Memory-Based Parsing for German

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Germany

German Tree

(1)

ich	habe	hier	übrigens	auch	schon	mir	Unterlagen	zuschicken	lassen	von
I	have	here	by the way	also	already	to me	brochures	sent	let	of

verschiedenen	Hotels
different	hotels

’by the way here I have also had brochures sent to me about different hotels already’

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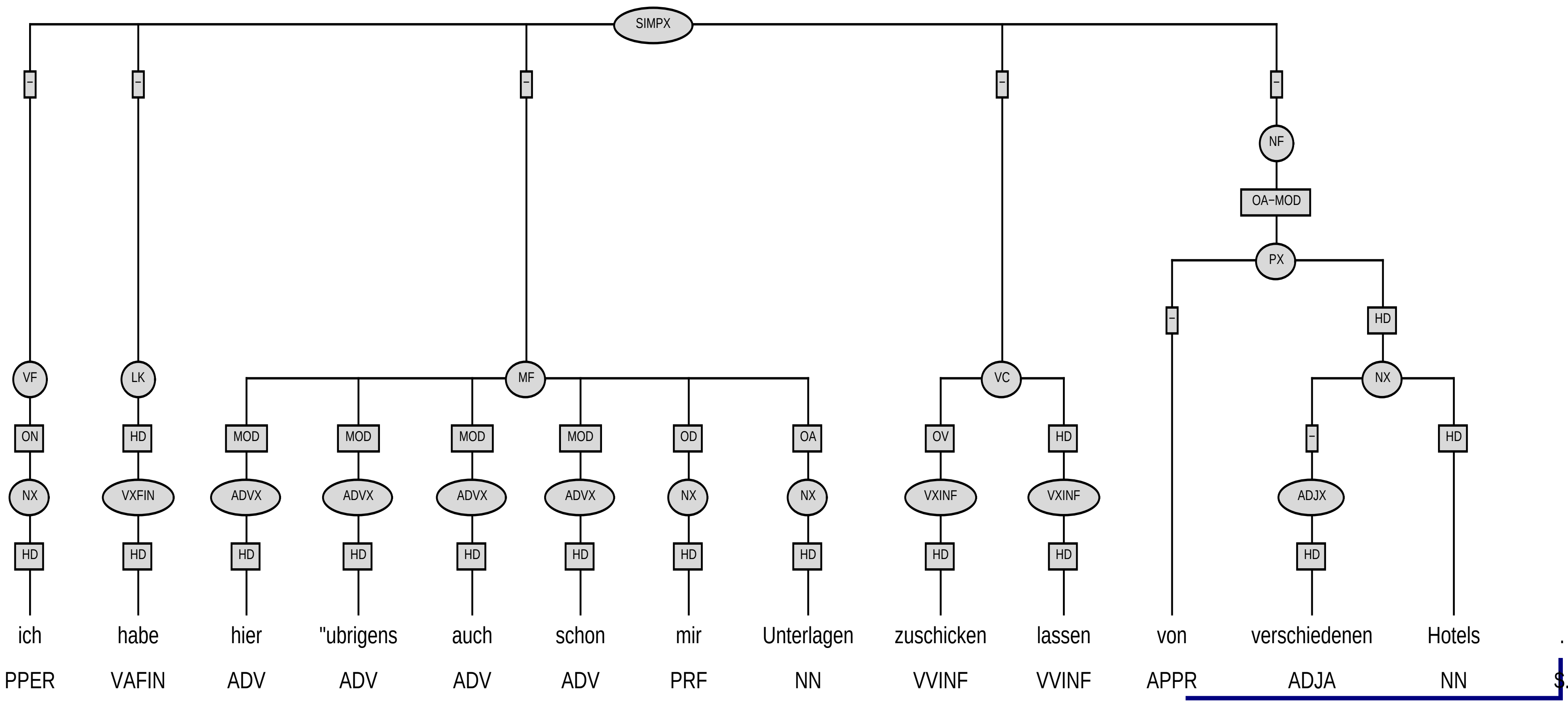

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- very appropriate for language learning: can deal with irregularities, subregularities, etc.
- intelligence = good similarity metric, good weighting of features

NP detection

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classification task: decide for each word: NP or not

instance: word + context

Memory-Based Learning – Example

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instance: word + context

instance base (= training data):

prev. w.	**word**	next w.	prev. POS	POS	next POS	class
will	book	two	md	vb	cd	no-NP
book	two	flights	vb	cd	nns	NP
two	flights	for	cd	nns	in	NP

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test instance:

prev. w.	**word**	next w.	prev. POS	POS	next POS	class
two	cars	for	cd	nns	in	**???**

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CL.:	[S							S]
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NP:	[NP]		[NP	NP]		[NP		NP]
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func:	SB			DO	–			
CL.:	[S							S]
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Problems with Cascades

- recursive structures such as complex clauses:

S_1:	[S							S]
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- in German: long-distance relations:

ON		OD	OA				OA-MOD
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- problem: what if structure of most similar tree is not identical?

Adapting the Most Similar Tree

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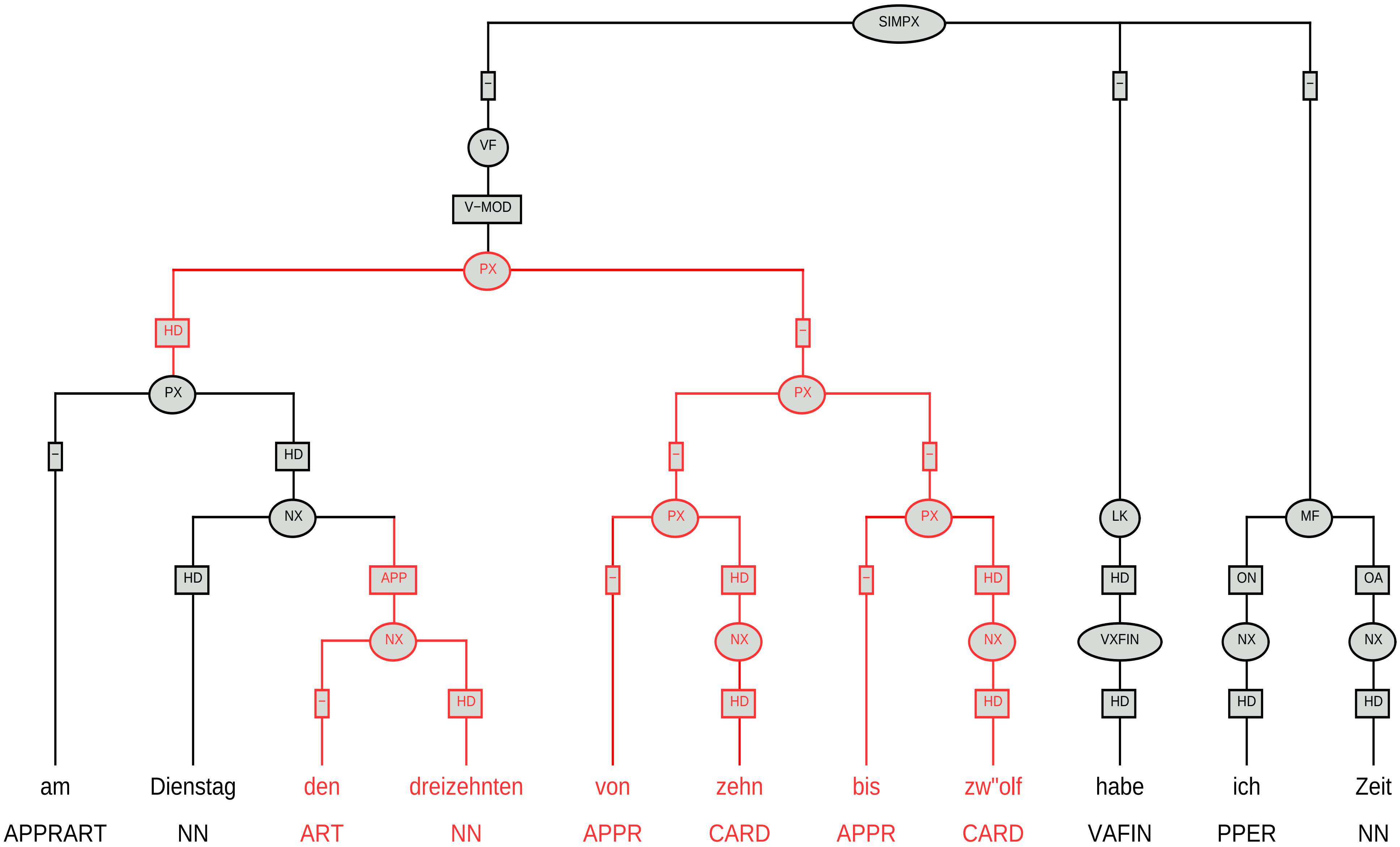
- example: new sentence `am Dienstag habe ich Zeit` (on Tuesday I have time)
  training sentence: `am Dienstag den dreizehnten von zehn bis zwölf habe ich Zeit` (on Tuesday the thirteenth from ten to twelve I have time)

Adapting the Most Similar Tree

- tree:



Preprocessing – Example

- sentence: `da muß ich leider zu einem Treffen nach Köln` (unfortunately I have to go to Cologne for a meeting)

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```
[simpx
    [da da]
    [vmfi nmuß]
    [nx4
        [pper ich]]
    [advx
        [adv leider]]
    [px
        [zu zu]
        [nx1
            [art einem]
            [nn Treffen]]]
    [px
        [appr nach]
        [nx1
            [ne Köln]]]]
```

TnT (Thorsten Brants)
tagfi xing (Steve Abney
CASS (Steve Abney)

Weighting Features?

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- selecting a complete tree: very difficult task ⇒ need **all words** and **all other types of information** as features
- suggested solution: backing off strategy instead of weighting

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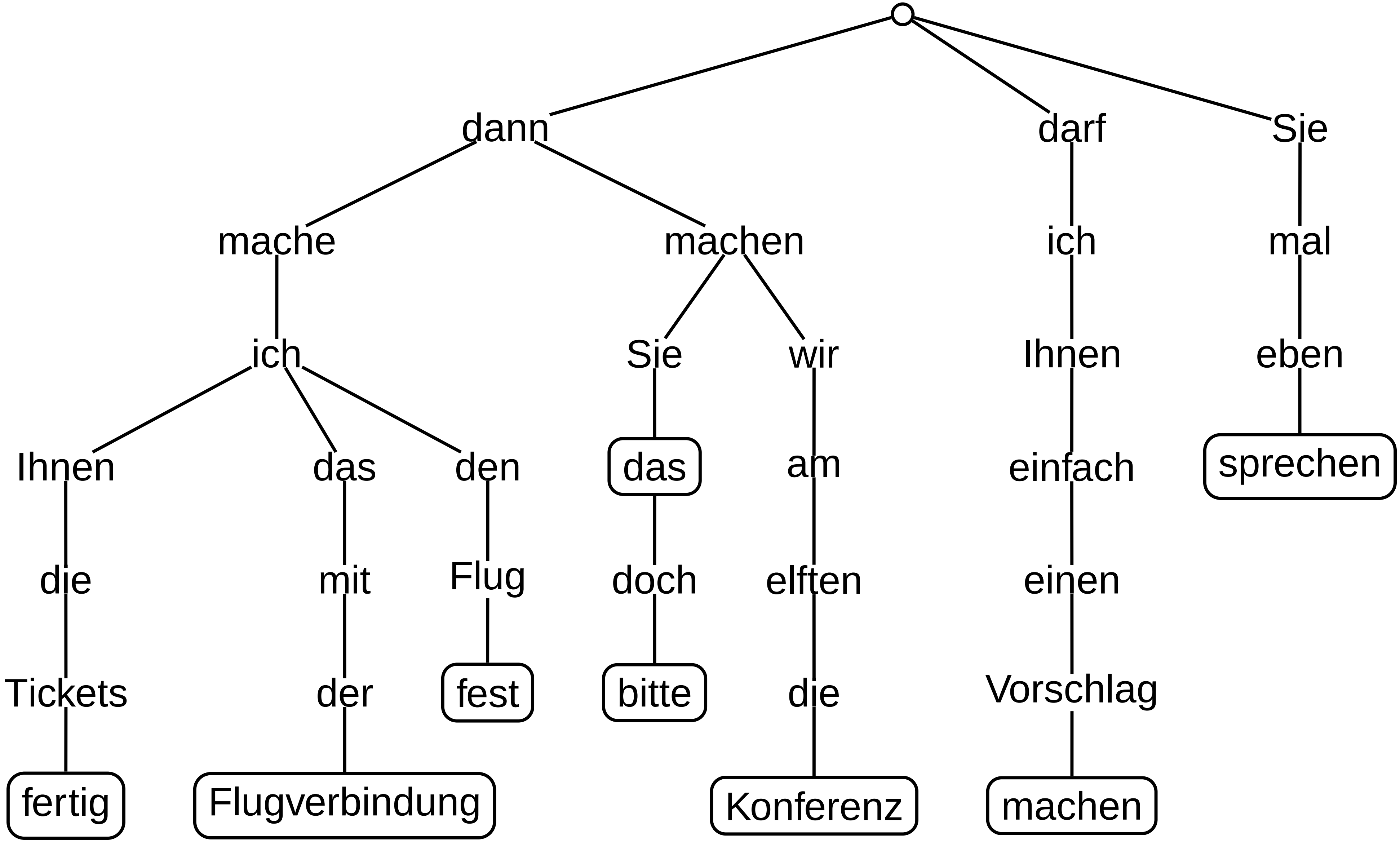
  3. search for chunk sequences with matching heads
  4. search for chunk sequences (without matching heads)

The Word Trie



The Omission of Words in the Trie

sentence: `wie sieht das ab dem fünfundzwanzigsten aus` (how does that look from the twenty fifth on)

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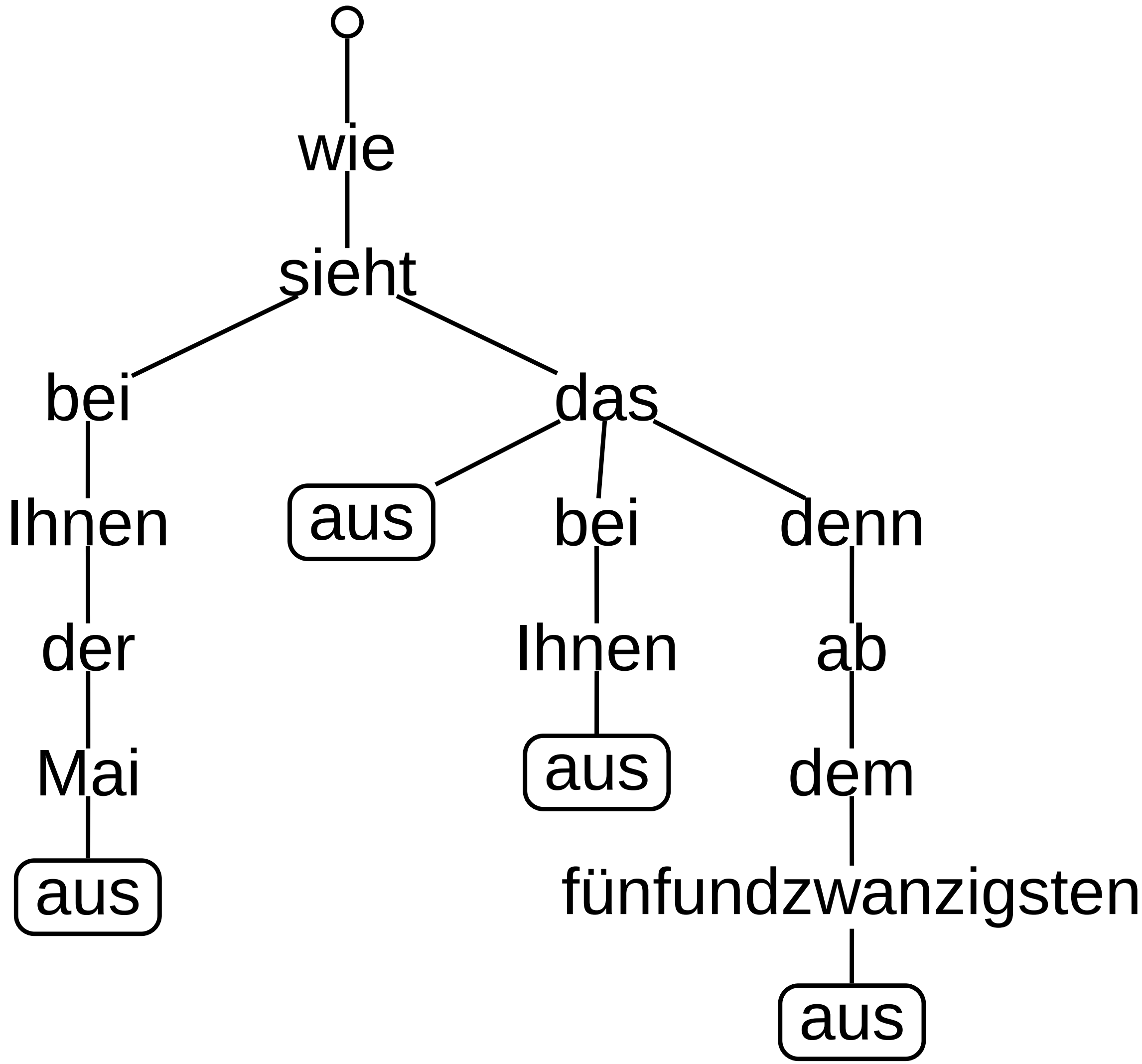

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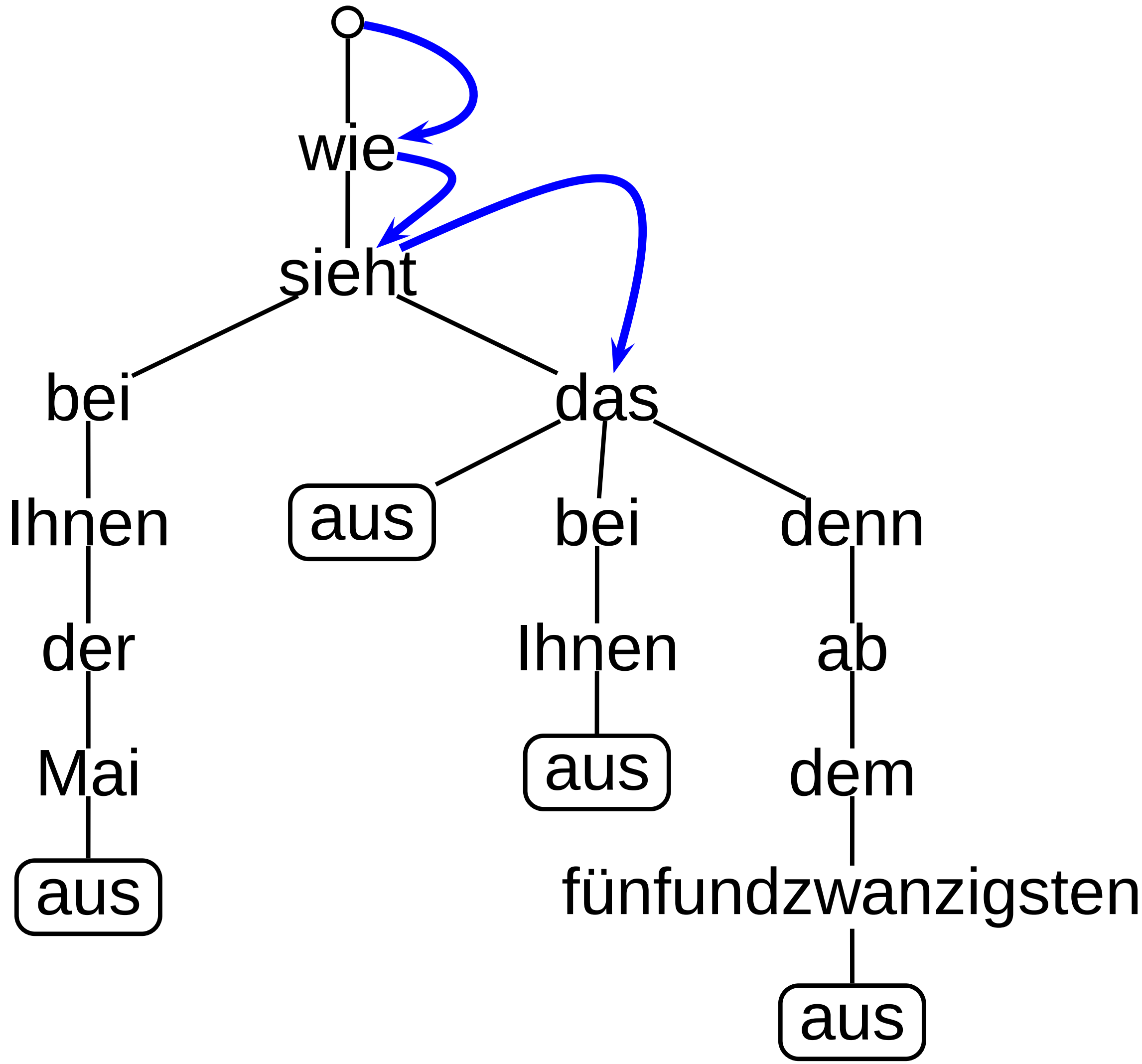

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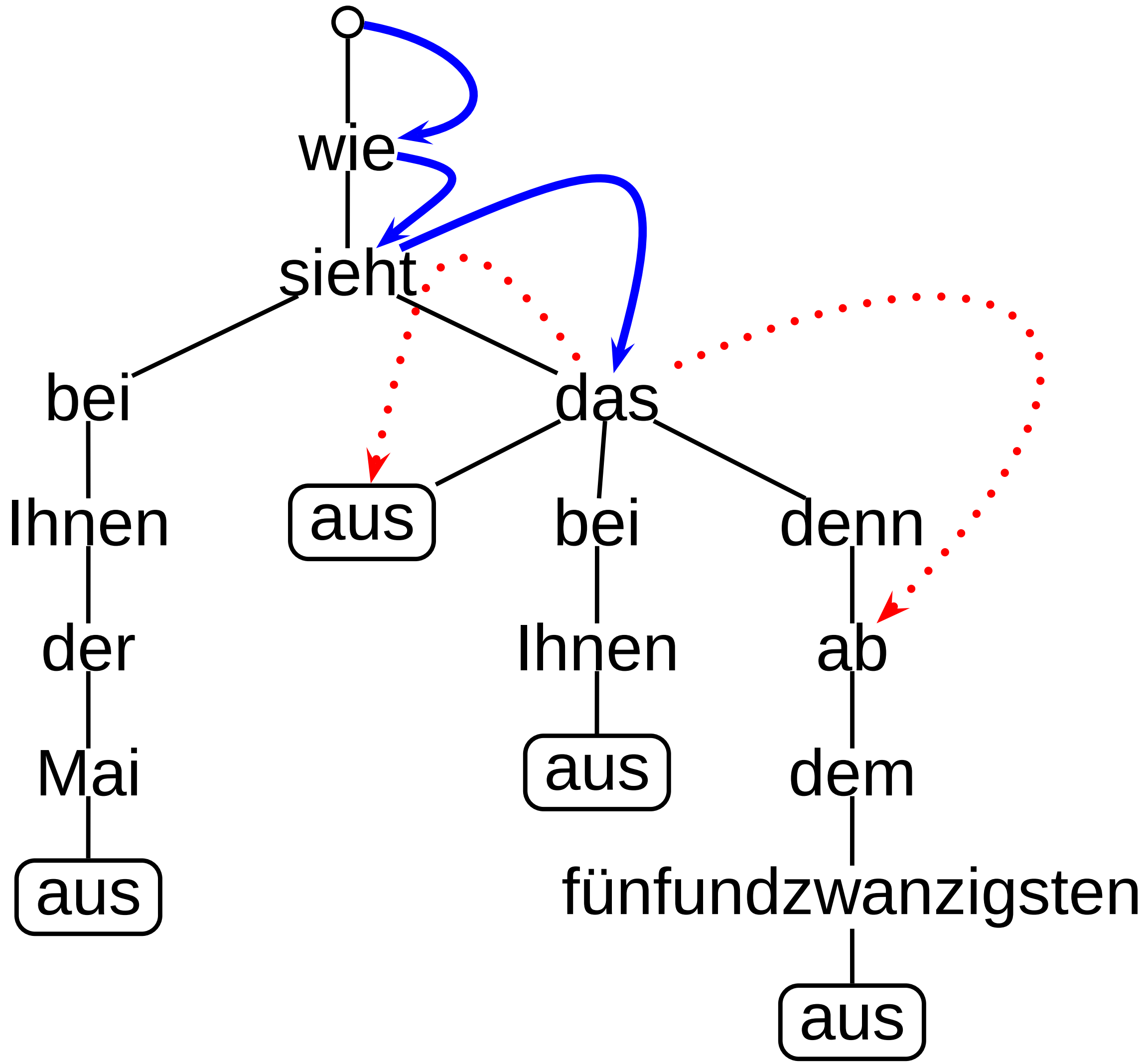

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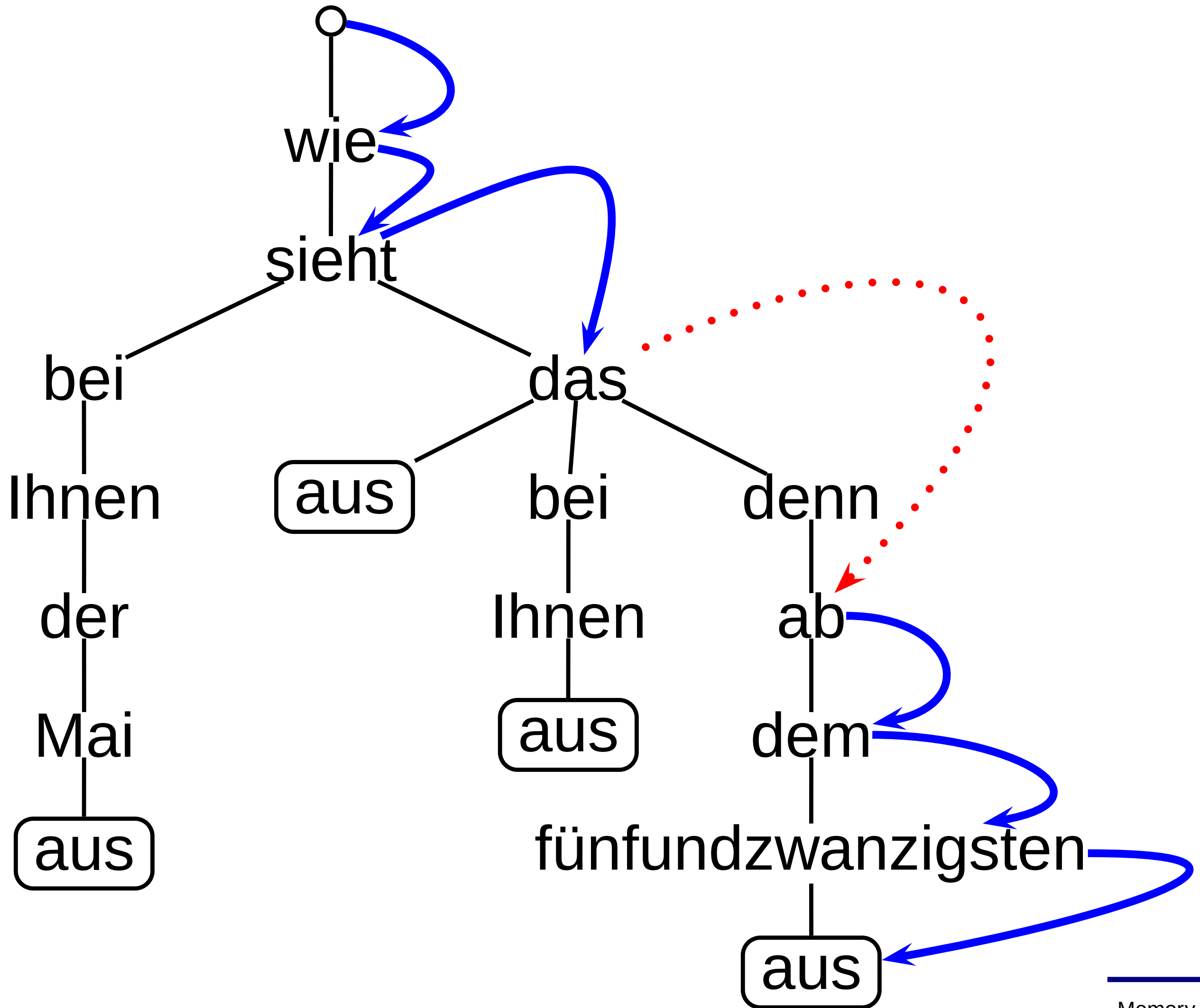

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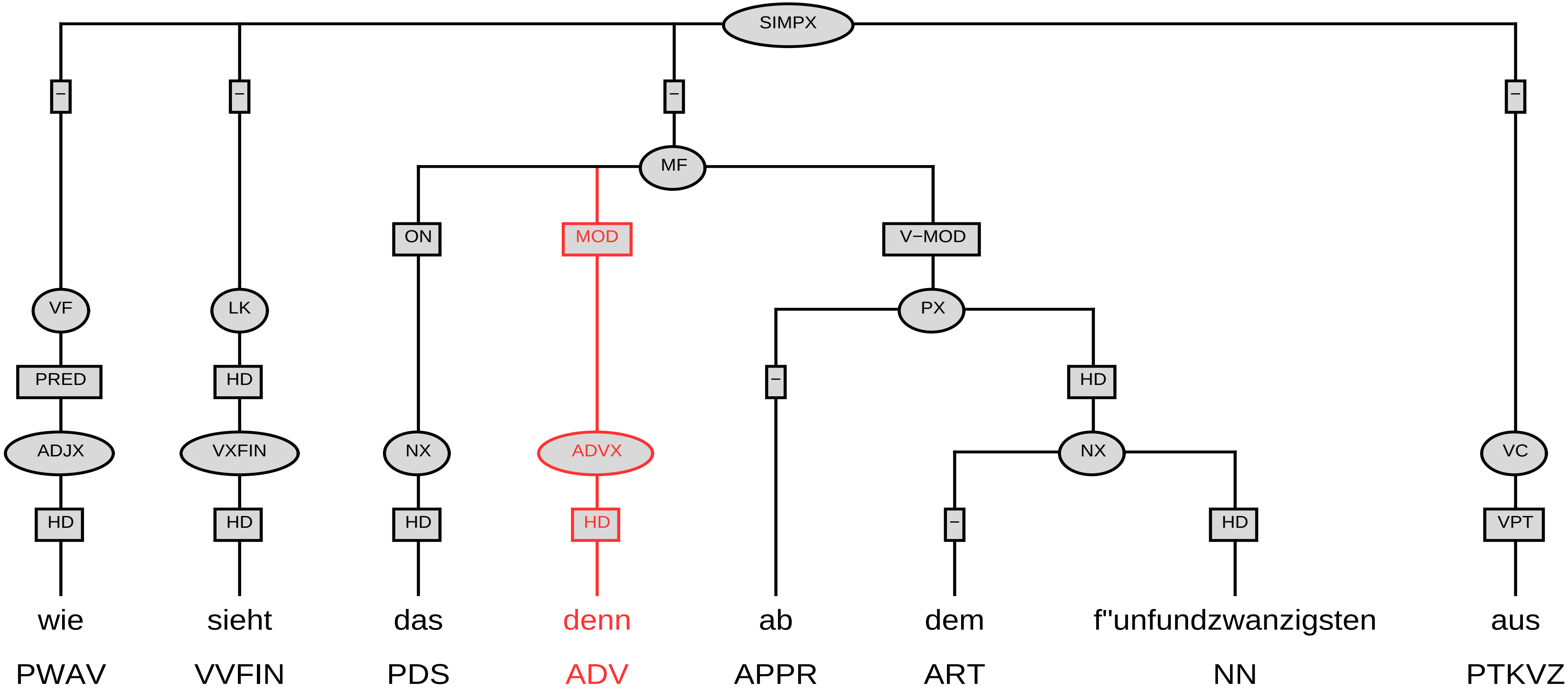
The Resulting Parse



Backing Off – Matching Chunks

- input sentence:
  [simpx [px `ab Donnerstag`] [fcop `bin`] [nx4 `ich`] [advx `wieder`] [advx `hier`]]

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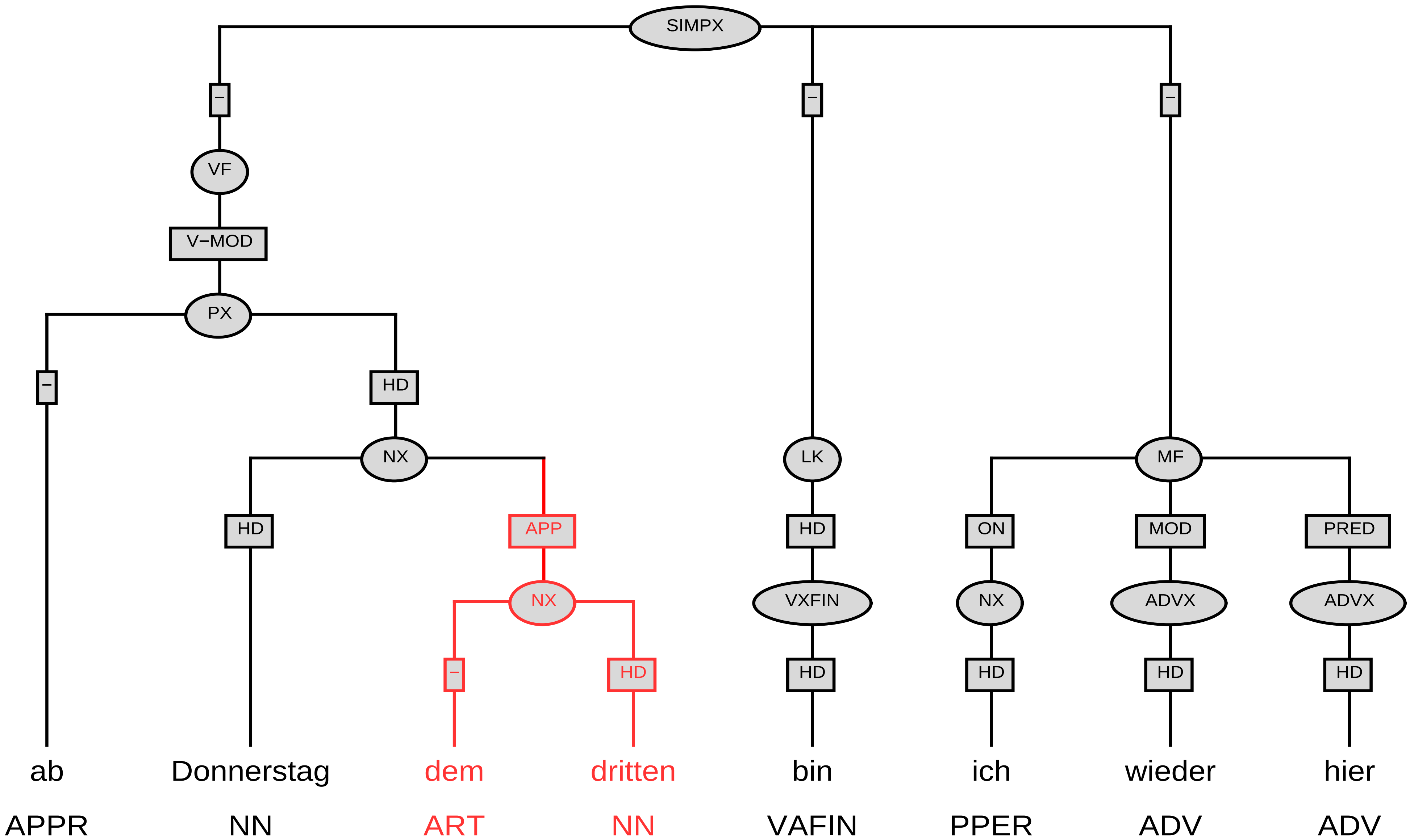
- identical chunk structure from training data:
  [simpx [px nach einer langen Woche] [fcop sind] [nx4 Sie] [advx wieder] [advx zurück]]
  (after a long week you will be back again)

Tree Modification



Evaluation

recall (syntactic)	82.45%
precision (syntactic)	87.25%
F_1	84.78
recall (+ func. cat.)	71.72%
precision (+ func. cat.)	75.79%
F_1	73.70
unattached const. in recall	7.14%
unattached const. in precision	7.60%
func. recall (att. const.)	95.31%
func. precision (att. const.)	95.21%

Leave-One-Out Evaluation

using **5 000 test sentences:**

recall (syntactic)	85.15%
precision (syntactic)	89.34%
F_1	87.19
recall (+ func. cat.)	76.00%
precision (+ func. cat.)	79.65%
F_1	77.78
func. recall (att. const.)	96.56%
func. precision (att. const.)	96.48%

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- needs: POS tagger, chunk parser, treebank
- uses a backing off strategy instead of (standard) feature weighting
- results still worse results than state of the art statistical parsers
- future work: increase training data, include morphological information, use different (ML) chunk parser, evaluate on different data sets