Experiments in Parsing German

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Motivation

Develop a **broad-coverage** probabilistic parser for German which recognizes constituents and **grammatical functions**.

- Method
  - Extract a symbolic context-free grammar from the NEGRA treebank.
  - Train probabilistic grammar versions using a treebank training method (similar to Charniak:1996), and some grammar transformation techniques like parent encoding (similar to Johnson:1998).
  - Evaluate the performance of the grammar on a test corpus.

Background Information

- Symbolic Parsing:
  - parse a given sentence and assign all possible structures (syntactic trees).
- Probabilistic Parsing:
  - use a symbolic parsing component to get all possible syntactic structures of a sentence
  - disambiguate the different analyses by using rule probabilities, i.e. choose the most probable analysis.

Symbolic Component

Example:

"Der Verein sucht noch kreative Erwachsene mit viel Elan."

(*The association still searches for creative adults full of verve.*)

Possible structures are:

- [Der Verein [sucht noch [kreative Erwachsene [mit Elan]]]],

  $[_{NP}$ kreative Erwachsene $[_{PP}$ mit Elan $]]$
- [Der Verein [sucht noch [kreative Erwachsene][mit Elan]]].

  $[_{VP}$ sucht noch $[_{NP}$ ...] $[_{PP}$ mit Elan $]]$

Problem: ambiguity

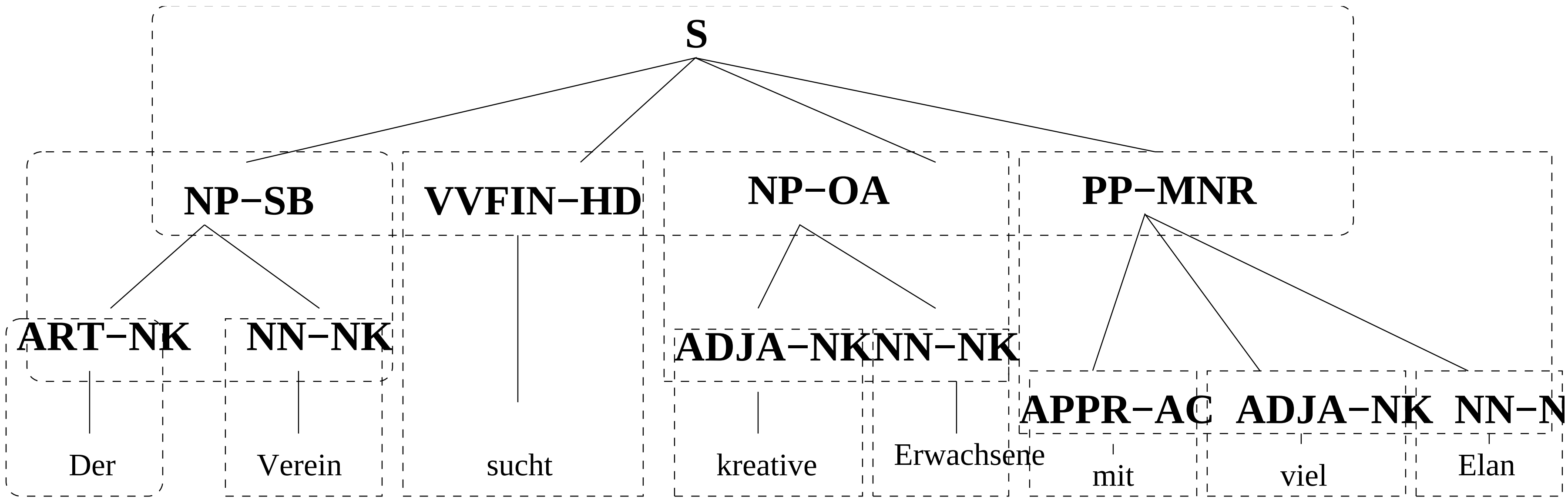
Probabilistic Component

- Resource: Negra treebank, a newspaper corpus (20,000), manually annotated with syntactic structure.
- Read the rules from the trees, collect the rules and their frequencies.
- Compute rule probabilities of each rule p(r).

$$p(r) = \frac{|r|}{\sum_{r' \in \{r' | \lambda(r') = \lambda(r)\}} |r'|}$$

- Several grammar variants comprising constituents with/without grammatical functions, and (partial) parent encoding have been investigated.

Collecting the rules



S	⟶	NP-SB VVFIN-HD NP-OA PP-MNR
NP-SB	⟶	ART-NK NN-NK
NP-OA	⟶	ADJA-NK NN-NK
PP-MNR	⟶	APPR-AC ADJA-NK NN-NK
ART-NK	⟶	Der
NN-NK	⟶	Verein

VVFIN-HD	⟶	sucht
ADJA-NK	⟶	kreative
NN-NK	⟶	Erwachsene
APPR-AC	⟶	mit
ADJA-NK	⟶	viel
NN-NK	⟶	Elan

Computing the probabilities

(1) 0.0031	S	$\longrightarrow$	NP-SB VVFIN-HD NP-OA PP-MNR
(2) 0.0109	S	$\longrightarrow$	NP-SB VVFIN-HD NP-OA
(3) 0.0059	NP-OA	$\longrightarrow$	ADJA-NK NN-NK PP-MNR
(4) 0.2396	NP-SB	$\longrightarrow$	ART-NK NN-NK
(5) 0.0518	NP-OA	$\longrightarrow$	ADJA-NK NN-NK
(6) 0.0355	PP-MNR	$\longrightarrow$	APPR-NK ADJA-NK NN-NK

● Part-of-speech tags are assigned to each sentence by a probabilistic tagger, i.e. no rules

$$\text{POS} \rightarrow \text{word}$$

are in the grammar.

Parsing a sentence

- Example: *The association searches for creative adults full of verve.*

Der	Verein	sucht	kreative	Erwachsene	mit	viel	Elan.
ART	NN	VVFIN	ADJA	NN	APPR	ADJA	NN

- Compute probability of the two readings:

(1)	(S $\rightarrow$ NP-SB VVFIN-HD NP-OA PP-MNR)	0.0031 $*$
	(NP-SB $\rightarrow$ ART-NK NN-NK)	0.2396 $*$
	(NP-OA $\rightarrow$ ADJA-NK NN-NK)	0.0518 $*$
	(PP-MNR $\rightarrow$ APPR-NK ADJA-NK NN-NK)	0.0355
		= $1,36e{-}06$
(2)	(S $\rightarrow$ NP-SB VVFIN-HD NP-OA)	0.0109 $*$
	(NP-SB $\rightarrow$ ART-NK NN-NK)	0.2396 $*$
	(NP-OA $\rightarrow$ ADJA-NK NN-NK PP-MNR)	0.0059 $*$
	(PP-MNR $\rightarrow$ APPR-NK ADJA-NK NN-NK)	0.0355
		= $5,47e{-}07$

- Choose the most probable one.

Experiments

- Split the corpus into 18,000 sentences for training, 2000 sentences for testing.
- Training corpus is divided into pieces of 1000 to investigate the influence of the size of the training data.
- Training
  - with different grammar variants
- Evaluate on the test corpus using standard evaluation measures (PARSEVAL).

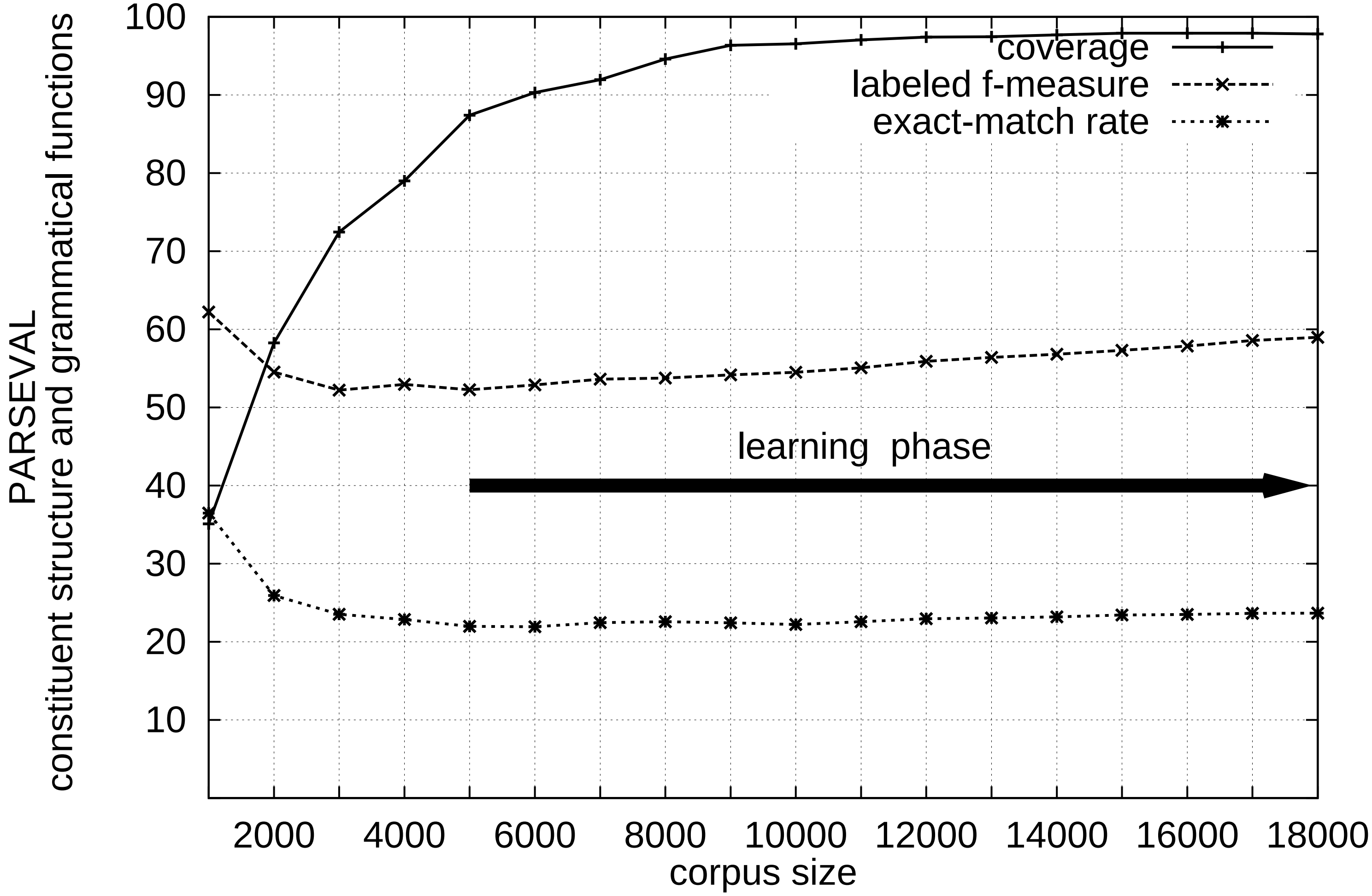
Experiment 1:

Grammar contains constituent structure & grammatical functions. The PCFG can predict both after training.

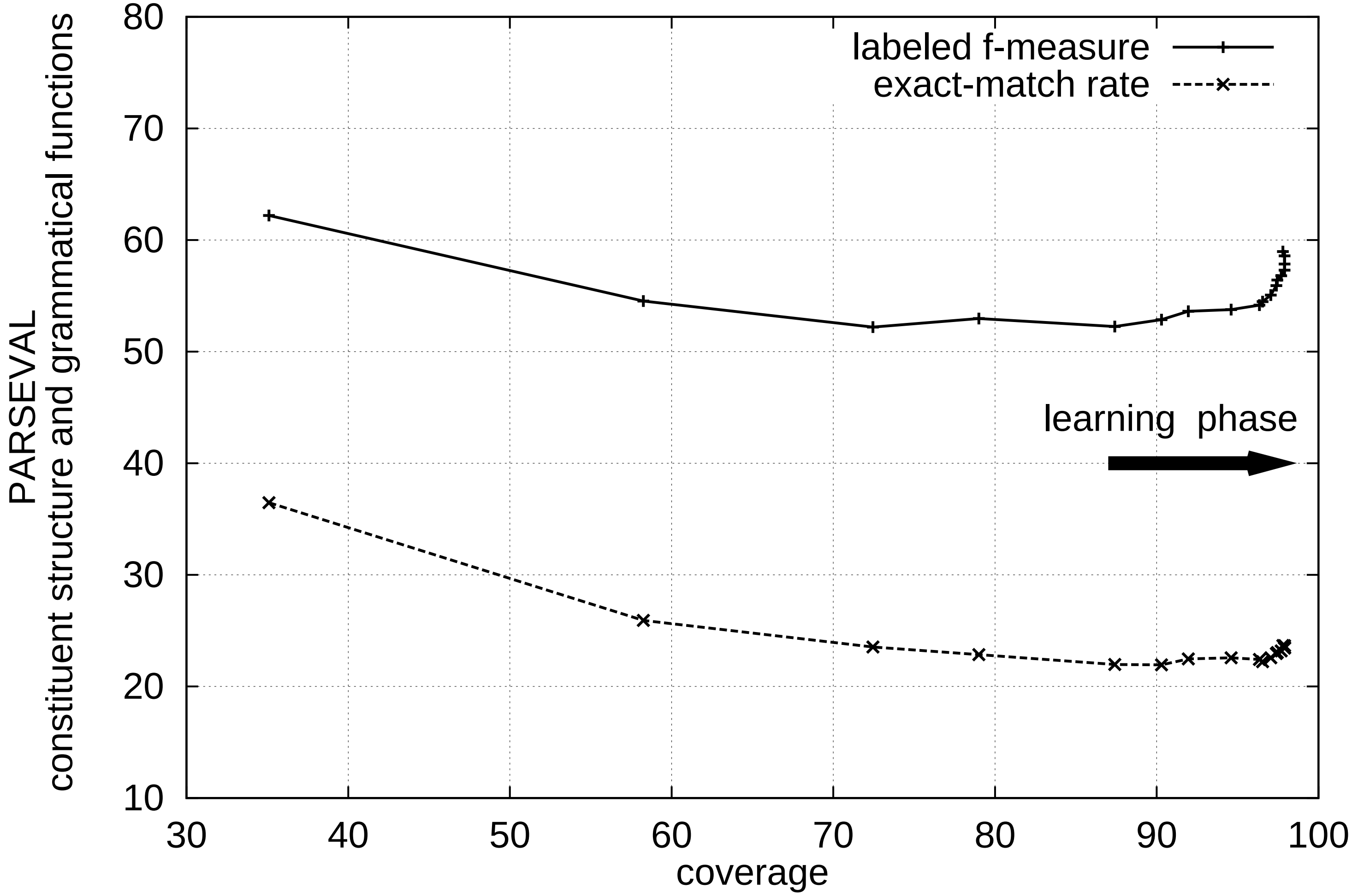
e.g. a noun phrase consisting of an article and a noun occur more often as subjects than as direct or indirect objects:

$$\begin{array}{lcll} \text{NP-SB} & \longrightarrow & \text{ART-NK} & \text{NN-NK (3,498)} \\ \text{NP-OA} & \longrightarrow & \text{ART-NK} & \text{NN-NK (1,385)} \\ \text{NP-DA} & \longrightarrow & \text{ART-NK} & \text{NN-NK (338)} \end{array}$$

Results of Experiment 1



Results of Experiment 1 - Alternative



Experiment 2: Influence of Grammatical Functions

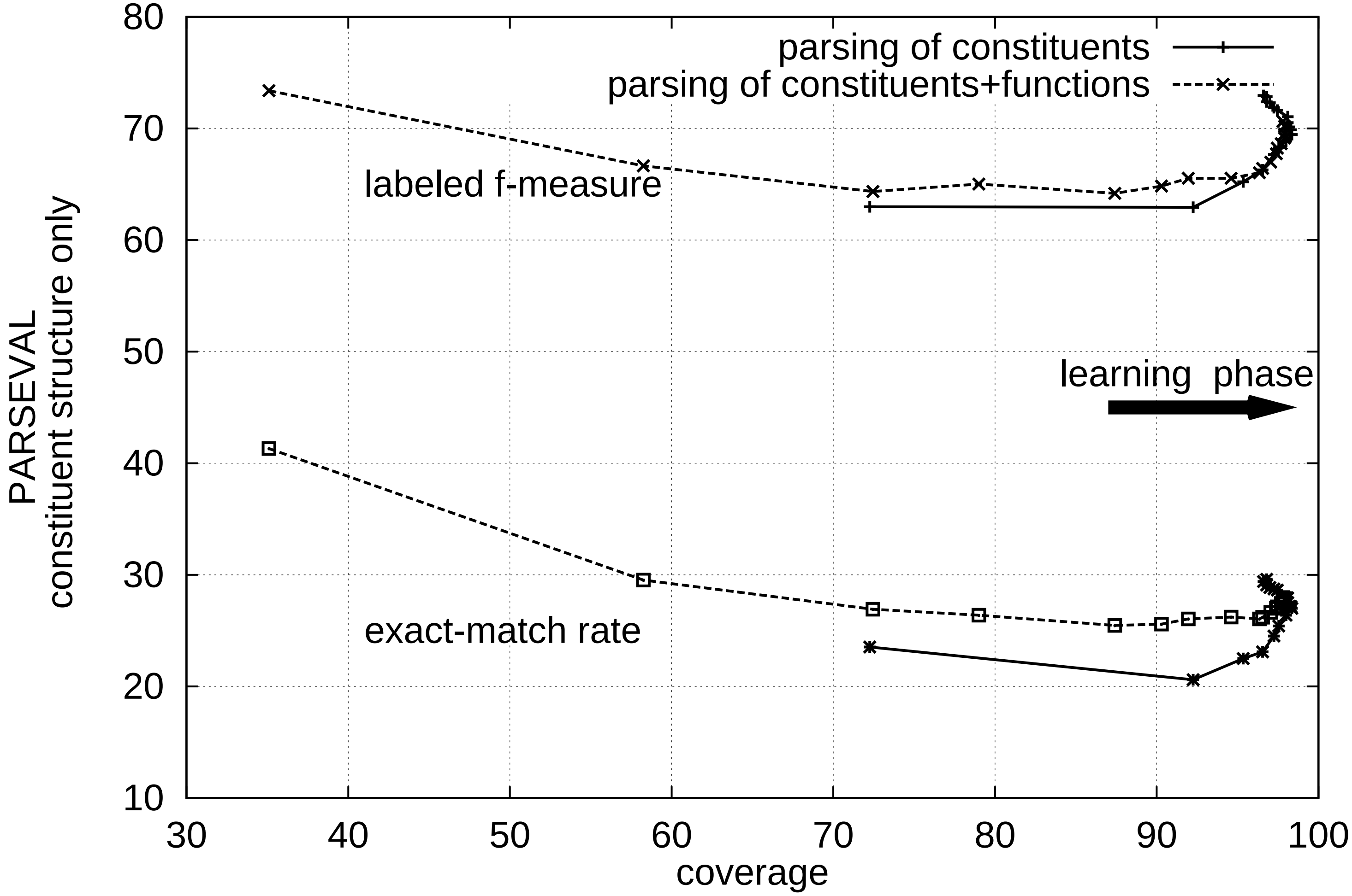
- Compare two grammar versions
  - using constituents only

    S $\longrightarrow$ NP VVFIN NP

  - using grammatical functions (previous experiment)

    S $\longrightarrow$ NP-SB VVFIN-HD NP-OA

Results of Experiment 2

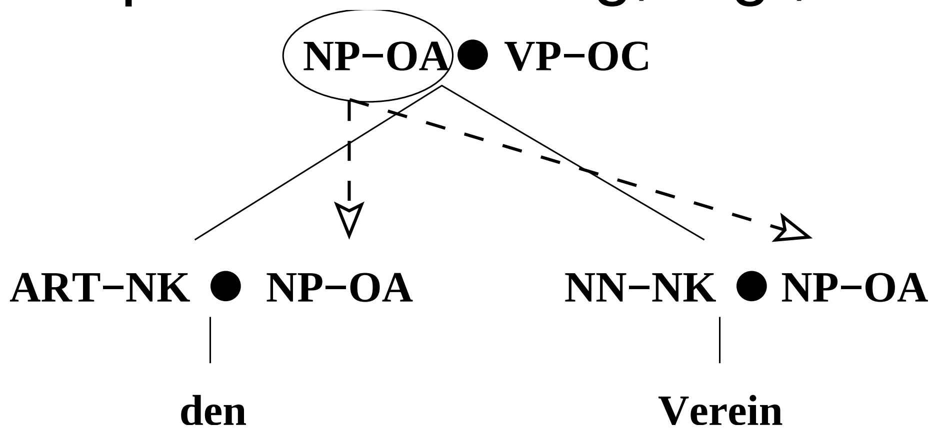


Experiment 3: Parent Encoding

Soften the independence assumption.

Lead to improvement of about 7% for English.

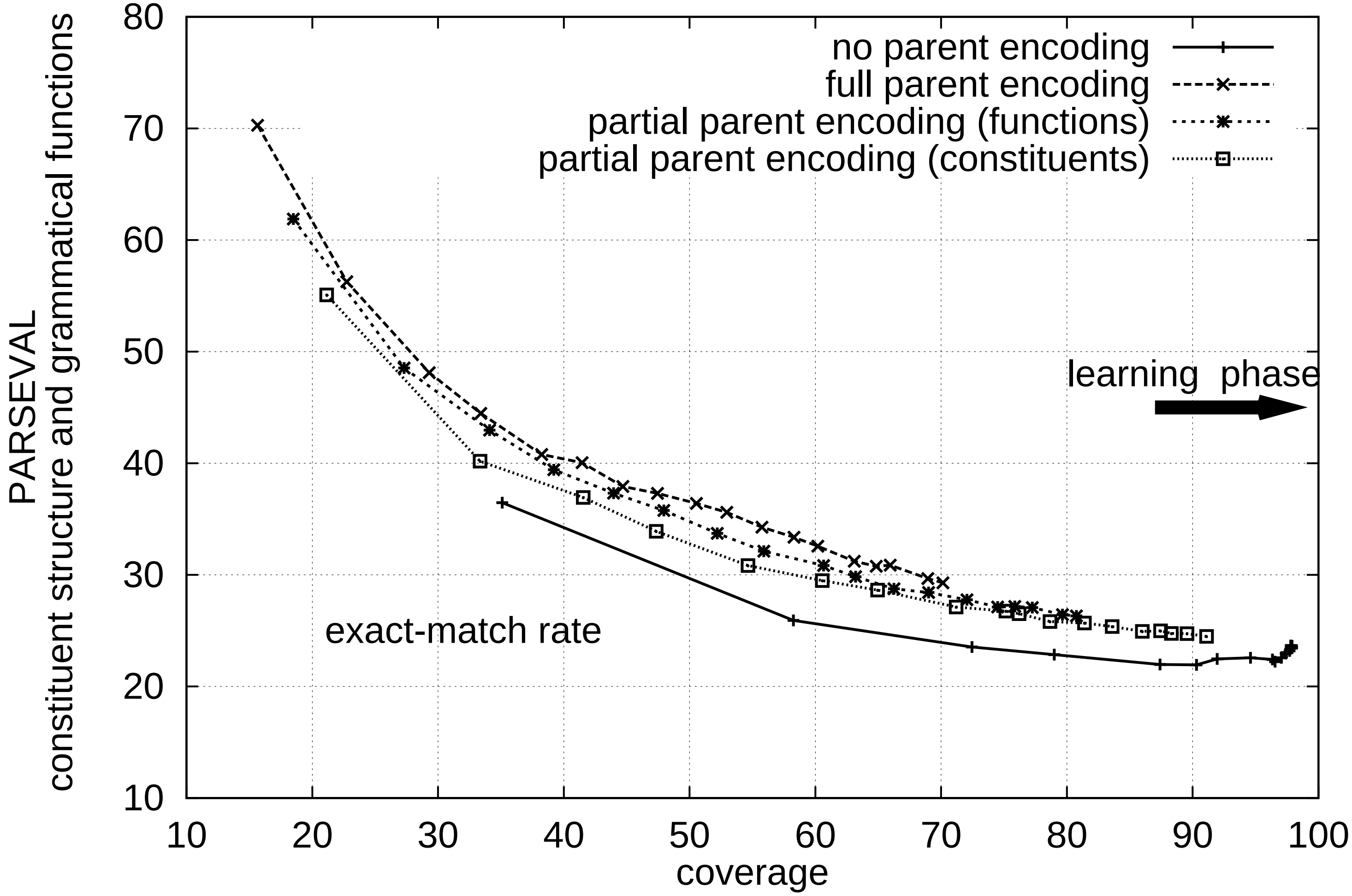
- full parent encoding, e.g., ART-NK●NP-OA



- partial parent encoding (constituent labels), ART-NK●NP

- partial parent encoding (grammatical functions), ART-NK●OA

Results of Experiment 3



Discussion (i)

- (i) High coverage parser providing both grammatical functions and constituent structure (18000): coverage 97.8%, precision 53%, recall 58%.
- (ii) In comparison to the constituent structure parsers, a parser using additionally grammatical functions perform better on comparable level of coverage.
- (iii) Full parent encoding outperformed partial parent encoding with functions and constituents at same level of coverage.
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parser	no PE	partial PE (const)	partial PE (GF)	full PE
coverage	97.8%	91.1%	80.8%	70.2%

Discussion (ii)

Compared to English, the precision for German is significantly lower. Possible reasons:

- free-er word order, complements and adjuncts can be shifted
- NEGRA follows the dependency grammar tradition
  - flat syntactic representation, e.g., no S $\longrightarrow$ NP VP rule), rather subject, objects are sisters.
  - coordination is expressed by a different category (e.g., CS $\longrightarrow$ NP VVFIN, S $\longrightarrow$ NP VVFIN).
- additional information: grammatical function labels.

Comparison to German

Results of Dubey & Keller 2003 (tagging with TnT):

	LP⋆	LR⋆	Cov
Baseline	71%	67%	94%
Baseline + Grammatical F	70%	65%	79%
C & R	68%	60%	94%
C & R + pool	69%	61%	94%
C & R + Grammatical F	68%	60%	79%
Collins	68%	66%	95%

⋆ on constituent structure only

Comparison to English

Penn Treebank: 30,000 sentences,

Negra Treebank: 20,000 sentences

language		LP	LR	Cov
English	constituents (Charniak 1996)	79%	80%	100%
German	constituents	71.8%	67.3%	98.4%
	constituents + GF	56.4%	61.8%	97.8%

Evaluation measures

PARSEVAL defines standard evaluation measures:

- **precision**: percentage of spans that also appear in the treebank
- **recall**: percentage of spans from the treebank that also appear in the in the most probable parse of the parser
- **f-score**: harmonic mean of precision and recall
- **coverage**: percentage of sentences which are parsed
- **exact match**: number of sentences which are totally correct parsed