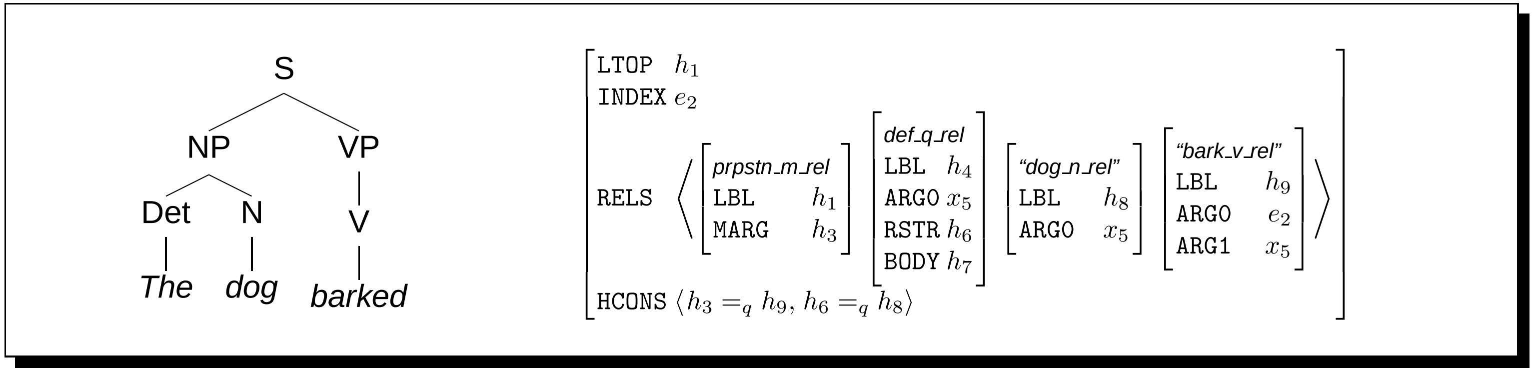

Algorithms for AI and NLP (INF4820 — PCFGs)

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

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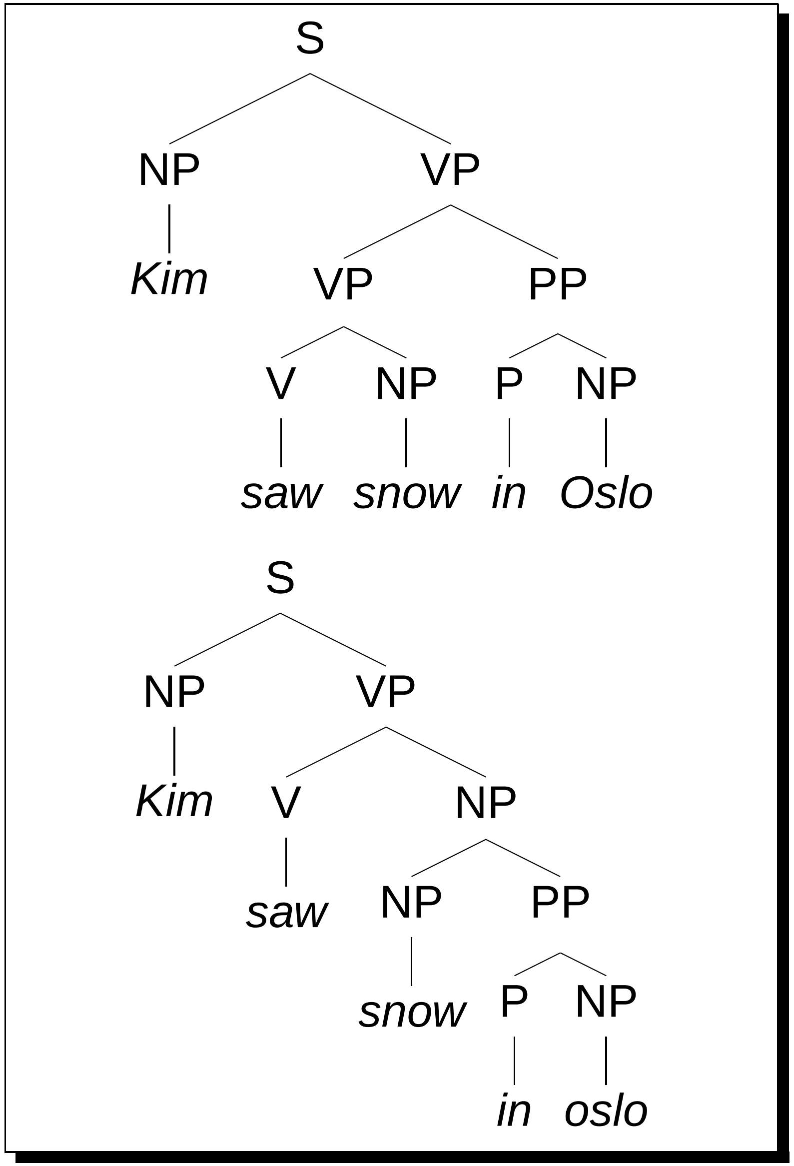
Parsing: Recognizing the Language of a Grammar

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 $\rightarrow$ saw
P $\rightarrow$ in

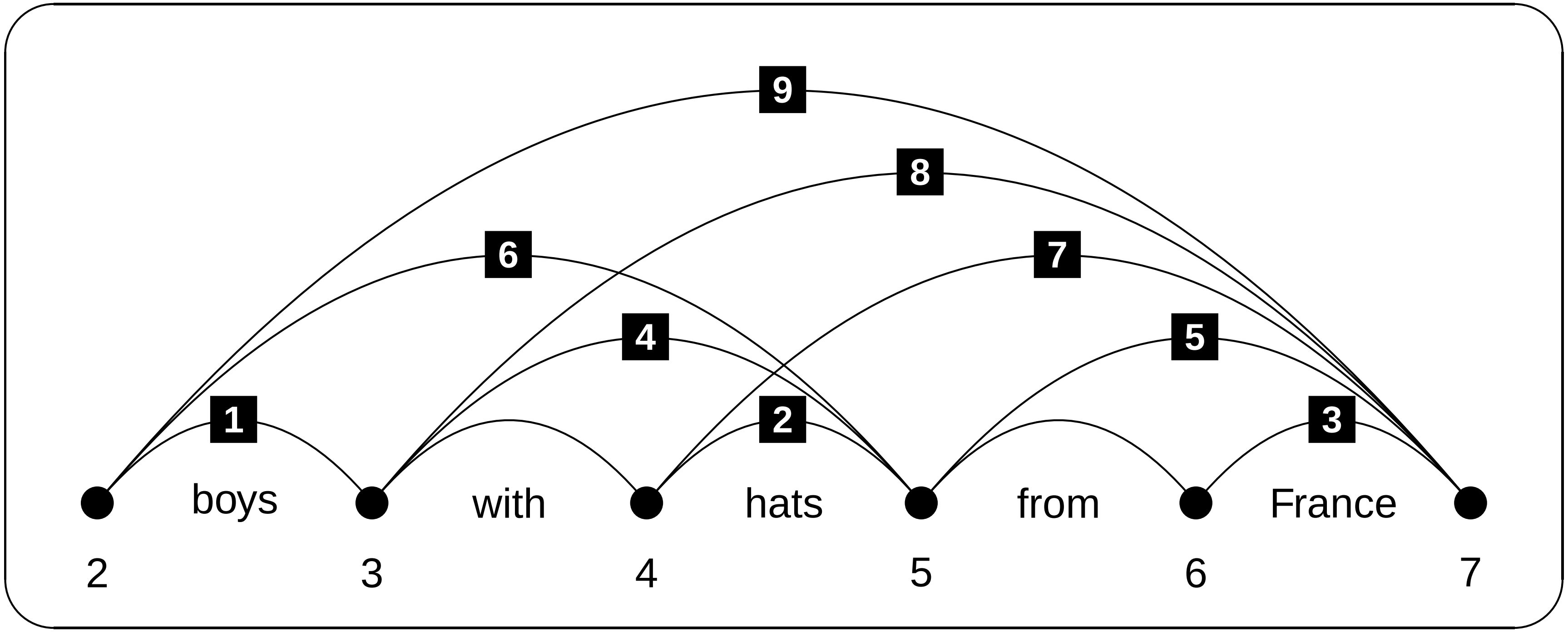
All Complete Derivations

- 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.



Bounding Ambiguity — The Parse Chart

- For many substrings, more than one way of deriving the same category;
- NPs: $\boxed{1}$ | $\boxed{2}$ | $\boxed{3}$ | $\boxed{6}$ | $\boxed{7}$ | $\boxed{9}$; PPs: $\boxed{4}$ | $\boxed{5}$ | $\boxed{8}$; $\boxed{9} \equiv \boxed{1} + \boxed{8} \mid \boxed{6} + \boxed{5}$;
- *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
        $\mathit{chart}_{[i,i+l+1]} \leftarrow \mathit{chart}_{[i,i+l+1]} \cup \{\alpha\}$;

$$[0,2] \leftarrow [0,1] + [1,2]$$
$$\ldots$$
$$[0,5] \leftarrow [0,1] + [1,5]$$
$$[0,5] \leftarrow [0,2] + [2,5]$$
$$[0,5] \leftarrow [0,3] + [3,5]$$
$$[0,5] \leftarrow [0,4] + [4,5]$$

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

Limitations of the CKY Algorithm

Built-In Assumptions

- *Chomsky Normal Form* grammars: $\alpha \rightarrow \beta_1\beta_2$ or $\alpha \rightarrow \gamma$ ($\beta_i \in C$, $\gamma \in \Sigma$);
- breadth-first (aka exhaustive): always compute all values for each cell;
- rigid control structure: bottom-up, left-to-right (one diagonal at a time).

Generalized Chart Parsing

- Liberate order of computation: no assumptions about earlier results;
- *active edges* encode partial rule instantiations, 'waiting' for additional (adjacent and passive) constituents to complete: $[1, 2, \text{VP} \rightarrow \text{V} \bullet \text{NP}]$;
- parser can fill in chart cells in *any* order and guarantee completeness.

Backpointers: Recording the Derivation History

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

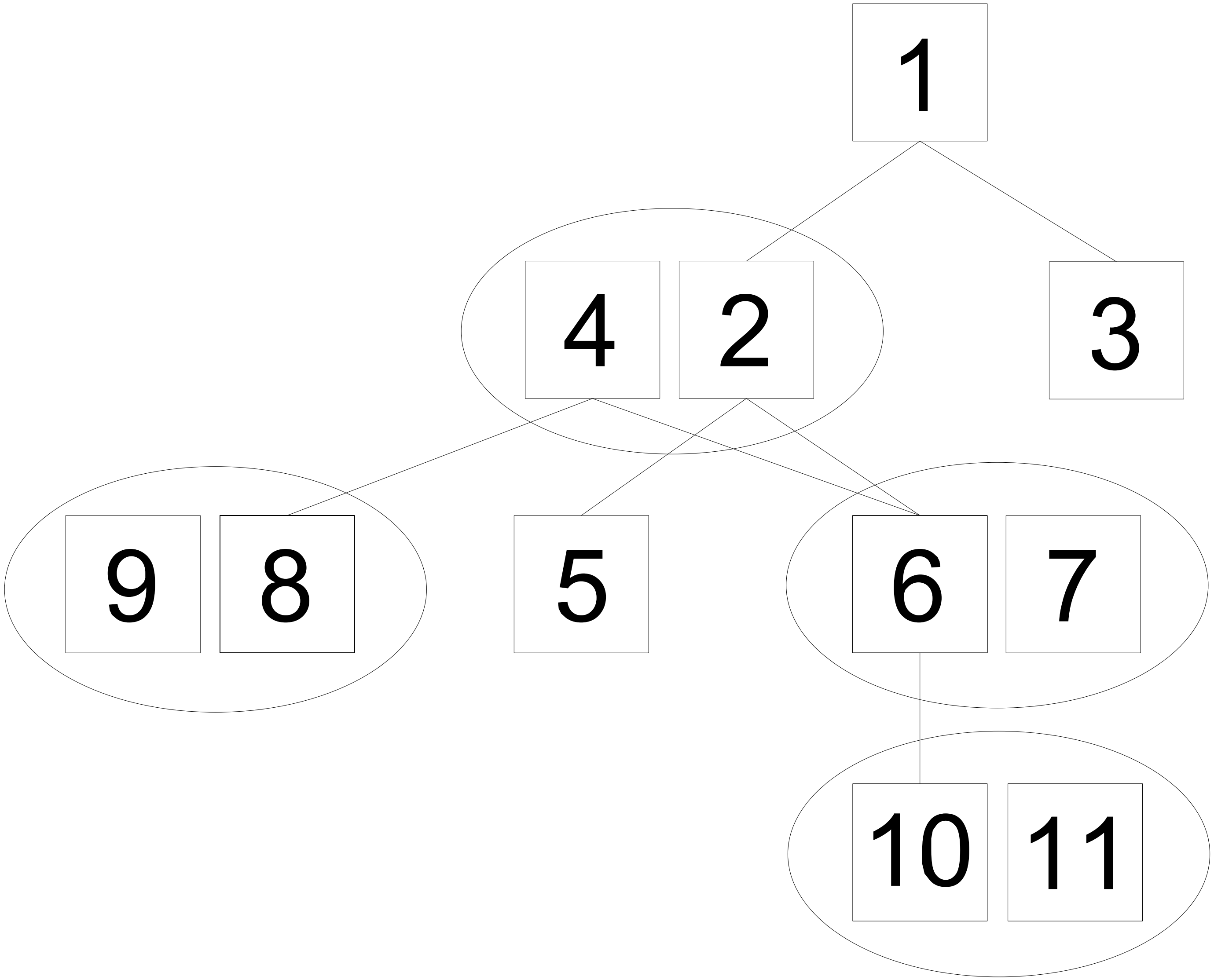
- Maintain only one edge for each α from i to j (the 'representative');
- record alternate sequences of daughters for α in the representative.

Implementation

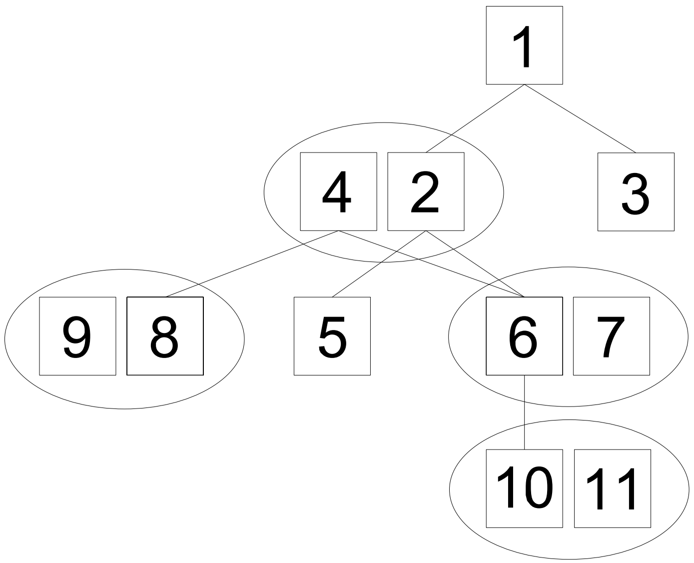
- Group passive edges into *equivalence classes* by identity of α, i, and j;
- search chart for existing equivalent edge (h, say) for each new edge e;
- when h (the 'host' edge) exists, *pack* e into h to record equivalence;
- e *not* added to the chart, no derivations with or further processing of e;

$\rightarrow$ *unpacking* multiply out all alternative daughters for all result edges.

An Example (Hypothetical) Parse Forest



Unpacking: Cross-Multiplying Local Ambiguity



$$\boxed{1} \longrightarrow \langle \boxed{2}\,\boxed{3} \rangle \mid \langle \boxed{4}\,\boxed{3} \rangle$$
$$\boxed{2} \longrightarrow \langle \boxed{5}\,\boxed{6} \rangle \mid \langle \boxed{5}\,\boxed{7} \rangle$$
$$\boxed{4} \longrightarrow \langle \boxed{8}\,\boxed{6} \rangle \mid \langle \boxed{8}\,\boxed{7} \rangle \mid \langle \boxed{9}\,\boxed{6} \rangle \mid \langle \boxed{9}\,\boxed{7} \rangle$$
$$\boxed{6} \longrightarrow \langle \boxed{10} \rangle \mid \langle \boxed{11} \rangle$$

How many complete trees in total?

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.

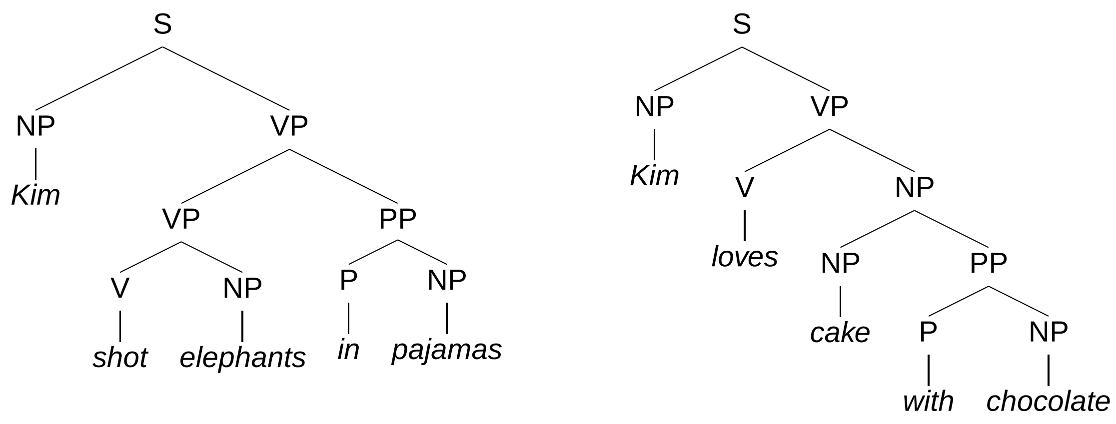
Typical Approaches

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

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

Probabilistic Context-Free Grammars

A (Simplified) PCFG Estimation Example



P(RHS|LHS)	CFG Rule
	S $\longrightarrow$ NP VP
	VP $\longrightarrow$ VP PP
	VP $\longrightarrow$ V NP
	PP $\longrightarrow$ P NP
	NP $\longrightarrow$ NP PP
	VP $\longrightarrow$ V

- Estimate rule probability from observed distribution;

$\longrightarrow$ conditional probabilities:

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

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(RHS|LHS), e.g.

...

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

...

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

...

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

Background: The Penn Treebank (PTB)

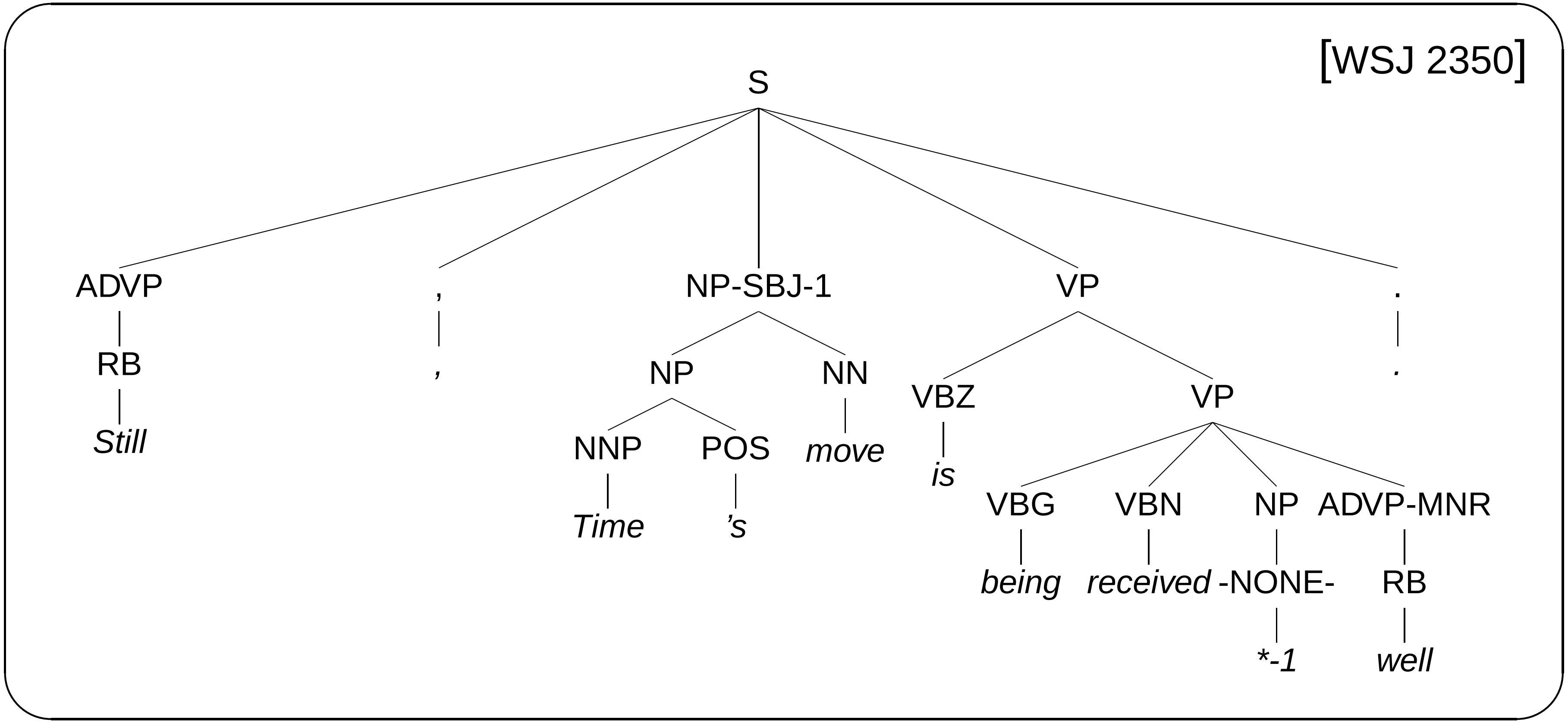
Quite Generally

- A *treebank* is a corpus paired with ‘gold-standard’ (syntactic) analyses;
- used for training and evaluation of NLP tasks, e.g. statistical parsing;
- variation in annotation types, e.g. phrase structure vs. dependencies;
- manual annotation vs. selection among parser outputs (plus correction).

Penn Treebank (Marcus et al., 1993)

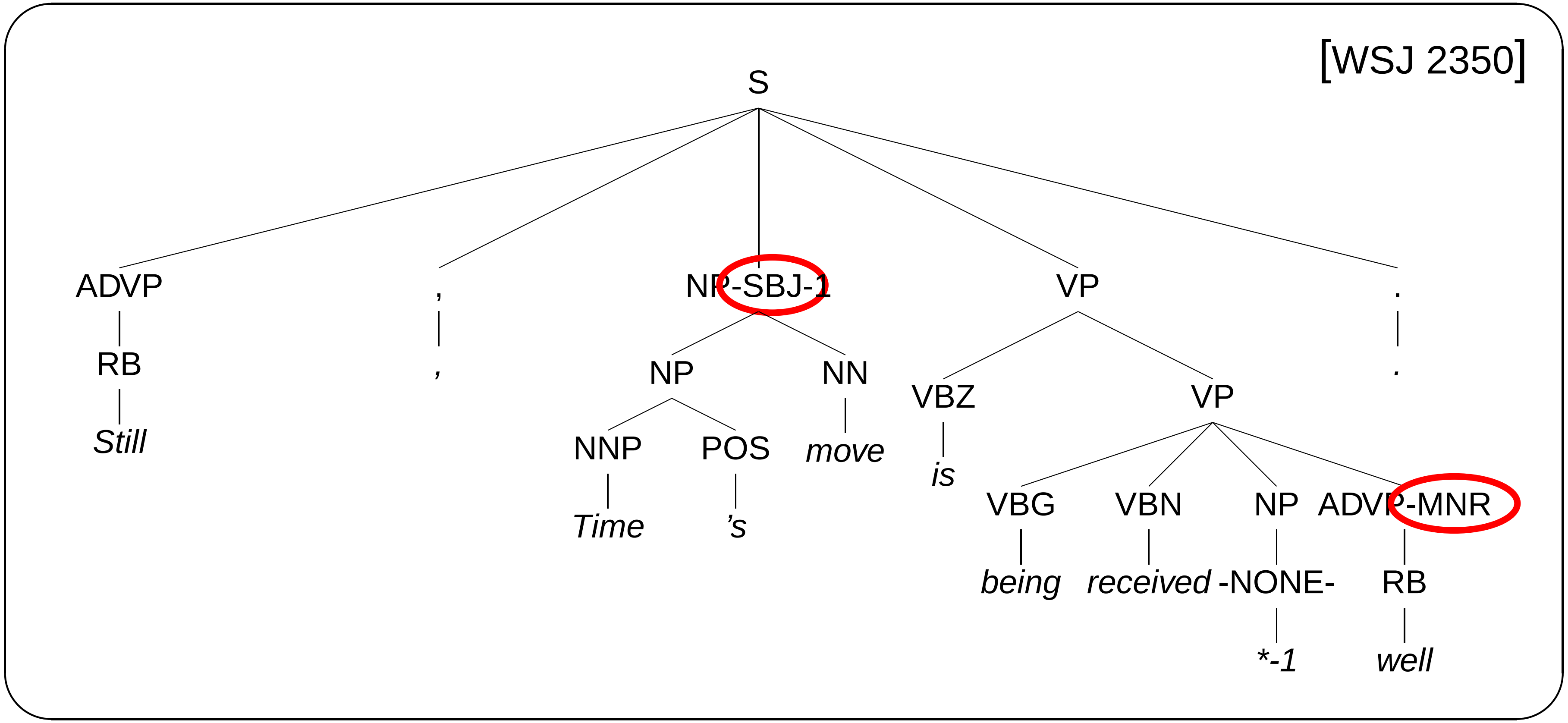
- About one million tokens of Wall Street Journal text (from late 1990s);
- hand-corrected PoS annotation using 45 word classes (the PTB tag set);
- manual syntactic annotation with (somewhat) coarse phrase structure.

One Example from the Penn Treebank



Still, Time's move is being received well.

One Example from the Penn Treebank



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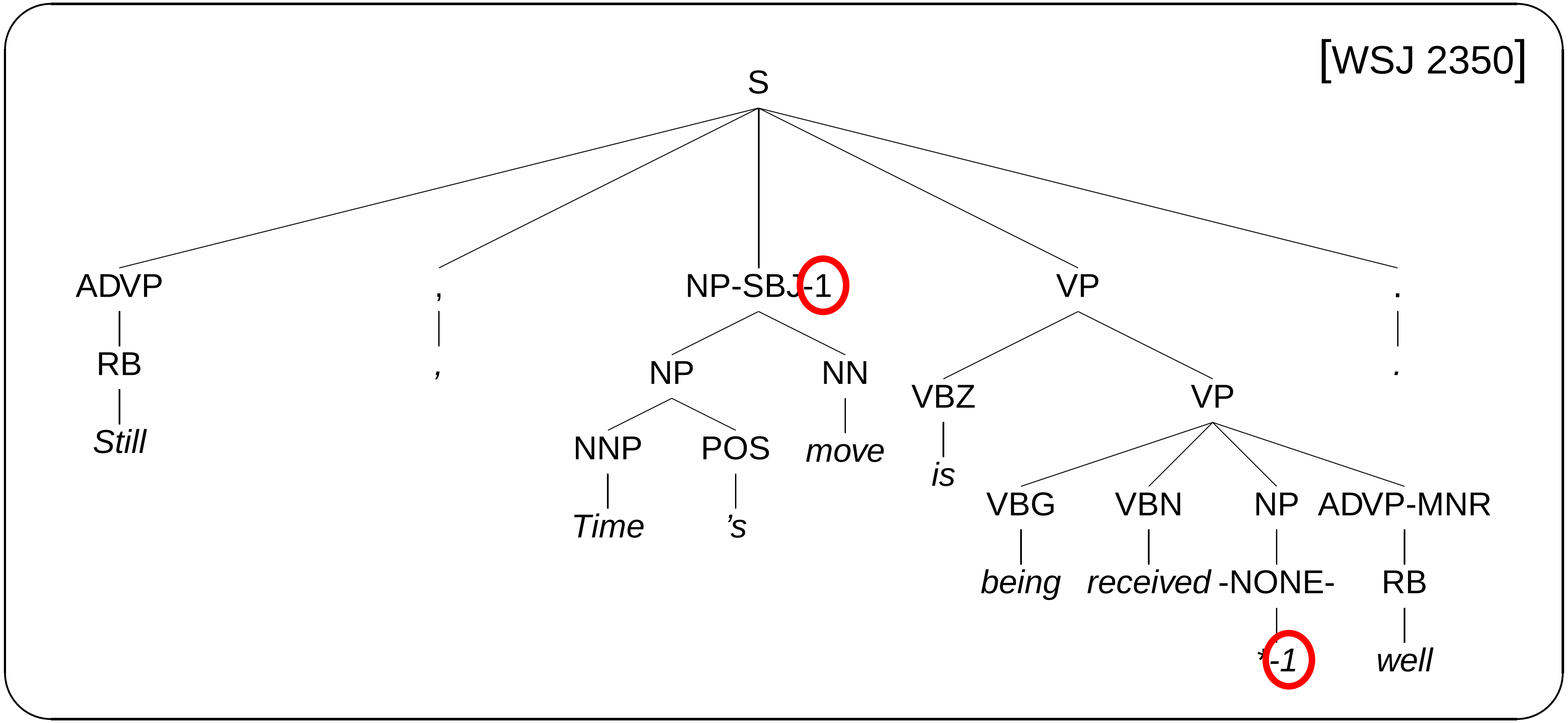
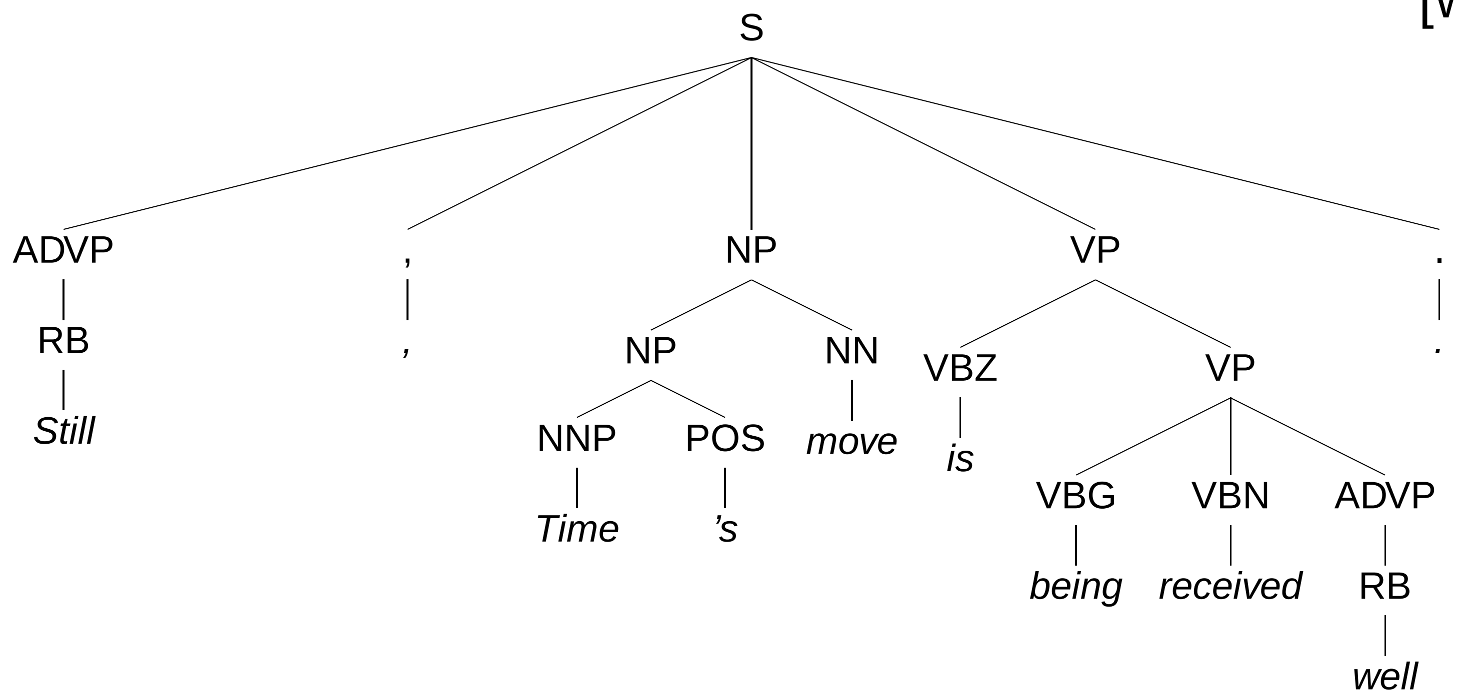
One Example from the Penn Treebank



Still, Time's move is being received well.

(Standard) Elimination of Traces and Functions

[WSJ 2350]



Still, Time's move is being received well.

How to Evaluate (Syntactic) Parsing Accuracy?

ParsEval — Constituent Overlap (Black, et al., 1991)

- Break up tree into bracketing plus labelling, for example:

$$\langle 0, 1, \text{ADVP} \rangle\ \langle 2, 5, \text{NP} \rangle\ \langle 5, 9, \text{VP} \rangle\ \langle 6, 9, \text{VP} \rangle\ \langle 0, 10, \text{S} \rangle$$

- quantify precision (P) and recall (R) of labelled bracketings, when contrasting the gold-standard tree vs. the actual parser output:

$$P = \frac{C(\textit{correct})}{C(\textit{parse})}; \quad R = \frac{C(\textit{correct})}{C(\textit{gold})};$$

- F Score, as the harmonic mean of precision and recall: $F_1 = \frac{2PR}{P+R}$;

$\rightarrow$ combined with crossing brackets, dominant metric in PTB parsing.