IN2110: Methods in Language Technology

(Statistical) CFG Parsing

Stephan Oepen

Language Technology Group (LTG)

April 9, 2019

Topics for Today

- Short recap: Formal grammar
  - A tool towards understanding
  - Context-free grammars (CFGs)
- Move on to statistical parsing
  - CFG Parsing
  - Bounding Ambiguity
  - Treebanks
  - Probability estimation
  - Viterbi adaptation
  - Parser Evaluation
- Sample exam questions

Recap: Grammar as a Tool towards Understanding

Formal grammars describe a language, providing key notions of:

Wellformedness

- *Kim was happy because ________ passed the exam.*
- *Kim was happy because ________ final grade was an A.*
- *Kim was happy when she saw ________ on television.*

Meaning

- *Kim gave Sandy the book.*
- *Kim gave the book to Sandy.*
- *Sandy was given the book by Kim.*

Ambiguity

- *Kim ate sushi with chopsticks.*
- *Have her report on my desk by Friday!*

Recap: Context-Free Grammars (CFGs)

Formally, a CFG is a quadruple: $G = \langle C, \Sigma, P, S \rangle$

- C is the set of categories (aka *non-terminals*),
  - {S, NP, VP, V}
- Σ is the vocabulary (aka *terminals*),
  - $\{\text{Kim}, \text{snow}, \text{adores}, \text{in}\}$
- P is a set of category rewrite rules (aka *productions*)

S $\rightarrow$ NP VP	NP $\rightarrow$ Kim
VP $\rightarrow$ V NP	NP $\rightarrow$ snow
	V $\rightarrow$ adores

- $S \in C$ is the *start symbol*, a filter on complete results;
- for each rule $\alpha \rightarrow \beta_1, \beta_2, ..., \beta_n \in P$: $\alpha \in C$ and $\beta_i \in C \cup \Sigma$

English–Norwegian Glossary of Key Terminology

syntax

semantics

constituent

constituent category

coordination

head

agreement

government

grammatical function

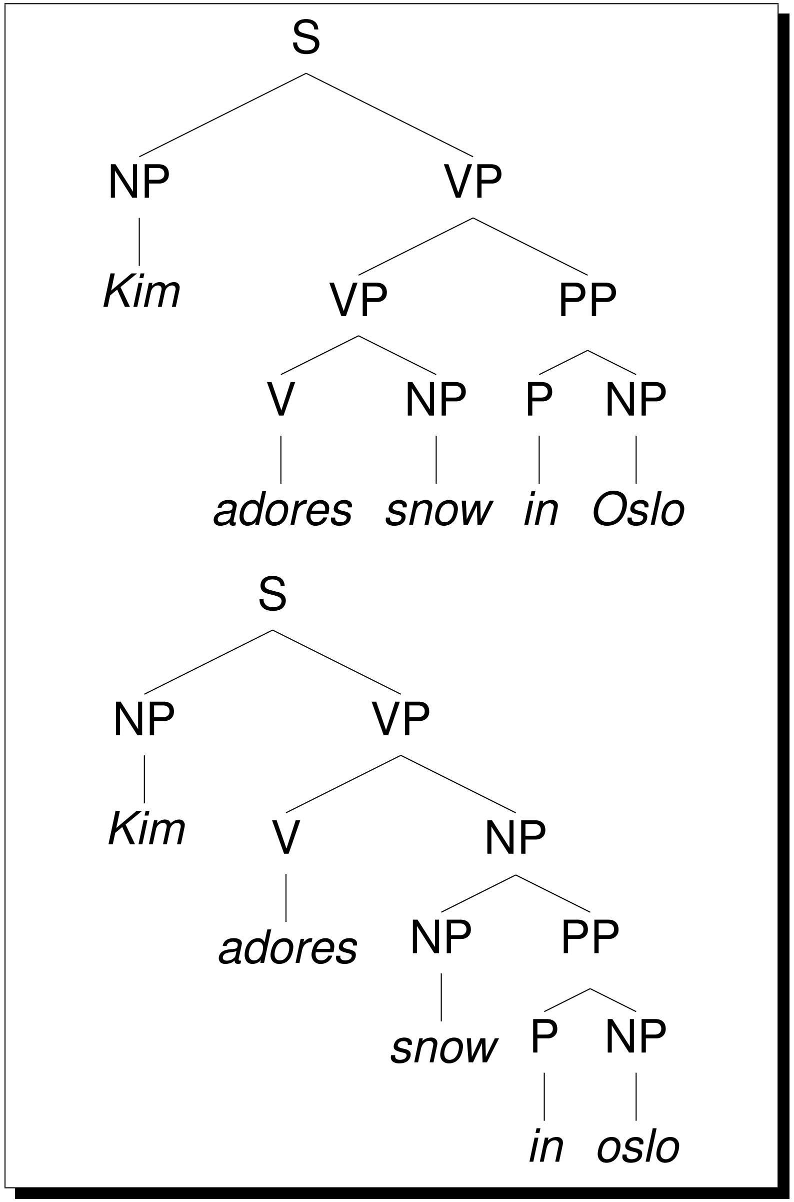
language of a CFG

Parsing with CFGs: Moving to a Procedural View

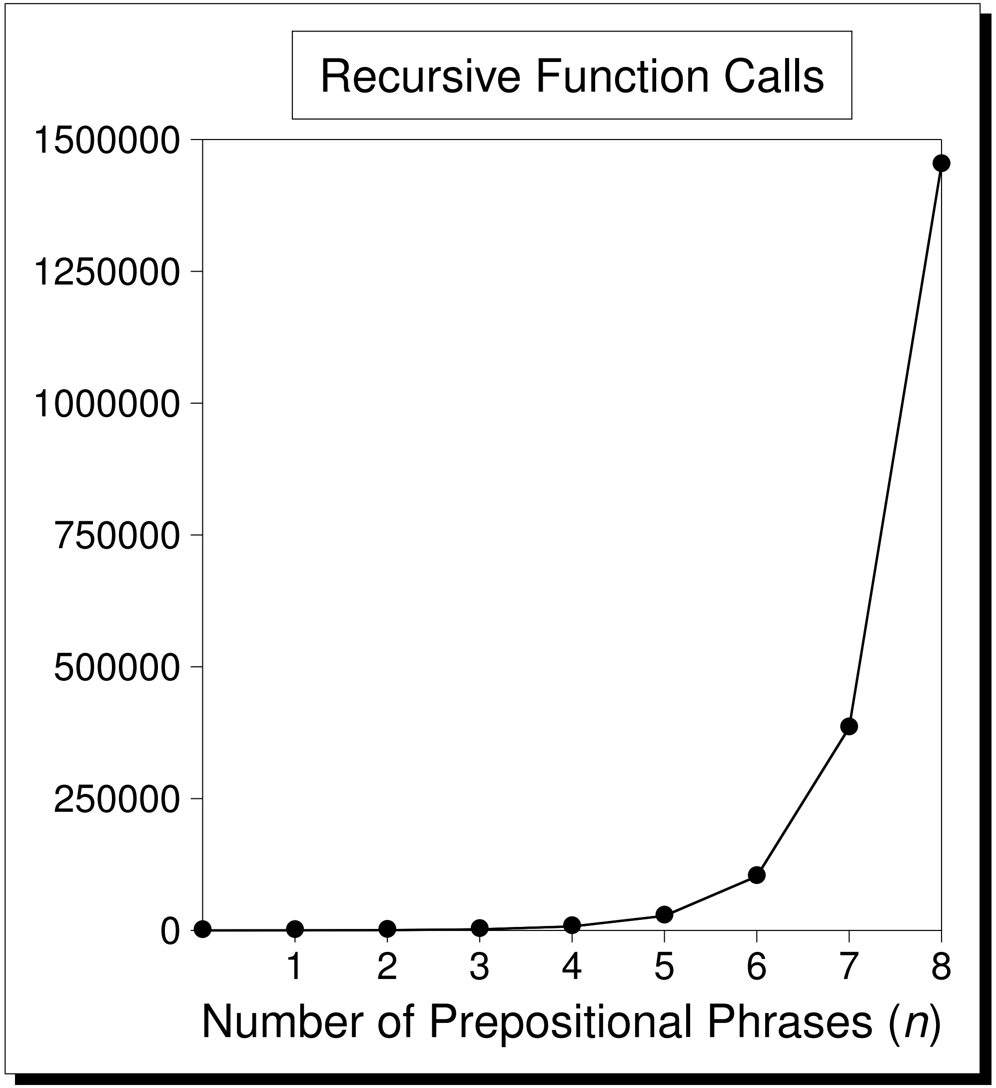
S $\rightarrow$ NP VP
VP $\rightarrow$ V | V NP | VP PP
NP $\rightarrow$ NP PP
PP $\rightarrow$ P NP
NP $\rightarrow$ Kim | snow | Oslo
V $\rightarrow$ adores
P $\rightarrow$ in

All Complete Derivations

- are rooted in the start symbol S;
- label internal nodes with categories $\in C$, leafs with words $\in \Sigma$;
- instantiate a grammar rule $\in P$ at each local subtree of depth one.



Quantifying the Complexity of the Parsing Task

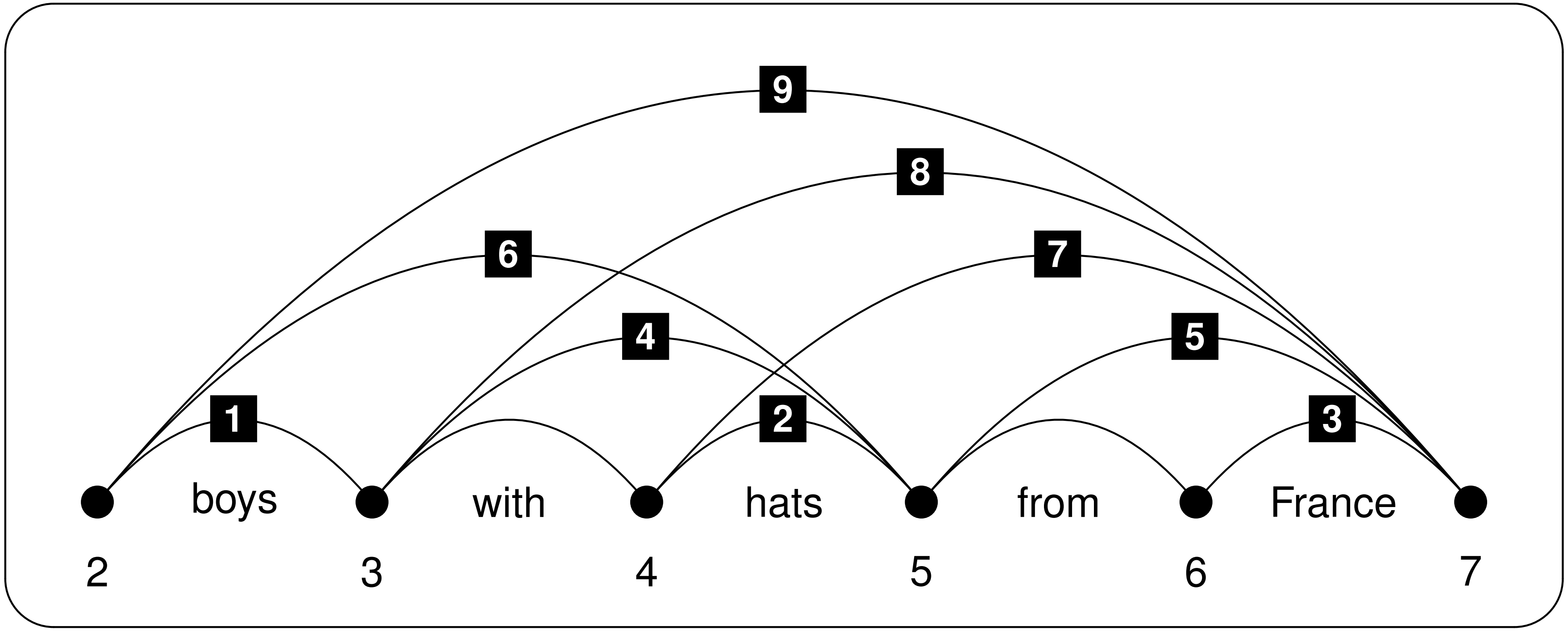


Kim adores snow (in Oslo)^n

n	trees	calls
0	1	46
1	2	170
2	5	593
3	14	2,093
4	42	7,539
5	132	27,627
6	429	102,570
7	1430	384,566
8	4862	1,452,776
⋮	⋮	⋮

A Key Insight: Local Ambiguity

- For many substrings, more than one way of deriving the same category;
- NPs: **1** | **2** | **3** | **6** | **7** | **9**; PPs: **4** | **5** | **8**; **9** $\equiv$ **1** + **8** | **6** + **5**;
- *parse forest* — a single item represents multiple trees [Billot & Lang, 89].



The CKY (Cocke, Kasami, & Younger) Algorithm

for ($0 \leq i < |\mathit{input}|$) do
  $\mathit{chart}_{[i,i+1]} \leftarrow \{\alpha \mid \alpha \rightarrow \mathit{input}_i \in P\}$;
for ($1 \leq l < |\mathit{input}|$) do
  for ($0 \leq i < |\mathit{input}| - l$) do
    for ($1 \leq j \leq l$) do
      if ($\alpha \rightarrow \beta_1\, \beta_2 \in P \wedge \beta_1 \in \mathit{chart}_{[i,i+j]} \wedge \beta_2 \in \mathit{chart}_{[i+j,i+l+1]}$) then
        $\mathit{chart}_{[i,i+l+1]} \leftarrow \mathit{chart}_{[i,i+l+1]} \cup \{\alpha\}$;

Kim adored snow in Oslo

	1	2	3	4	5
0	NP		S		S
1		V	VP		VP
2			NP		NP
3				P	PP
4					NP

Chart Parsing — Specialized Dynamic Programming

Basic Notions

- Use *chart* to record partial analyses, indexing them by string positions;
- count inter-word vertices; CKY: chart row is *start*, column *end* vertex;
- treat multiple ways of deriving the same category for some substring as *equivalent*; pursue only once when combining with other constituents.

Key Benefits

- Dynamic programming (memoization): avoid recomputation of results;
- efficient indexing of constituents: no search by start or end positions;
- compute *parse forest* with exponential 'extension' in *polynomial* time.

In Conclusion—What Happened this Far

Syntactic Structure

- Languages (formal or natural) exhibit complex, hierarchical structures;
- grammars encode rules of the language: dominance and sequencing;
- context-free grammar 'generates' a language: strings and derivations;
- ambiguity in natural language grows exponentially: a search problem;
- bounding (or 'packing') of local ambiguity is mandatory for tractability;
- chart parsing uses dynamic programming: free order of computation.

Coming up Next

- Treebank parsing; Viterbi adaptation on parse forest; parser evaluation.

Ambiguity Resolution is a (Major) Challenge

The Problem

- Even moderately complex sentences often have (very) *many* analyses;
- in most applications, computing all possible readings is hardly helpful;
- identifying the 'correct' (intended) analysis is an 'AI-complete' problem.

Once Again: Probabilities to the Rescue

- Design and use statistical models to select among competing analyses;
- for string S, some analyses T_i are more or less likely: maximize $P(T_i|S)$;

$\rightarrow$ Probabilistic Context Free Grammar (PCFG) is a CFG plus probabilities.

Treebanks

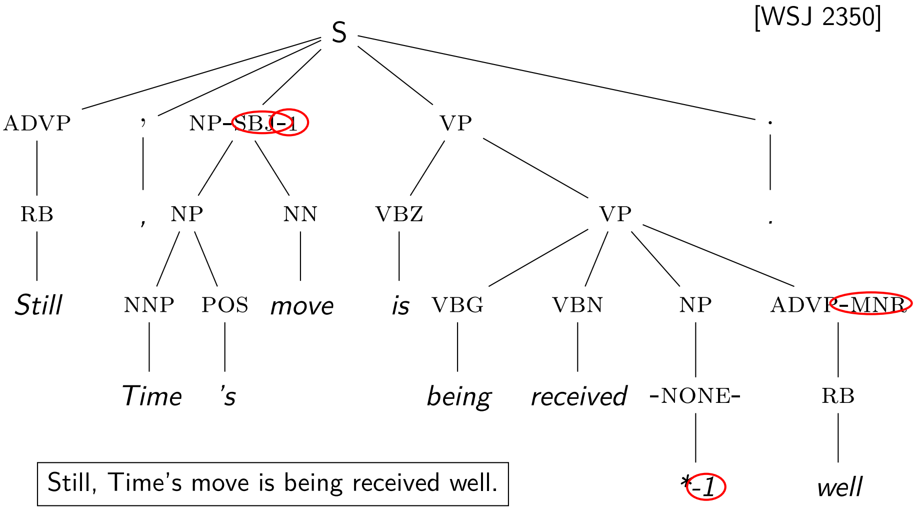
Generally

- A *treebank* is a corpus paired with 'gold-standard' (syntactico-semantic) analyses
- Created by manual annotation, typically with computational support (e.g. some automated processing plus correction)
- Can provide training data for machine learning (of parsers).

Penn Treebank (Marcus et al., 1993)

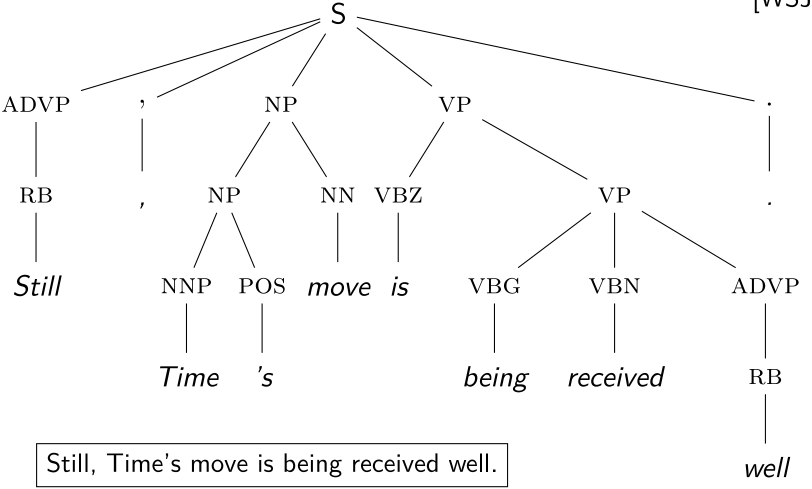
- About one million tokens of Wall Street Journal text
- Hand-corrected PoS annotation using 45 word classes
- Manual annotation with (somewhat) coarse constituent structure
- The 'mother' of all treebanks; still in wide use today.

One Example from the Penn Treebank



Still, Time's move is being received well.

[WSJ 2350]

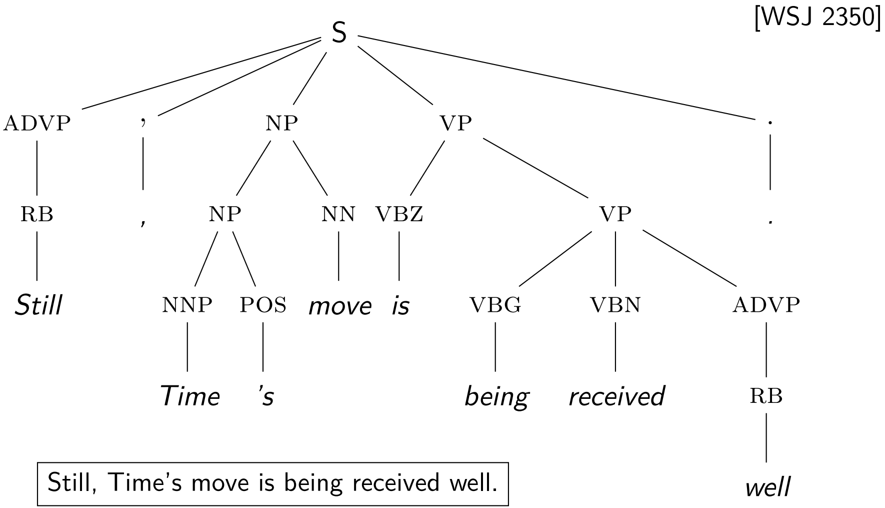


Still, Time's move is being received well.

Probabilistic Context-Free Grammars

- Towards statistical parsing: Not just interested in which trees can apply to a sentence, but also which tree is most likely.
- Probabilistic context-free grammars (PCFGs) augment CFGs by adding probabilities to each production, e.g.
  - S $\rightarrow$ NP VP   0.6
  - S $\rightarrow$ NP VP PP   0.4
- These are conditional probabilities: the probability of the right hand side (RHS), given the left hand side (LHS)
  - $P(S \rightarrow NP\ VP) = P(NP\ VP|S)$
- The probability of a complete tree is the product of rule probabilities
- We can learn these probabilities from a treebank, much like the estimation of HMM probabilities: Maximum Likelihood Estimation.

Estimating PCFGs (1/3)



Still, Time’s move is being received well.

Estimating PCFGs (2/3)

```
(S
   (ADVP (RB "Still"))
   (, ",")
   (NP
      (NP (NNP "Time") (POS "'s"))
      (NN "move"))
   (VP
      (VBZ "is")
      (VP
         (VBG "being")
         (VP
           (VBN "received")
           (ADVP (RB "well")))))
   (. "."))
```

RB → Still	1
ADVP → RB	2
, → ,	1
NNP → Time	1
POS → 's	1
NP → NNP POS	1
NN → move	1
NP → NP NN	1
VBZ → is	1
VBG → being	1
VBN → received	1
RB → well	1
VP → VBN ADVP	1
VP → VBG VP	1
. → .	1
S → ADVP , NP VP .	1
START → S	1

Estimating PCFGs (3/3)

Once we have counts of all the rules, we turn them into probabilities.

S → ADVP , NP VP .	50	S → NP VP .	400
S → NP VP PP .	350	S → VP !	100
S → NP VP S .	200	S → NP VP	50

$$
\begin{aligned}
P(S \to ADVP\ ,\ NP\ VP\ .) &\approx \frac{C(S \to ADVP\ ,\ NP\ VP\ .)}{C(S)} \\
&= \frac{50}{1150} \\
&= 0.0435
\end{aligned}
$$

Viterbi Decoding over the Parse Forest

- Recall the Viterbi algorithm for HMMs

$$v_i(s) = \max_{k=1}^{L} \left[v_{i-1}(k) \cdot P(s|k) \cdot P(o_i|s) \right]$$

- Over the (result edges from the) parse forest, compute Viterbi scores for sub-trees of increasing size:

$$v(\alpha) = \max \left[P(\beta_1, \ldots \beta_n|\alpha) \times \prod_{i=1}^{n} v(\beta_i) \right]$$

- Similar to HMM decoding, we also need to keep track of the set of daughters that led to the maximum probability.

Exercise (1): Natural Language Ambiguity

Assume the following 'toy' grammar of English:

$$S \rightarrow NP$$
$$NP \rightarrow Det\ N$$
$$N \rightarrow N\ N$$

$$Det \rightarrow \textit{the}$$
$$N \rightarrow \textit{kitchen} \mid \textit{gold} \mid \textit{towel} \mid \textit{rack}$$

(1) How many different syntactic analyses, if any, does the grammar assign to the following strings?

(a) *the kitchen towel rack*
(b) *the kitchen gold towel rack*

Exercise (2): CKY Parsing

Assume the following grammar and CKY parse table:

S → NP VP
VP → V NP
VP → VP PP
NP → NP VP
PP → P NP

	1	2	3	4	5
0	NP		S		S
1		V	VP		VP
2			NP		NP
3				P	PP
4					NP

(2) Which pair(s) of 'input' cells and which production(s) give rise to the derivation of category S in 'target' cell $\langle 0, 5 \rangle$?

Outlook

After the Easter Break

- Dependency syntax
- Transition-based dependency parsing
- Using syntactic structure