



Treebanks of German – Annotation Schemes and NLP Applications

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- Clause Structure of German
- Negra/TIGER and TüBa-D/Z treebanks for German
- Using Treebanks for NLP tasks:
 - Statistical Parsing of German: Is it really that difficult to parse German?
 - Computational Anaphora Resolution for German



(1) a. V2 clause:

Peter **wird** das Buch gelesen haben.

Peter will the book read have

'Peter will have read the book.'

b. V1 clause:

Wird Peter das Buch gelesen haben?

Will Peter the book have read

'Will Peter have read the book?'

c. VL clause:

dass Peter das Buch gelesen haben **wird**.

that Peter the book read have will

'... that Peter will have read the book.'



- (2) a. Der Mann hat gestern den Roman gelesen.
The man has yesterday the novel read
'The man read the novel yesterday.'
- b. Gestern hat der Mann den Roman gelesen
- c. Den Roman hat der Mann gestern gelesen

- (3) Der Mann hat gestern den Roman gelesen, den ihm
The man has yesterday the novel read which him
Peter empfahl.
Peter recommended
'Yesterday the man read the novel which Peter recommended to
him.'
- (4) Peter soll dem Mann empfohlen haben, den Roman zu
Peter is to the man recommended have the novel to
lesen.
read
'Peter is said to have recommended to the man to read the novel.'



- (5) a. $[VF [NP \text{ Peter}]] [LK \text{ wird}] [MF [NP \text{ das Buch}]]$
 $[RK [VC \text{ gelesen haben.}]]$
- b. $[LK \text{ Wird}] [MF [NP \text{ Peter}]] [NP \text{ das Buch}]$
 $[RK [VC \text{ gelesen haben?}]]$
- c. $[LK [CF \text{ dass}]] [MF [NP \text{ Peter}]] [NP \text{ das Buch}]$
 $[RK [VC \text{ gelesen haben wird.}]]$



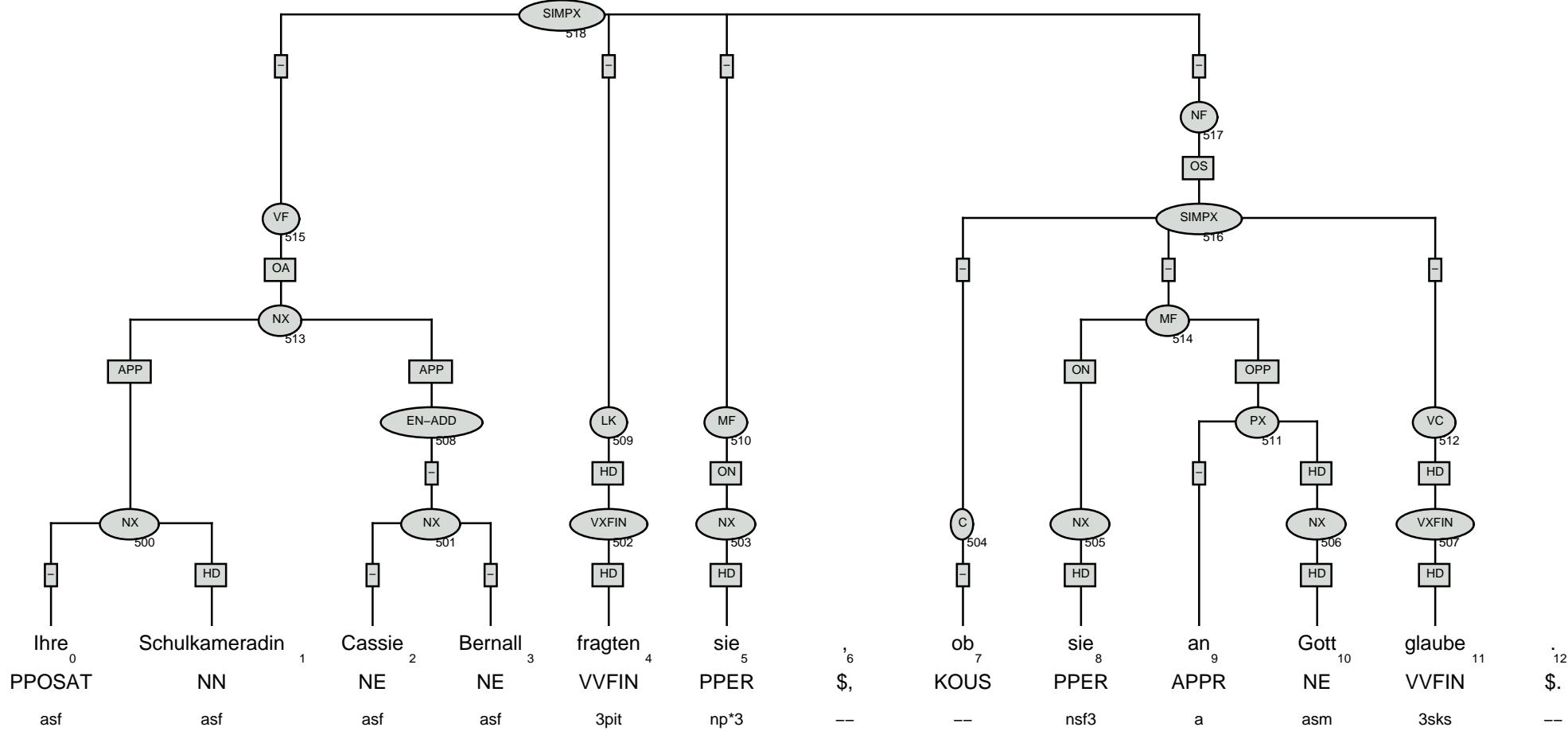
- Linguistically annotated German newspaper corpus
- Based on data taken from the daily issues of 'die tageszeitung' (taz)
- Manual annotation supported by annotate tool
- release 3.0: appr. 27 000 sentences (470 000 words).



- inflectional morphology
- syntactic constituency
- grammatical functions
- (complex) named entities
- anaphora and coreference relations



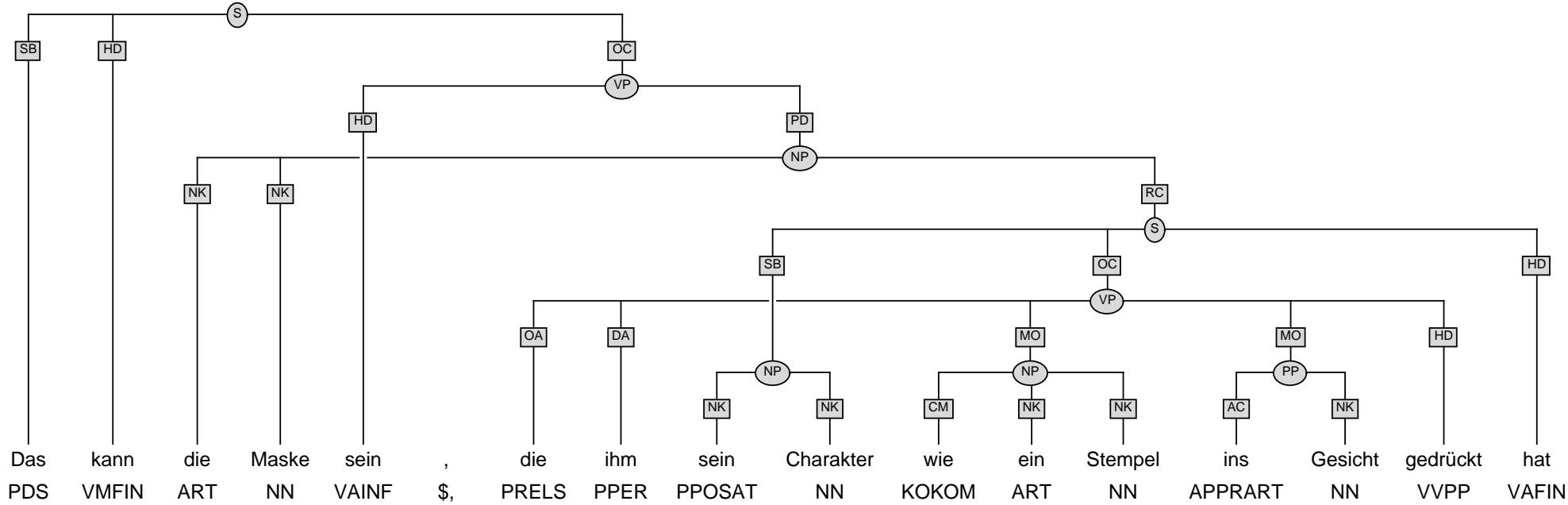
Example



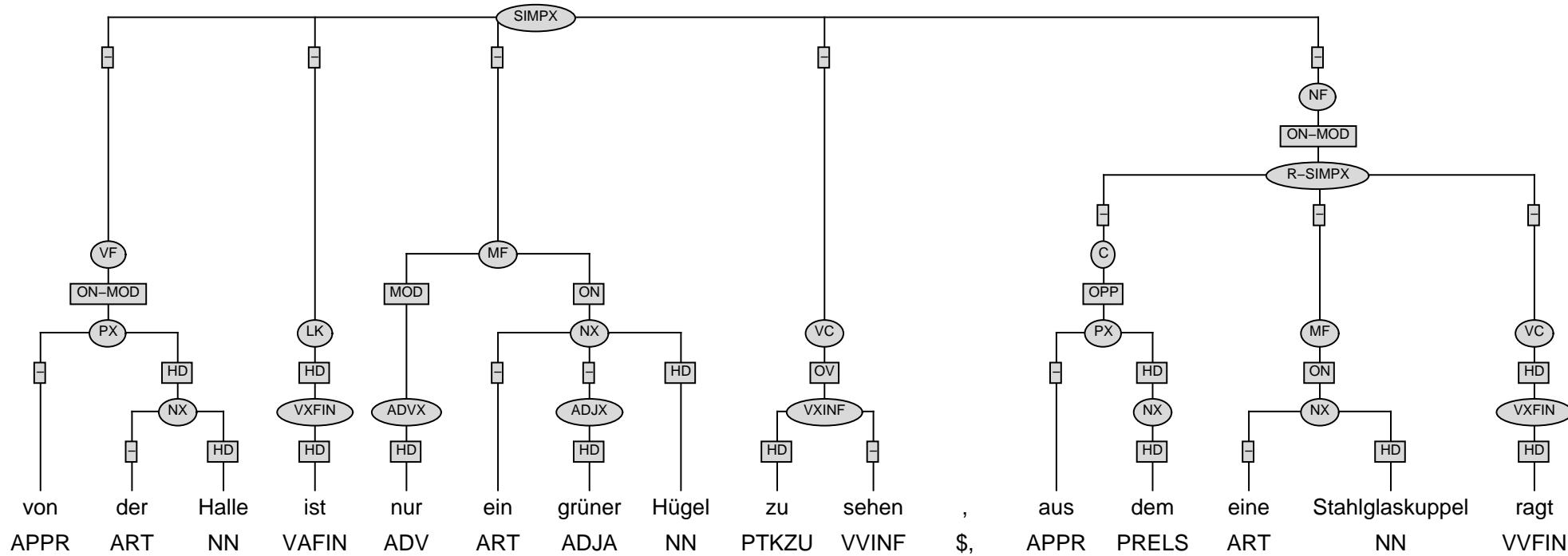
They asked their fellow student Cassie Bernall
whether she believes in God.



- both are based on newspaper texts: Frankfurter Rundschau, taz
- both use same POS tagset: STTS
- both annotate constituent structure and function-argument structure
- Negra/Tiger: 40 000 sentences; TüBa-D/Z: 27 000 sentences
- **different annotation decisions**



That could be the mask that his character pressed
like a stamp on his face.



From the hall, only a green hill can be seen, over which looms a steel and glass cupola.

- phrase structure
 - Negra: extremely flat
 - TüBa-D/Z: premodification flat, postmodification high
- clause structure
 - Negra: VP \Rightarrow crossing branches
no unary nodes
 - TüBa-D/Z: topological fields
- long-distance relationships
 - Negra: crossing branches
 - TüBa-D/Z: pure tree structure + special labels

	prec.	recall	F-score
English			
Collins (1999)	88.7	88.6	88.6
Charniak (2000)	89.8	89.6	89.7
Klein & Manning (2003)	86.9	85.7	86.3
German			
Dubey & Keller (2003)	73.9	74.2	74.0
Dubey & Keller lex.	67.9	66.1	67.0
Schiehlen (2005)			68.4



Research Questions

comparison of 2 treebanks, Negra und TüBa-D/Z:

1. different lexicalization: Stanford parser
2. test different parsers: comparison of treebanks with LoPar and Stanford Parser; with and without markovization
3. structure vs. content: comparison of treebanks concerning grammatical functions (Stanford Parser)

- preprocessing:
 - both: insert virtual root that covers single trees of a sentence
 - TüBa-D/Z: attach parentheses to surrounding tree
 - NEGRA: resolve crossing branches: attach non-head daughters higher
- 10 fold cross validation
- labeled / unlabeled precision and recall

		precision	recall	F-score
Negra				
Stanford PCFG	unlab.	71.24	72.68	71.95
	labeled	66.26	67.59	66.92
Stanford lex.	unlab.	71.31	73.12	72.20
	labeled	66.30	67.99	67.13
TüBa-D/Z				
Stanford PCFG	unlab.	93.07	89.41	91.20
	labeled	88.25	84.78	86.48
Stanford lex.	unlab.	91.60	91.21	91.36
	labeled	89.12	88.65	88.88

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Results: Lexicalization

- slightly improved results for lexicalization
 - different data split from Dubey and Keller?
 - Stanford Parser miracle cure?
- TüBa-D/Z ca. 20 points better than Negra
 - Stanford Parser miracle cure?
 - deeper structures easier to parse?



Experiment with Different Parsers

- LoPar and Stanford
- Stanford with and without markovization
- Markov parameters: vertical = 1; horizontal = 2
- no lexicalization, only constituent structure

	lab. prec.	lab. rec.	lab. F-score
Negra			
LoPar	65.86	67.41	66.62
Stanford	66.26	67.59	66.92
Stanford + markov	69.96	69.95	69.95

	lab. prec.	lab. rec.	lab. F-score
TüBa-D/Z			
LoPar	87.39	83.57	85.44
Stanford	88.25	84.78	86.48
Stanford + markov	89.86	88.51	89.18

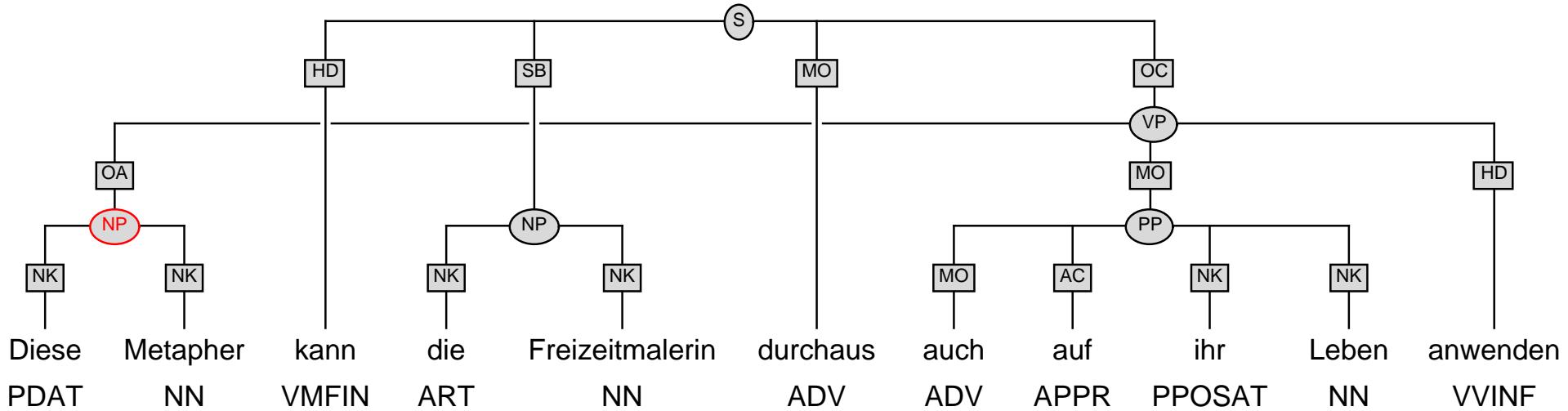
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- difference between treebanks constant
 - deeper structures better than many daughters
 - good structure by topological fields
 - conversion from crossing branches to CFG tree leads to inconsistencies
- markovization better than lexicalization
- Stanford Parser PCFG better than LoPar



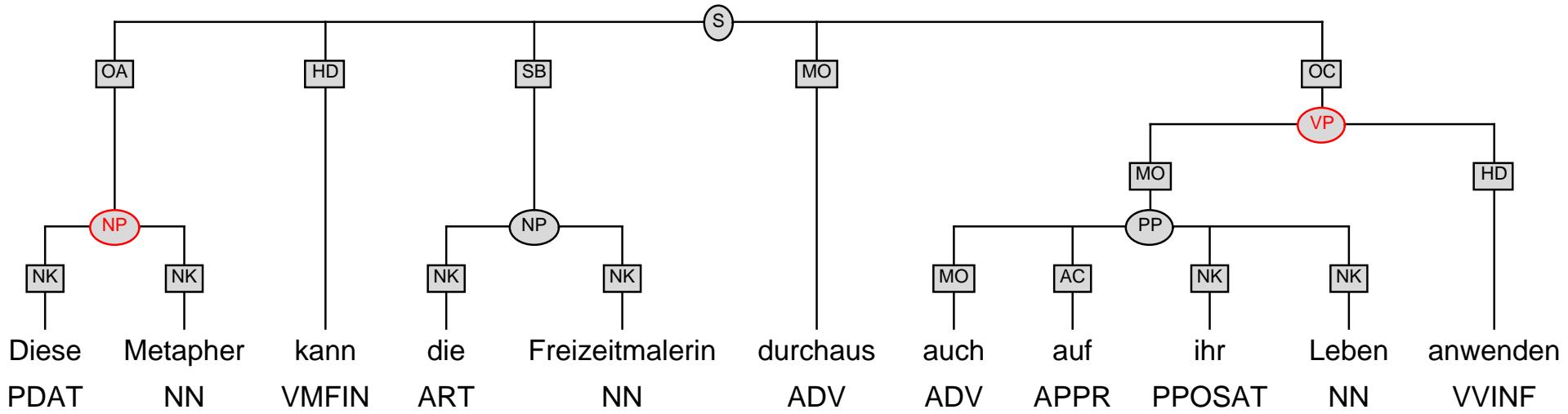
Crossing Branches



The amateur painter can by all means apply this metaphor also to her life.

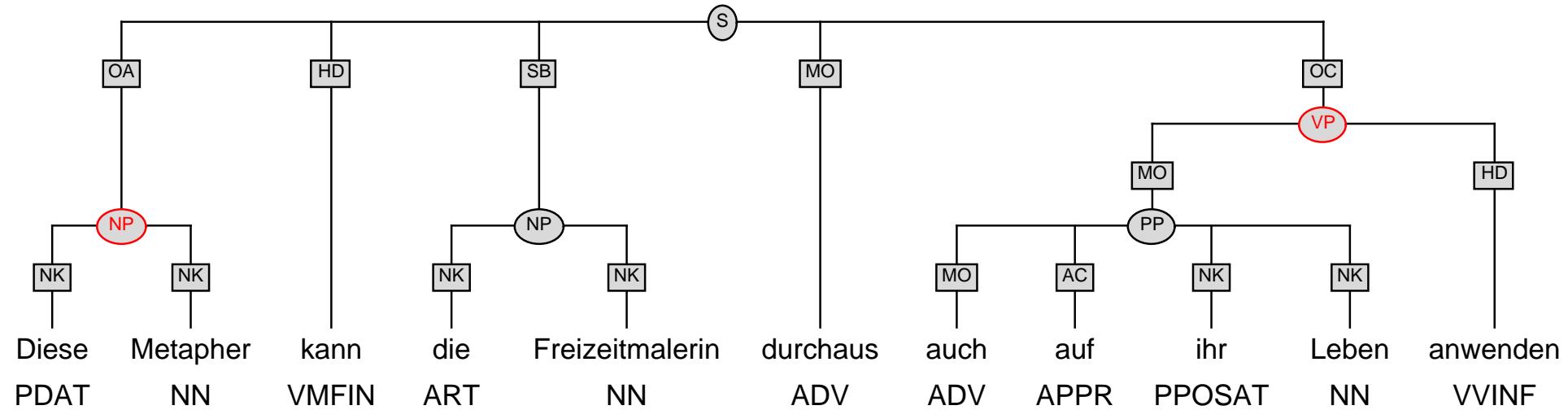


Resolved Structure





Resolved Structure



$S \rightarrow NP \text{ VMFIN } NP \text{ ADV } VP$



- Stanford Parser unlexicalized, with markovization
- constituent labels + grammatical functions: NP-SB, NX-ON, etc.
- evaluation of all grammatical functions
- evaluation of single, selected functions: arguments: subject, accusative object, dative object

		lab. prec.	lab. rec.	lab. F-score
Negra	no GF	69.96	69.95	69.95
	all GF	47.20	56.43	51.41
	subject	52.50	58.02	55.12
	acc. object	35.14	36.30	35.71
	dat. object	8.38	3.58	5.00
TüBa	no GF	89.86	88.51	89.18
	all GF	75.73	74.93	75.33
	subject	66.82	75.93	71.08
	acc. object	43.84	47.31	45.50
	dat. object	24.46	9.96	14.07

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- German:

Die Mutter gab **dem Mädchen eine Tomate**. **Es** mochte **sie** nicht.

- English:

The mother gave **the girl** a tomato. **It** did not like **her**.



High-quality MT is hard

- German:

Die Mutter gab **dem Mädchen [neuter]** eine Tomate
[fem]. **Es [neuter]** mochte **sie [fem]** nicht.

- German:

Die Mutter gab **dem Mädchen [neuter]** eine Tomate
[fem]. **Es [neuter]** mochte **sie [fem]** nicht.

- English:

The mother gave **the girl** a tomato. **She** did not like
it.



- definite NPs
- personal, possessive, relative, reflexive and reciprocal pronouns
- demonstrative and indefinite pronouns
- automatically extracted from the treebank

- relations based on the MATE inventory
- categories used in annotation:
 - coreferential
 - anaphoric
 - cataphoric
 - bound
 - part-of
 - instance
 - expletive

schreibt die anonyme AWO-Mitarbeiterin an die Staatsanwaltschaft . Obwohl Frau Wedemeier " vor allem Privatgespräche über das Handy " führe , würde alles von der AWO bezahlt . Ute Wedemeier hält es für " selbstverständlich ", daß sie als ehrenamtliche Vorsitzende ein dienstliches Handy hat . Insbesondere wegen ihrer Aktivitäten in Riga und Danzig müsse sie erreichbar sein und auch telefonieren können . Wieviel da monatlich fällig wird , weiß sie aber nicht - " die Rechnung geht direkt an die AWO " . Hintergrund der gegenseitigen Vorwürfe in der Arbeiterwohlfahrt sind offenbar scharfe Konkurrenzen zwischen Bremern und Bremerhavenern . Als es in dieser Woche um die Neubesetzung des ehrenamtlichen Geschäftsführer-Postens im Landesverband ging , da sind diese Differenzen wieder aufgebrochen . Lothar Koring , Bremerhavener AWO-Vorsitzender , wollte seinen Bremerhavener Geschäftsführer Volker Tegeler auch im Landesverband zum Geschäftsführer machen . Koring selbst hatte früher auch gegen Ute Wedemeier für den Landesvorsitz kandidiert . Gegen Tegeler sprach allerdings , daß noch ein staatsanwaltschaftliches Ermittlungsverfahren gegen ihn läuft . Und Koring war früher einmal in schiefes Licht geraten , weil er bei einer Prüfgesellschaft im Vorstand war , die die AWO , wo er Kreisvorsitzender ist , prüfte . Seine Position bei der Prüfgesellschaft mußte er damals niederlegen , den AWO-Posten nicht . K. W.

Current Markable File: C:\Programme\MMAX094\all\1_tcc_kn_markables.xml

Koring (markable_247)

Member	set_68
Pointer	
mp_form	<input checked="" type="radio"/> none <input type="radio"/> ne <input type="radio"/> defnp <input type="radio"/> indefnp <input type="radio"/> pper <input type="radio"/> ppos <input type="radio"/> pds <input type="radio"/> other
grammatical_role	<input checked="" type="radio"/> none <input type="radio"/> sbj <input type="radio"/> obj <input type="radio"/> other
agreement	<input checked="" type="radio"/> none <input type="radio"/> 3m <input type="radio"/> 3f <input type="radio"/> 3n <input type="radio"/> 3p <input type="radio"/> 1s <input type="radio"/> 2s <input type="radio"/> 1p <input type="radio"/> 2p <input type="radio"/> other
semantic_class	<input checked="" type="radio"/> none <input type="radio"/> abstract <input type="radio"/> human <input type="radio"/> phys_obj <input type="radio"/> other
Type	<input type="radio"/> none <input type="radio"/> anaphoric <input type="radio"/> cataphoric <input checked="" type="radio"/> coreferential <input type="radio"/> expletive <input type="radio"/> bound <input type="radio"/> part_of <input type="radio"/> instance

to front suppress check warn on extra attributes
AutoApply is OFF!



Hybrid architecture:

- Rule-based morphological pre-filter
 - Substantial reduction of candidate search space
 - Implemented using the Xerox XIP Tools
- Memory-based resolution module
 - Uses the Tilburg Memory-Based Learner (TiMBL)
 - Anaphora resolution is encoded as a binary encoding problem



Features

Feature	Comment
Pronoun type	personal possessive reflexive
Position	anaphoric cataphoric
Syntactic parallelism	parallel different n/a
Distance in sentences	loc 0/1/2/3
Distance in words	1...n
Features contributing to discourse history	ON OA OD OPP APP FOPP X-MOD PRED KONJ HD -- -

3 Experiments with different encodings of discourse history during training:

- Experiment 1: Number of times members of the coreference chain occur in each of the 12 syntactic roles
- Experiment 2: Distance of the pronoun to the closest member in the coreference chain realized in each of the 12 syntactic roles
- Experiment 0: Only syntactic features of the closest antecedent
→ No information about discourse history (baseline)

Backoff when no antecedent found: Choose closest subject as the antecedent

	Precision	Recall	F-Measure
Exp. 0	78.8%	63.7%	70.4%
Exp. 1	83.8%	66.8%	74.3%
Exp. 2	84.2%	66.4%	74.2%
Exp. 1.subj	79.1%	75.1%	77%
Exp. 2.subj	78.2%	74.1%	76.1%
<i>RAP</i>	76.6%	76.5%	76.6%

- Discourse history matters
- Competitive performance of machine-learning approaches given the usage of informative features



- Treebanks provide useful information for anaphora resolution
- Rule-based approach and memory-based system achieve roughly equal results on the same data
- Machine-learning approaches can successfully simulate functionality of hand-crafted systems, when given proper features



- Incorporating lexical semantics
(predicate-argument frequencies, GermaNet)
- Investigating alternative machine learning paradigms
- Using parsing input