

Algorithms for AI and NLP (INF4820 — PCFGs)

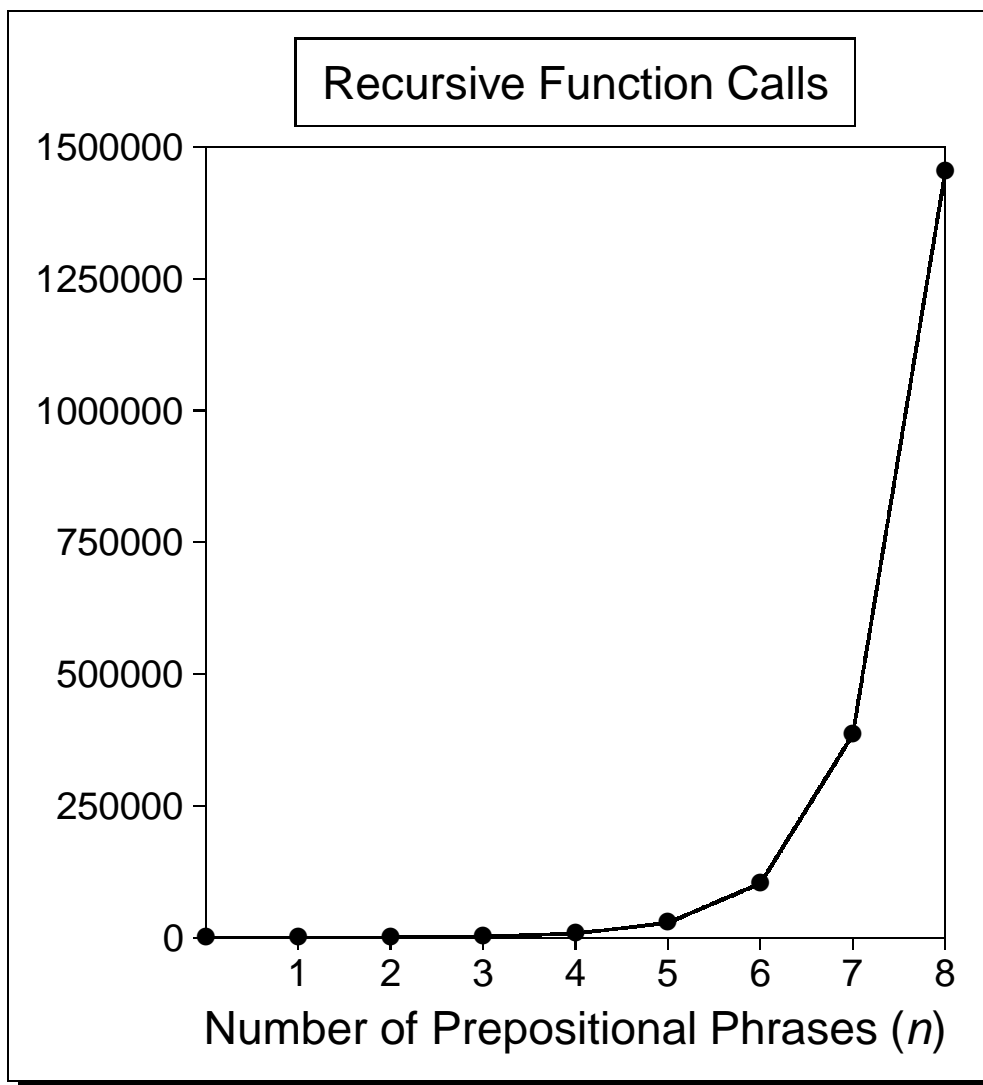
$$P(S \rightarrow NP VP) = 1.0; P(NP \rightarrow Det N) = 0.6$$

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Quantifying the Complexity of the Parsing Task



Kim adores snow (in Oslo)ⁿ

<i>n</i>	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
⋮	⋮	⋮



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.

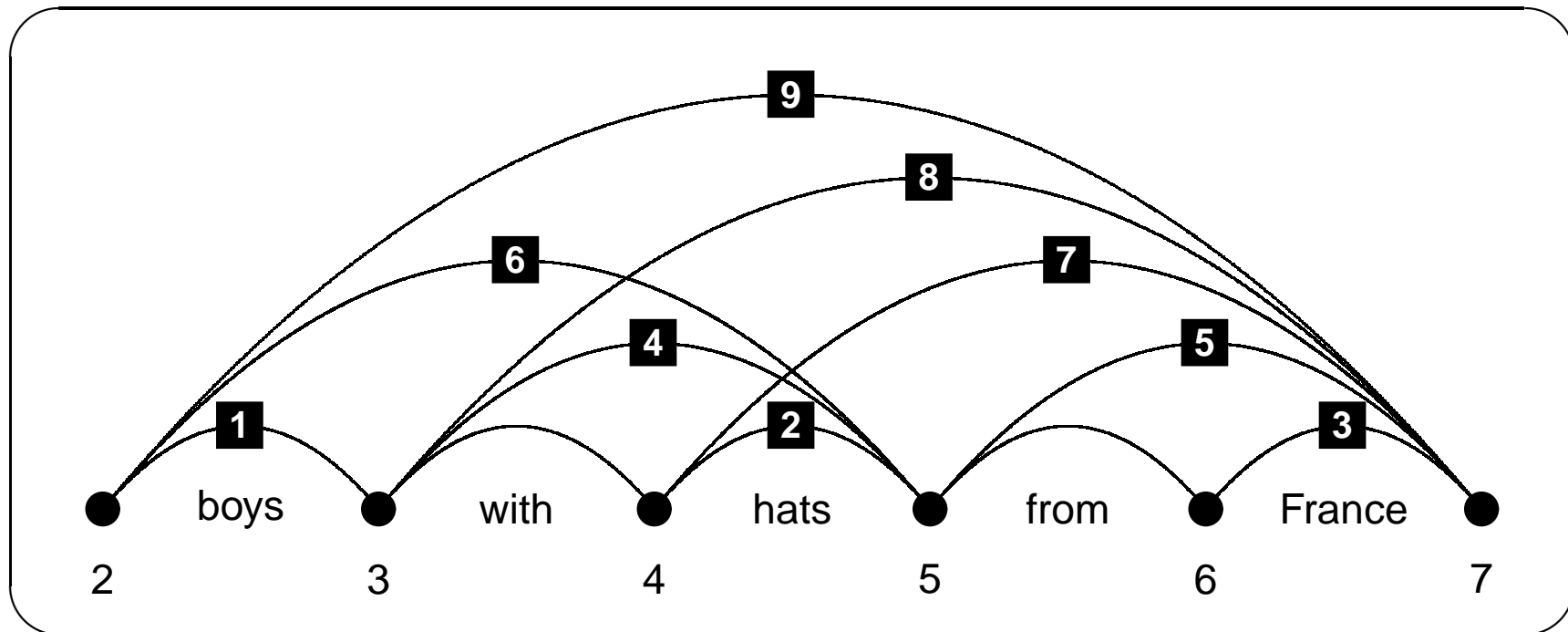
Key Benefits

- 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.



Bounding Ambiguity — The Parse Chart

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

```

$$[0,2] \leftarrow [0,1] + [1,2]$$

...

$$[0,5] \leftarrow [0,1] + [1,5]$$

$$[0,5] \leftarrow [0,2] + [2,5]$$

$$[0,5] \leftarrow [0,3] + [3,5]$$

$$[0,5] \leftarrow [0,4] + [4,5]$$

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



Generalized Chart Parsing

- The parse *chart* is a two-dimensional matrix of *edges* (aka chart items);
- an edge is a (possibly partial) rule instantiation over a substring of input;
- the chart indexes edges by start and end string position (aka vertices);
- dot in rule RHS indicates degree of completion: $\alpha \rightarrow \beta_1 \dots \beta_{i-1} \bullet \beta_i \dots \beta_n$
- *active* edges (aka *incomplete* items) — partial RHS: $[1, 2, VP \rightarrow V \bullet NP]$;
- *passive* edges (aka *complete* items) — full RHS: $[1, 3, VP \rightarrow V NP \bullet]$;

The Fundamental Rule

$$[i, j, \alpha \rightarrow \beta_1 \dots \beta_{i-1} \bullet \beta_i \dots \beta_n] + [j, k, \beta_i \rightarrow \gamma^+ \bullet] \\ \mapsto [i, k, \alpha \rightarrow \beta_1 \dots \beta_i \bullet \beta_{i+1} \dots \beta_n]$$



Backpointers: Recording the Derivation History

	0	1	2	3
0	2: S → • NP VP 1: NP → • NP PP 0: NP → • kim	10: S → 8 • VP 9: NP → 8 • PP 8: NP → kim •		17: S → 8 15 •
1		5: VP → • VP PP 4: VP → • V NP 3: V → • adored	12: VP → 11 • NP 11: V → adored •	16: VP → 15 • PP 15: VP → 11 13 •
2			7: NP → • NP PP 6: NP → • snow	14: NP → 13 • PP 13: NP → snow •
3				

- Use edges to record derivation trees: backpointers to daughters;
- a single edge can represent multiple derivations: backpointer sets.



Ambiguity Packing in the Chart

General Idea

- Maintain only one edge for each α from i to j (the ‘representative’);
- record alternate sequences of daughters for α in the representative.

Implementation

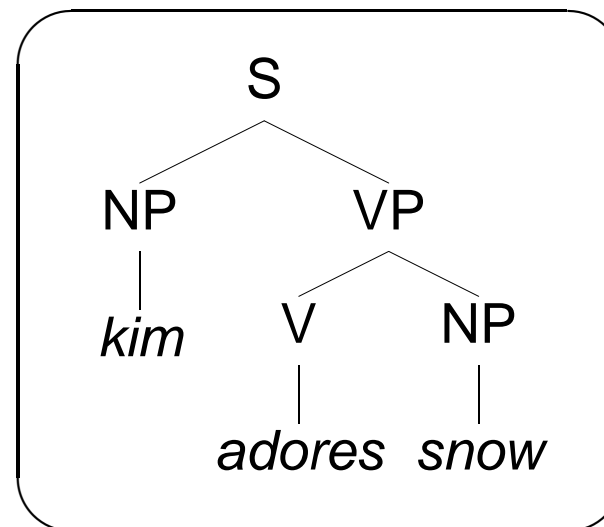
- Group passive edges into *equivalence classes* by identity of α , i , and j ;
 - search chart for existing equivalent edge (h , say) for each new edge e ;
 - when h (the ‘host’ edge) exists, *pack* e into h to record equivalence;
 - e *not* added to the chart, no derivations with or further processing of e ;
- *unpacking* multiply out all alternative daughters for all result edges.



Background: Trees as Bracketed Sequences

- Trees can be encoded as sequences (*dominance plus precedence*):

```
(S (NP kim)
   (VP (V adored)
        (NP snow)))
```



- the `first()` element (at each level) represents the tree root (or mother);
- all other elements (i.e. the `rest()`) correspond to immediate daughters.



Ambiguity Resolution Remains a (Major) Challenge

The Problem

- With broad-coverage grammars, even moderately complex sentences typically have multiple analyses (tens or hundreds, rarely thousands);
- unlike in grammar writing, exhaustive parsing is useless for applications;
- identifying the ‘right’ (intended) analysis is an ‘AI-complete’ problem;
- inclusion of (non-grammatical) sortal constraints is generally undesirable.

Typical Approaches

- Design and use statistical models to select among competing analyses;
 - for string S , some analyses T_i are more or less likely: maximize $P(T_i|S)$;
- Probabilistic Context Free Grammar (PCFG) is a CFG plus probabilities.



Probability Theory and Linguistics?

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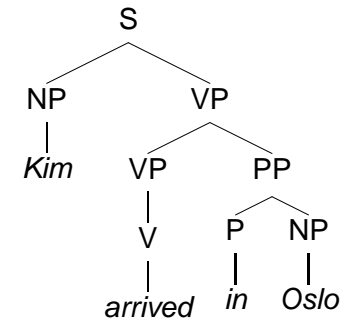
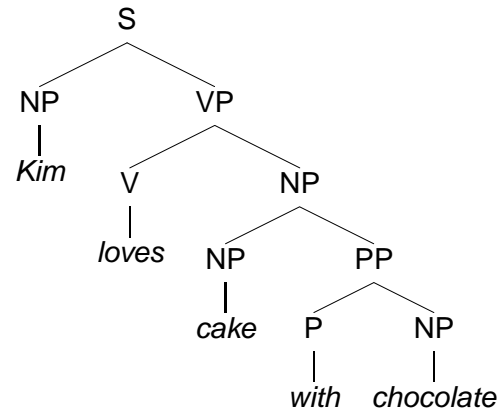
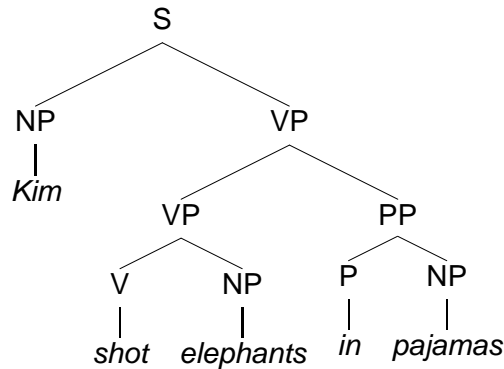
Every time I fire a linguist, system performance improves. (Fredrick Jelinek, 1980s)



Probabilistic Context-Free Grammars



A (Simplified) PCFG Estimation Example



P(RHS|LHS)

CFG Rule

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

- Estimate rule probability from observed distribution;
- conditional probabilities:

$$P(\text{RHS}|\text{LHS}) = \frac{C(\text{LHS}, \text{RHS})}{C(\text{LHS})}$$



Formally: Probabilistic Context-Free Grammars

- Formally, a *context-free grammar* (CFG) is a quadruple: $\langle C, \Sigma, P, S \rangle$

...

- P is a set of category rewrite rules (aka *productions*), each with a conditional probability $P(\text{RHS}|\text{LHS})$, e.g.

...

NP \rightarrow Kim [0.6]
NP \rightarrow snow [0.4]
...

- for each rule ' $\alpha \rightarrow \beta_1, \beta_2, \dots, \beta_n$ ' $\in P$: $\alpha \in C$ and $\beta_i \in C \cup \Sigma$; $1 \leq i \leq n$;

...

- for each $\alpha \in C$, the probabilities of all rules R ' $\alpha \rightarrow \dots$ ' must sum to 1.



Limitations of Context-Free Grammar

Agreement and Valency (For Example)

That dog barks.

**That dogs barks.*

**Those dogs barks.*

The dog chased a cat.

**The dog barks a cat.*

**The dog chased.*

**The dog chased a cat my neighbours.*

The cat was chased by a dog.

**The cat was chased of a dog.*

...



Unification-Based Grammar: Structured Categories

- All (constituent) categories in the grammar are *typed feature structures*;
- feature structures are recursive, record-like objects: attribute – value sets;
- typing very similar to OO programming: a multiple-inheritance hierarchy;
- specific TFS configurations may correspond to ‘traditional’ categories;
- labels like ‘S’ or ‘NP’ are mere abbreviations, not elements of the theory.

word $\left[\begin{array}{l} \text{HEAD } \textit{noun} \\ \text{SPR } \langle \langle \text{HEAD } \textit{det} \rangle \rangle \\ \text{COMPS } \langle \rangle \end{array} \right]$

‘N’

phrase $\left[\begin{array}{l} \text{HEAD } \textit{verb} \\ \text{SPR } \langle \rangle \\ \text{COMPS } \langle \rangle \end{array} \right]$

‘S’

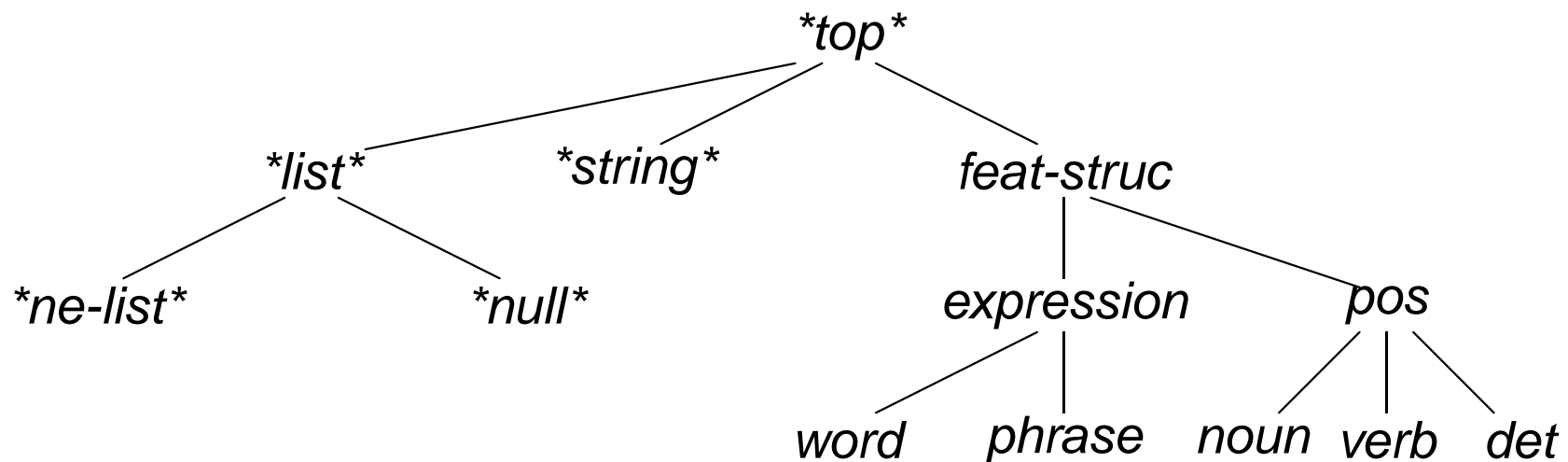
phrase $\left[\begin{array}{l} \text{HEAD } \textit{verb} \\ \text{SPR } \langle \langle \text{HEAD } \textit{noun} \rangle \rangle \\ \text{COMPS } \langle \rangle \end{array} \right]$

‘VP’



The Type Hierarchy: Fundamentals

- Types ‘represent’ groups of entities with similar properties (‘classes’);
- types ordered by specificity: subtypes inherit properties of (all) parents;
- type hierarchy determines which types are compatible (and which not).



Typed Feature Structure Subsumption

- Typed feature structures can be partially ordered by information content;
- a more general structure is said to *subsume* a more specific one;
- $*top*$ is the most general feature structure (while \perp is inconsistent);
- \sqsubseteq ('square subset or equal') conventionally used to depict subsumption.

Feature structure F subsumes feature structure G ($F \sqsubseteq G$) iff: (1) if path p is defined in F then p is also defined in G and the type of the value of p in F is a supertype or equal to the type of the value of p in G , and (2) all paths that are reentrant in F are also reentrant in G .



Feature Structure Subsumption: Examples

$$\text{TFS}_1: \begin{matrix} a \\ \left[\begin{array}{l} \text{FOO } x \\ \text{BAR } x \end{array} \right] \end{matrix}$$
$$\text{TFS}_2: \begin{matrix} a \\ \left[\begin{array}{l} \text{FOO } x \\ \text{BAR } y \end{array} \right] \end{matrix}$$
$$\text{TFS}_3: \begin{matrix} b \\ \left[\begin{array}{l} \text{FOO } y \\ \text{BAR } x \\ \text{BAZ } x \end{array} \right] \end{matrix}$$
$$\text{TFS}_4: \begin{matrix} a \\ \left[\begin{array}{l} \text{FOO } \boxed{1} x \\ \text{BAR } \boxed{1} \end{array} \right] \end{matrix}$$

Hierarchy

a	FOO		x
	BAR		
b	BAZ		y

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Typed Feature Structure Unification

- Decide whether two typed feature structures are mutually compatible;
- determine combination of two TFSs to give the most general feature structure which retains all information which they individually contain;
- if there is no such feature structure, unification fails (depicted as \perp);
- unification *monotonically* combines information from both 'input' TFSs;
- *relation to subsumption* the unification of two structures F and G is the most general TFS which is subsumed by both F and G (if it exists).
- \sqcap ('square set intersection') conventionally used to depict unification.



Typed Feature Structure Unification: Examples

$$\text{TFS}_1: a \begin{bmatrix} \text{FOO } x \\ \text{BAR } x \end{bmatrix}$$

$$\text{TFS}_2: a \begin{bmatrix} \text{FOO } x \\ \text{BAR } y \end{bmatrix}$$

$$\text{TFS}_3: b \begin{bmatrix} \text{FOO } y \\ \text{BAR } x \\ \text{BAZ } x \end{bmatrix}$$

$$\text{TFS}_4: a \begin{bmatrix} \text{FOO } \boxed{1} x \\ \text{BAR } \boxed{1} \end{bmatrix}$$

Hierarchy



$$\text{TFS}_1 \sqcap \text{TFS}_2 \equiv \text{TFS}_2 \quad \text{TFS}_1 \sqcap \text{TFS}_3 \equiv \text{TFS}_3 \quad \text{TFS}_3 \sqcap \text{TFS}_4 \equiv b \begin{bmatrix} \text{FOO } \boxed{1} y \\ \text{BAR } \boxed{1} \\ \text{BAZ } x \end{bmatrix}$$

