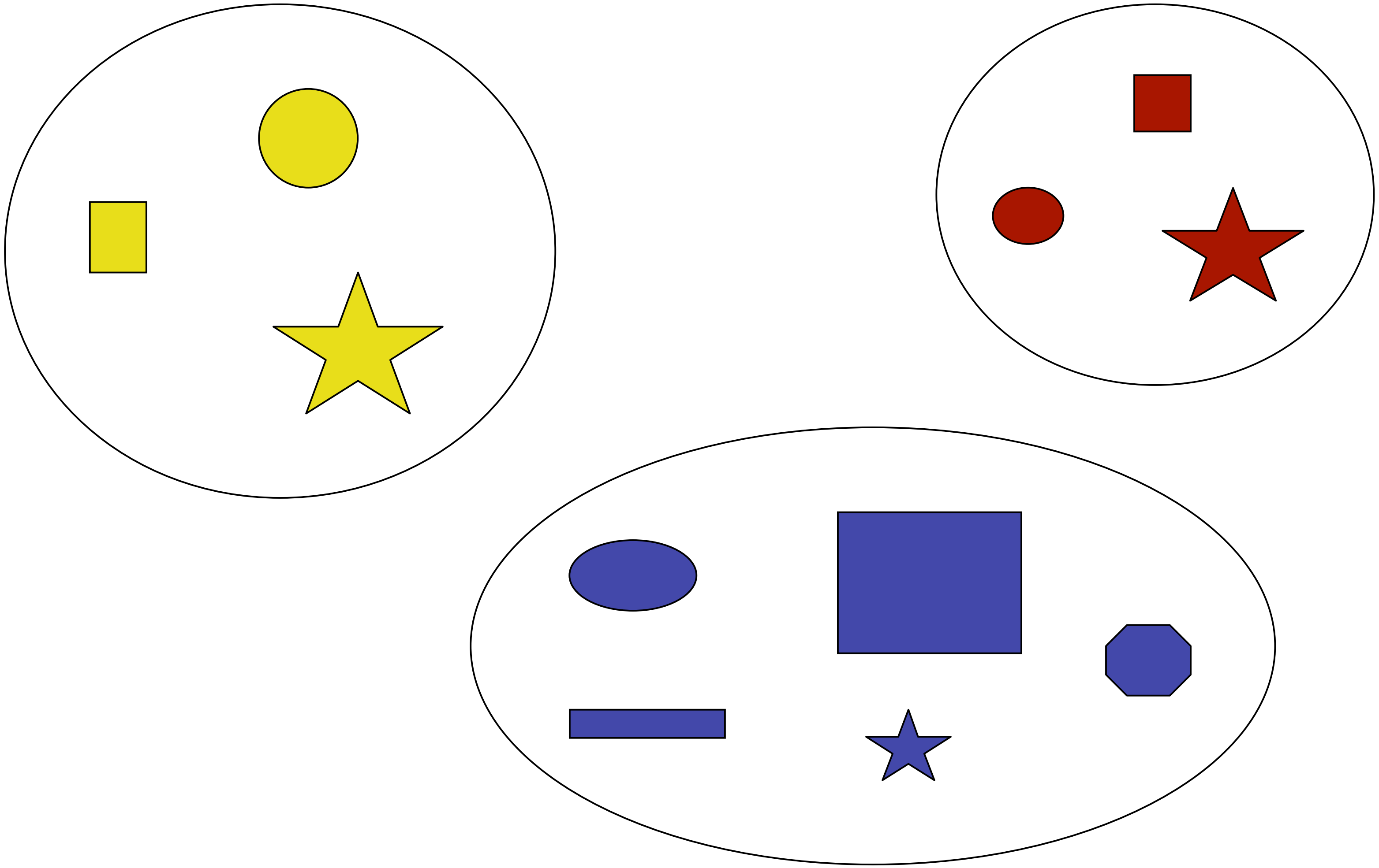
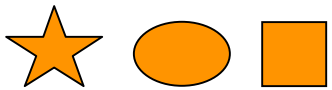


Illustration (3)



Clustering / Classification

- **Objects → Classes** (process and result)
- Objects in common classes: as similar as possible
- Objects in different classes: as dissimilar as possible
- Goals:
  - » Overview of objects
  - » Detection of data structures (clustering vs. classification)
  - » Comparability of objects
  - » Generalisation over objects {  }
  - » Assignment of individual objects

Classification Examples

- topographic maps
- size or hair colour of human beings
- judging a movie

- biology: systematics of plants/animals
- medicine: classification of symptoms → detect illnesses
- sociology: role behaviour in groups

- part-of-speech tagging
- pp-attachment
- semantic verb/noun/adjective/etc. classes

Classification in CL

- Multitude of (potential) classification problems
- Algorithms from Artificial Intelligence
- Difficulty: selection of classification algorithm and parameter setting
- Degree of difficulty depends on theoretical task definition (example: part-of-speech vs. semantic class)

Classification Parameters

- Purpose of classification
- Objects: relevant and representative data
- Properties of objects → feature selection
- Similarity measure for comparing objects
- Algorithm for class formation and assignment
- Interpretation, evaluation und application

Automatic Induction of SVCs

Overview

- Hypothesis:

  verb behaviour ↔ verb meaning aspects

- Distributional verb descriptions:

  syntactic frames, PPs, selectional preferences

- Clustering with k-Means algorithm

- Result: semantic verb classes

Data Objects, Features, and Purpose

- Data objects:

  German verbs

- Clustering purpose:

  Semantic verb classification

- Object features:

  Empirical verb properties at syntax-semantic interface

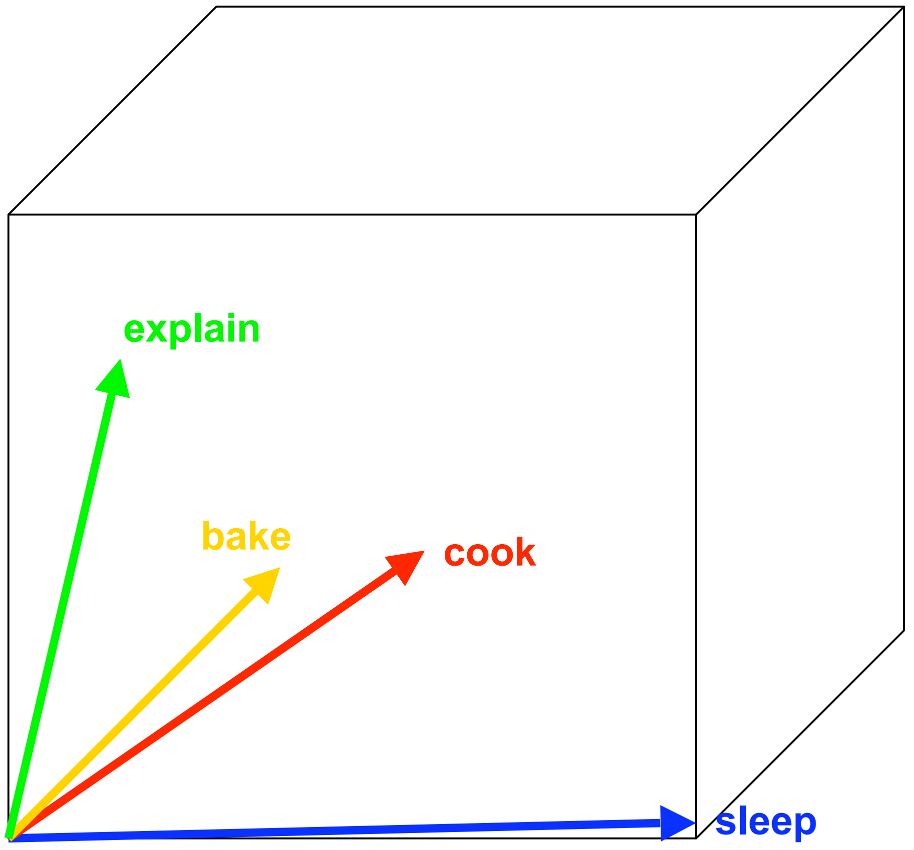
  → alternation behaviour

Example: Object Properties

Subcategorisation frames of verbs

	NP_{nom}	NP_{nom} NP_{acc}	NP_{nom} NP_{acc} NP_{dat}
schlafen *'sleep'*	98	1	1
kochen *'cook'*	35	50	15
backen *'bake'*	14	70	16
erklären *'explain'*	10	32	58

Example: Object Properties & Vectors



Verb Properties

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

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

Subcategorisation Frame Elements

n	noun phrase (case: nominative)
a	noun phrase (case: accusative)
d	noun phrase (case: dative)
r	reflexive pronoun
p	prepositional phrase
x	expletive *es*
i	non-finite clause
s-2	finite verb second clause
s-dass	finite *dass*-clause
s-ob	finite *ob*-clause
s-w	indirect *wh*-question
k	copula construction

Examples:

- na
- np
- npr
- nds-dass

Subcategorisation Frame Distribution

glauben

\`to think, to believe´

Frame Type	Freq
ns-dass	1,929
ns-2	1,888
np	687
n	608
na	555
ni	346
nd	234
nad	160
nds-2	70
nai	62

Prepositional Phrase Types

- Acc: an, auf, bis, durch, für, gegen, in, ohne, um, unter, vgl, über
- Dat: ab, an, auf, aus, bei, in, mit, nach, seit, unter, von, vor, zu, zwischen, über
- Gen: wegen, während
- Nom: vgl

Examples: Acc.an, Dat.nach, Gen.wegen, Nom.vgl

Subcategorisation Frame+PP Distribution

reden

`to talk´

Frame Type		Freq
np		1,121
np:Acc.über	`about´	480
np:Dat.von	`about´	463
np:Dat.mit	`with´	280
np:Dat.in	`in´	81
np:Nom.vgl	`as´	14
np:Dat.bei	`at´$_{place}$	13
np:Dat.über	`about´	13
np:Dat.an	`at´$_{tense}$	12
np:Acc.für	`for´	10
np:Dat.nach	`after´	8

Nominal Preferences

reden *über$_{Acc}$*

\`to talk about´

→ np:Acc.über

Noun		Freq
Geld	\`money´	19
Politik	\`politics´	14
Problem	\`problem´	13
Thema	\`topic´	10
Inhalt	\`content´	9
Koalition	\`coalition´	6
Ding	\`thing´	5
Freiheit	\`freedom´	5
Kunst	\`art´	5
Film	\`movie´	5

Nominal Preferences

verfolgen

\`to follow´

→ na

Noun		Freq
Ziel	\`goal´	86
Strategie	\`strategy´	27
Politik	\`policy´	25
Interesse	\`interest´	22
Konzept	\`concept´	17
Entwicklung	\`development´	16
Kurs	\`direction´	14
Spiel	\`game´	12
Plan	\`plan´	11
Spur	\`trace´	11

GermaNet Top-Level Preferences

verfolgen
\`to follow´

→ na

Synset		Freq
Situation	\`situation´	141
Kognitives Objekt	\`cognitive object´	110
Zustand	\`state´	81
Sache	\`thing´	61
Attribut	\`attribute´	53
Lebewesen	\`animate´	47
Ort	\`place´	46
Struktur	\`structure´	14
Kognitiver Prozess	\`cognitive process´	12
Zeit	\`time´	5
Besitz	\`possession´	3
Substanz	\`substance´	2
Nahrung	\`food´	2
Physis	\`physis´	1

Algorithm

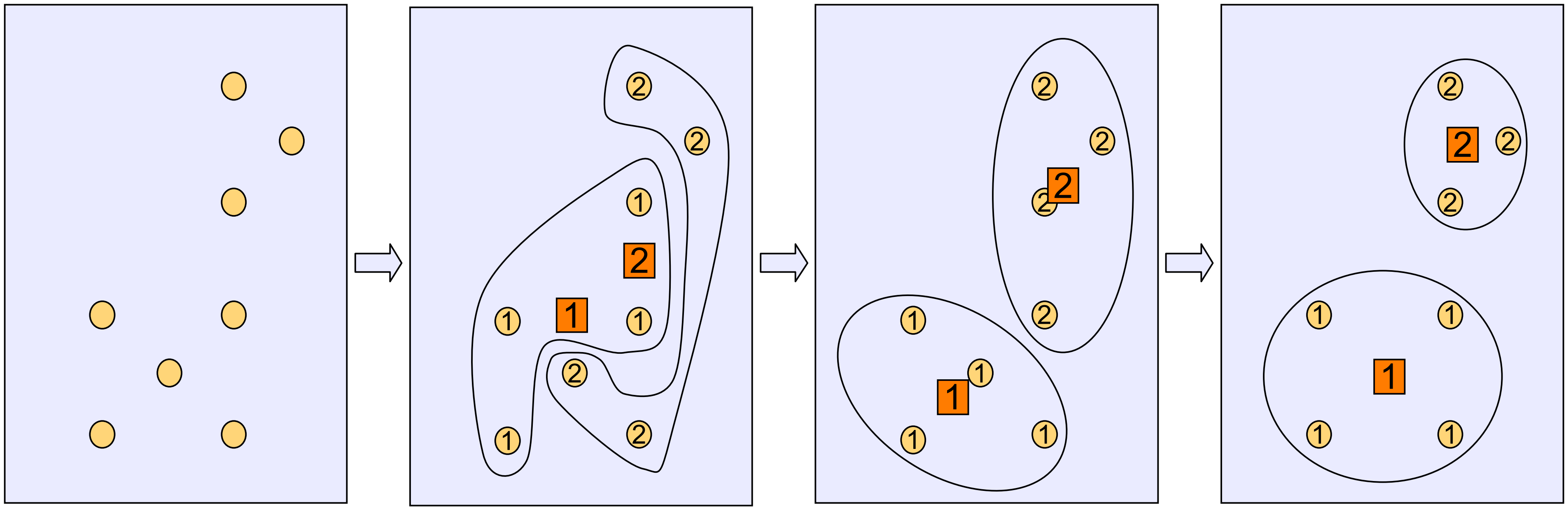
There is no unique solution!

- Supervision of learning (supervised vs. unsupervised)
- Position, size, shape, density of classes
- Number of classes (in unsupervised cases)
- Ambiguity (hard vs. soft)

Example: k-Means Algorithm

- k-Means algorithm (Forgy, 1965)
- Unsupervised hard clustering
- *n* objects → *k* clusters
- Iterative re-organisation of cluster membership:
  1. Initial cluster assignment
  2. Calculation of cluster centroids
  3. Determining closest cluster (centroid)
  4. Re-arrangement of cluster membership

k-Means Algorithm



Similarity and Distance

Similarity:

How similar are two objects *x* and *y*?

Distance:

How distanct / dissimilar are two objects *x* und *y*?

Similarity Measures

- Minkowski Metric / L_q Norm: $L_q(x,y) = \sqrt[q]{\sum_{i=1}^{n} (x_i - y_i)^q}$

- Cosine: $\cos(x,y) = \frac{\sum_{i=1}^{n} x_i * y_i}{\sqrt{\sum_{i=1}^{n} x_i^2} \sqrt{\sum_{i=1}^{n} y_i^2}}$

- Kullback-Leibler Divergence: $D(x \| y) = \sum_{i=1}^{n} x_i * \log \frac{x_i}{y_i}$

  (smoothed variant: Skew Divergence (Lee 2001))

Similarity Measure: L_q *metric*

Minkowski / L_q metric:

$$L_q(x,y) = \sqrt[q]{\sum_{i=1}^{n} (x_i - y_i)^q}$$

$q = 1$ → Manhattan distance

$$L_1(x,y) = \sum_{i=1}^{n} |x_i - y_i|$$

$q = 2$ → Euclidean distance

$$L_2(x,y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

$$L2(x,y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

Example: Similarity (1)

	NP_{nom}	NP_{nom} NP_{acc}	NP_{nom} NP_{acc} NP_{dat}
sleep	98	1	1
cook	35	50	15
bake	14	70	16
explain	10	32	58

schnarchen *'snore'* = <90,1,9> → ?

L_2(snore,sleep) = $(8^2 + 0^2 + 8^2)^{0.5}$ = **11.31**
L_2(snore,cook) = $(55^2 + 49^2 + 6^2)^{0.5}$ = **73.91**
L_2(snore,bake) = $(76^2 + 69^2 + 7^2)^{0.5}$ = **102.89**
L_2(snore,explain) = $(80^2 + 31^2 + 49^2)^{0.5}$ = **98.80**

Similarity Measure: *Cosine of Vector Angle*

Cosine of vector angle:

$$\cos(x,y) = \frac{\sum_{i=1}^{n} x_i * y_i}{\sqrt{\sum_{i=1}^{n} x_i^2}\sqrt{\sum_{i=1}^{n} y_i^2}}$$

Also: normalised correlation coefficient
(correlation divided by length to scale for magnitude)

Range: [-1 (angle: 180°) ; 1 (angle: 0°]

Example: Similarity (2)

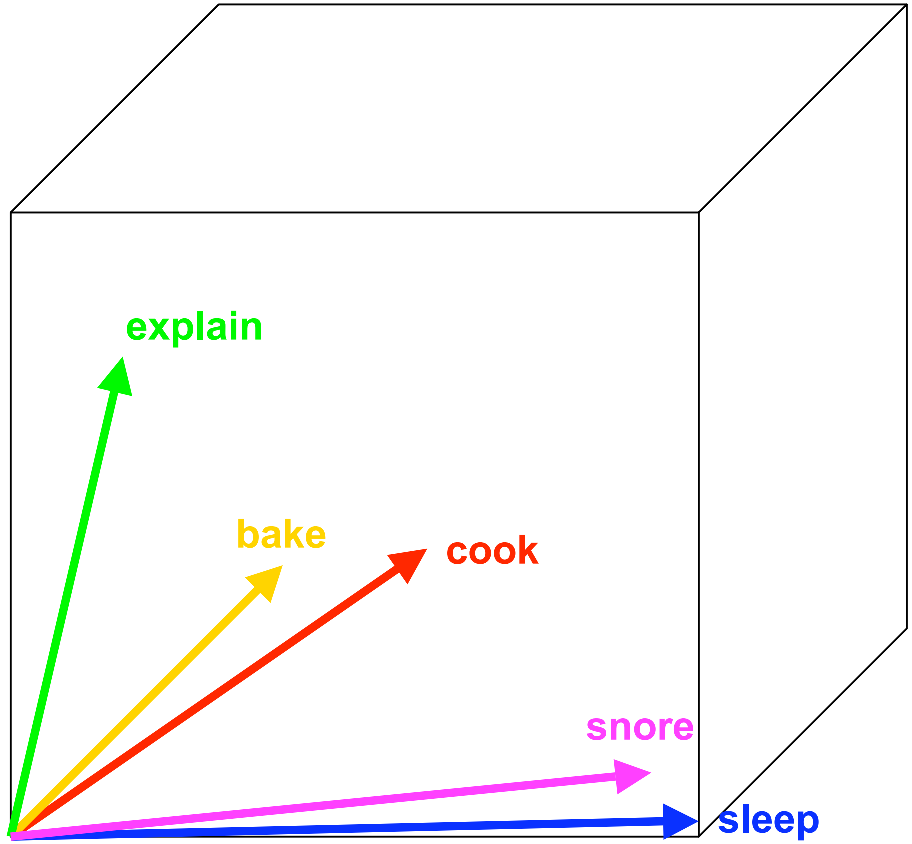
$$\cos(x,y) = \frac{\sum_{i=1}^{n} x_i * y_i}{\sqrt{\sum_{i=1}^{n} x_i^2}\sqrt{\sum_{i=1}^{n} y_i^2}}$$

	NP_{nom}	NP_{nom} NP_{acc}	NP_{nom} NP_{acc} NP_{dat}
sleep	98	1	1
cook	35	50	15
bake	14	70	16
explain	10	32	58

schnarchen *'snore'* = <90,1,9> → ?

cos(snore,sleep) = 8830 / ($8182^{0.5}$ * $9604^{0.5}$) = **0.99**
cos(snore,cook) = 3336 / ($8182^{0.5}$ * $3950^{0.5}$) = **0.59**
cos(snore,bake) = 1474 / ($8182^{0.5}$ * $5352^{0.5}$) = **0.22**
cos(snore,explain) = 2454 / ($8182^{0.5}$ * $4488^{0.5}$) = **0.41**

Example: Object Properties & Vectors



Overview, repeated

- Hypothesis:

  verb behaviour ↔ verb meaning aspects

- Distributional verb descriptions:

  syntactic frames, PPs, selectional preferences

- Clustering with k-Means algorithm

- Result: semantic verb classes

Clustering Example: Random Input

- **konsumieren kriegen vermuten**
- **anfangen**
- **ahnen bekanntgeben bestehen fahren fliegen liegen nieseln pochen**
- **aufhören bekommen erhalten essen insistieren regnen segeln vermitteln**
- **beginnen freuen interpretieren**
- **rudern saufen schneien ärgern**
- **eröffnen folgen glauben**
- **zustellen**
- **charakterisieren dämmern stehen**
- **blitzen verkünden wissen**
- **beschreiben dienen donnern schließen unterstützen**
- **beenden darstellen liegen sitzen**
- **ankündigen denken enden lesen schicken öffnen**
- **beharren bringen erlangen helfen trinken**

Clustering Example: Output

- ahnen vermuten wissen - *Propositional Attitude*
- denken glauben - *Propositional Attitude*
- anfangen aufhören beginnen beharren enden insistieren rudern - *Aspect*
- liegen sitzen stehen - *Position*
- dienen folgen helfen - *Support*
- nieseln regnen schneien - *Weather*
- dämmern
- blitzen donnern segeln - *Weather*
- bestehen fahren fliegen pochen - *Insistence, Manner of Motion*
- freuen ärgern - *Emotion*
- essen konsumieren saufen trinken verkünden - *Consumption*
- bringen eröffnen lesen liefern schicken schließen vermitteln öffnen - *Supply*
- ankündigen beenden bekanntgeben bekommen beschreiben charakterisieren darstellen erhalten erlangen interpretieren kriegen unterstützen - *Description, Obtain*
- zustellen

Clustering Results: *Examples*

C_1 **nieseln regnen schneien** - ***Weather***

dämmern - ***Weather*** C_2

C_3
kriechen rennen - ***Manner of Motion: Locomotion***
eilen - ***Manner of Motion: Rush***
gleiten - ***Manner of Motion: Flotation***
starren - ***Facial Expression***

C_4
klettern wandern - ***Manner of Motion: Locomotion***
fahren fliegen segeln - ***Manner of Motion: Vehicle***
fließen - ***Manner of Motion: Flotation***

C_5
beginnen enden - ***Aspect***
bestehen existieren - ***Existence***
liegen sitzen stehen - ***Position***
laufen - ***Manner of Motion: Locomotion***

C_6
festlegen - ***Constitution***
bilden - ***Production***
erhöhen senken steigern vergrößern verkleinern - ***Quantum Change***

C_7
töten - ***Elimination***
unterrichten - ***Teaching***

Summary & Feature Selection

- Considerable agreement between clustering results and manual classification → successful linguistic and technical parameters
- Choice of verb features is promising
- But: idiosyncratic properties destroy class coherence
- Integration of further semantic relations?
- Types of semantic classification?

befragen	\`to interrogate´
entlassen	\`to release´
ermorden	\`to assassinate´
erschießen	\`to shoot´
festnehmen	\`to arrest´
töten	\`to kill´
verhaften	\`to arrest´

Human Associations → Feature Selection

Associations → Feature Selection

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

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?

Collection of Associations to Verbs

- 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

schneien \`to snow´

kalt	\`cold´
rodeln	\`sledge´
Schneemann	\`snowman´
weiß	\`white´
dämmern	\`dawn´

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

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 as based on verb associations* and a *standard clustering setting* 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)
  » GermaNet 62.69% (upper bound: 82.35%),
  » FrameNet 34.68% (upper bound: 49.90%)

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
- 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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Corpus-based Clustering: Results

no correlation!

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Corpus-based Clustering: Results

no significant difference!

	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

Corpus-based Clustering: Results

	frames		grammar relations						
	f-pp	f-pref	n	na	na	NP	PP	NP&PP	ADV
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significant difference!

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

Overall Summary

- Distributional hypothesis is successful in automatic induction of semantic verb classes
- Choice of features is difficult:
  - » granularity (generalisation vs. idiosyncracy)
  - » features ↔ semantic content
- Application-directed semantic verb classification?