Context-Free Parsing: CKY & Earley Algorithms and Probabilistic Parsing

Natural Language Processing
CS 4120/6120—Spring 2017
Northeastern University

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with some slides
from Jason Eisner & Andrew McCallum

From Shift-Reduce to CKY

- Shift-reduce parsing can make wrong turns, needs backtracking
- Shift-reduce must pop the top of the stack, but how many items to pop?
- Time-space tradeoff
- Chomsky normal form

Chomsky Normal Form

- Any CFL can be generated by an equivalent grammar in CNF
- Rules of three types
  - $X \rightarrow Y\ Z$ X, Y, Z nonterminals
  - $X \rightarrow a$ X nonterminal, a terminal
  - $S \rightarrow \varepsilon$ S the start symbol
- NB: the derivation of a given string may change

CNF Conversion

- Create new start symbol
- Remove NTs that can generate epsilon
- Remove NTs that can generate each other, (unary rule cycles)
- Chain rules with RHS > 2
- Related topic: rule Markovization (later)

CKY Algorithm

- Input: string of n words
- Output (of recognizer): grammatical or not
- Dynamic programming in a **chart**:
  - rows labeled 0 to n-1
  - columns labeled 1 to n
  - cell [i,j] lists possible constituents spanning words between i and j

CKY Algorithm

- for i := 1 to n
  - Add to [i-1,i] all (part-of-speech) categories for the i^{th} word
- for width := 2 to n
  - for start := 0 to n-width
    - Define end := start + width
    - for mid := start+1 to end-1
    - for every constituent X in [start,mid]
    - for every constituent Y in [mid,end]
    - for all ways of combining X and Y (if any)
    - Add the resulting constituent to [start,end] ~~if it's not already there.~~

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Time complexity?

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Time complexity? $O(Gn^3)$

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Time complexity? $O(Gn^3)$

Space complexity?

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Time complexity? $O(Gn^3)$

Space complexity? $O(Tn^2)$

	time **1**	flies **2**	like **3**	an **4**	arrow **5**
0	**NP 3** **Vst 3**				
1		**NP 4** **VP 4**			
2			**P 2** **V 5**		
3				**Det 1**	
4					**N 8**

NP → time
Vst → time
NP → flies
VP → flies
P → like
V → like
Det → an
N → arrow

1 S → NP VP
6 S → Vst NP
2 S → S PP

1 VP → V NP
2 VP → VP PP

1 NP → Det N
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time	1	flies	2	like	3	an	4	arrow	5
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	time 1	flies 2	like 3	an 4	arrow 5
0	NP 3 Vst 3	NP 10			
1		NP 4 VP 4			
2			P 2 V 5		
3				Det 1	
4					N 8

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	time 1	flies 2	like 3	an 4	arrow 5
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1		**NP 4** **VP 4**	–	–	
2			**P 2** **V 5**	–	**PP 12**
3				**Det 1**	**NP 10**
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time	1 flies	2 like	3 an	4 arrow	5
0	NP 3 Vst 3	NP 10 S 8 S 13	–		
1		NP 4 VP 4	–	–	
2			P 2 V 5	–	PP 12 VP 16
3				Det 1	NP 10
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1		NP 4 VP 4	–	–	NP 18
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	time 1	flies 2	like 3	an 4	arrow 5
0	NP 3 Vst 3	NP 10 S 8 S 13	–	–	NP 24
1		NP 4 VP 4	–	–	NP 18 S 21 VP 18
2			P 2 V 5	–	PP 12 VP 16
3				Det 1	NP 10
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	time 1	flies 2	like 3	an 4	arrow 5
0	NP 3 Vst 3	NP 10 S 8 S 13	–	–	NP 24 S 22
1		NP 4 VP 4	–	–	NP 18 S 21 VP 18
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Follow backpointers …

S

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1		**NP 4** **VP 4**	–	–	**NP 18** **S 21** **VP 18**
2			**P 2** **V 5**	–	**PP 12** **VP 16**
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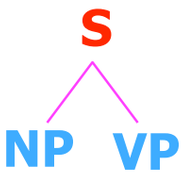

time 1 flies 2 like 3 an 4 arrow 5

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1		NP 4 VP 4	–	–	NP 18 S 21 VP 18
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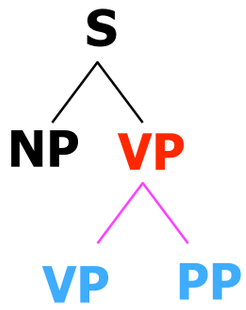

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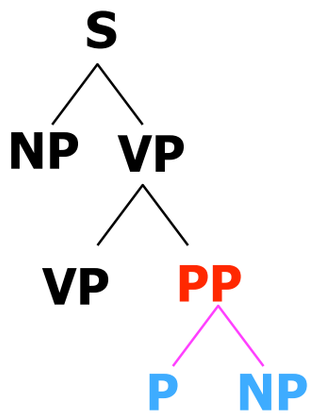

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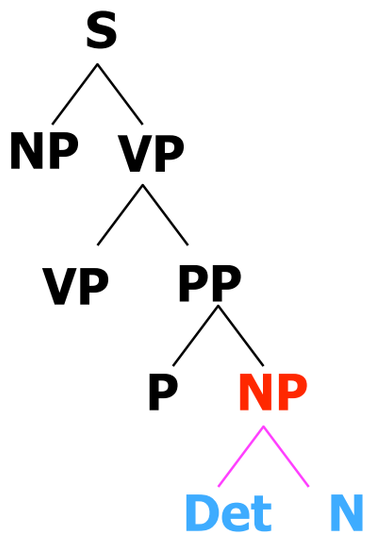

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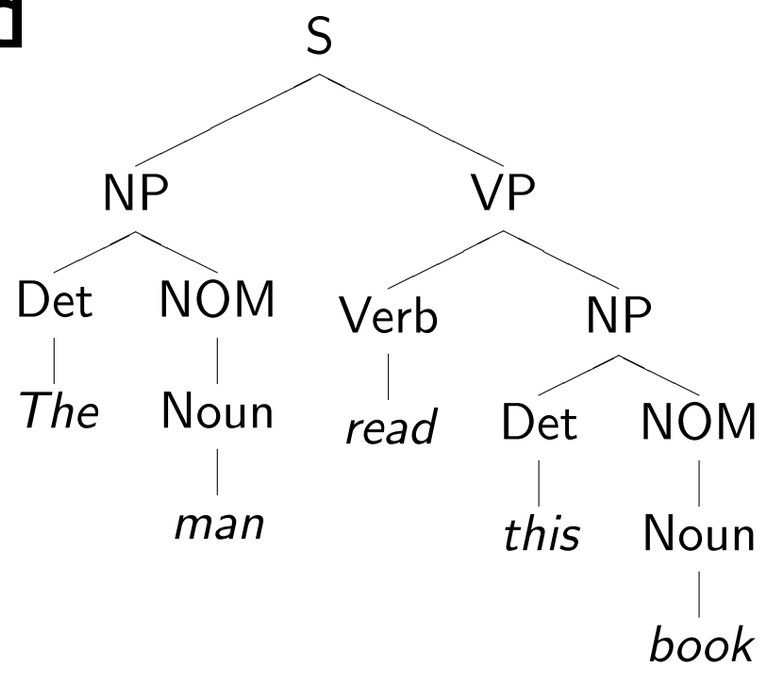
Treebank Grammars

- What rules would you extract from this tree?
- What probabilities would you assign them?



Treebank Grammars

- Penn Treebank
- Lots of rules have high fanout (flat phrases)
- Lots of unary cycles
- How should we evaluate?
- What are the consequences of CNF conversion?

Parsing as Deduction

- CKY as inference rules
- CKY as Prolog program
  - But Prolog is top-down with backtracking
    - i.e., "backward chaining", CKY is "forward chaining"
  - Inference rules as Boolean semiring

Probabilistic CFGs

- Generative process (already familiar)
- It's context free: Rules are applied independently, therefore we multiply their probabilities
- How to estimate probabilities?
  - Supervised and unsupervised

Questions for PCFGs

- What is the most likely parse for a sentence? (parsing)
- What is the probability of a sentence? (language modeling)
- What rule probabilities maximize the probability of a sentence? (parameter estimation)

Algorithms for PCFGs

- Exact analogues to HMM algorithms
- Parsing: Viterbi CKY
- Language modeling: inside probabilities
- Parameter estimation: inside-outside probabilities with EM

Parsing as Deduction

$$\forall A, B, C \in N, W \in V, 0 \leq i, j, k \leq m$$

$$constit(B, i, j) \wedge constit(C, j, k) \wedge A \rightarrow BC \Rightarrow constit(A, i, k)$$

$$word(W, i) \wedge A \rightarrow W \Rightarrow constit(A, i, i + 1)$$

In Prolog:

```
constit(A, I1, I) :-
  word(I, W),
  (A ---> [W]),
  I1 is I - 1.
```

```
constit(A, I, K) :-
  constit(B, I, J),
  constit(C, J, K),
  (A ---> [B, C]).
```

But Prolog uses top-down search with backtracking...

Parsing as Deduction

$$\forall A, B, C \in N, W \in V, 0 \leq i, j, k \leq m$$

$$constit(B, i, j) \wedge constit(C, j, k) \wedge A \rightarrow BC \Rightarrow constit(A, i, k)$$

$$word(W, i) \wedge A \rightarrow W \Rightarrow constit(A, i, i+1)$$

$$constit(A, i, k) = \bigvee_{B,C,j} constit(B, i, j) \wedge constit(C, j, k) \wedge A \rightarrow B\ C$$

$$constit(A, i, j) = \bigvee_{W} word(W, i, j) \wedge A \rightarrow W$$

Parsing as Deduction

$$constit(A, i, k) = \bigvee_{B,C,j} constit(B, i, j) \wedge constit(C, j, k) \wedge A \rightarrow B\ C$$

$$constit(A, i, j) = \bigvee_{W} word(W, i, j) \wedge A \rightarrow W$$

$$score(constit(A, i, k)) = \max_{B,C,j} score(constit(B, i, j)) \cdot score(constit(C, j, k)) \cdot score(A \rightarrow B\ C)$$

$$score(constit(A, i, j)) = \max_{W} score(word(W, i, j)) \cdot score(A \rightarrow W)$$

And how about the inside algorithm?

Inside & Viterbi Algorithms

Let $\beta_A(i,j) = p(constit(A,i,j))$

$= p(w_{ij} \mid \text{nonterminal A from i to j})$

NB: index *between* words; M&S index words

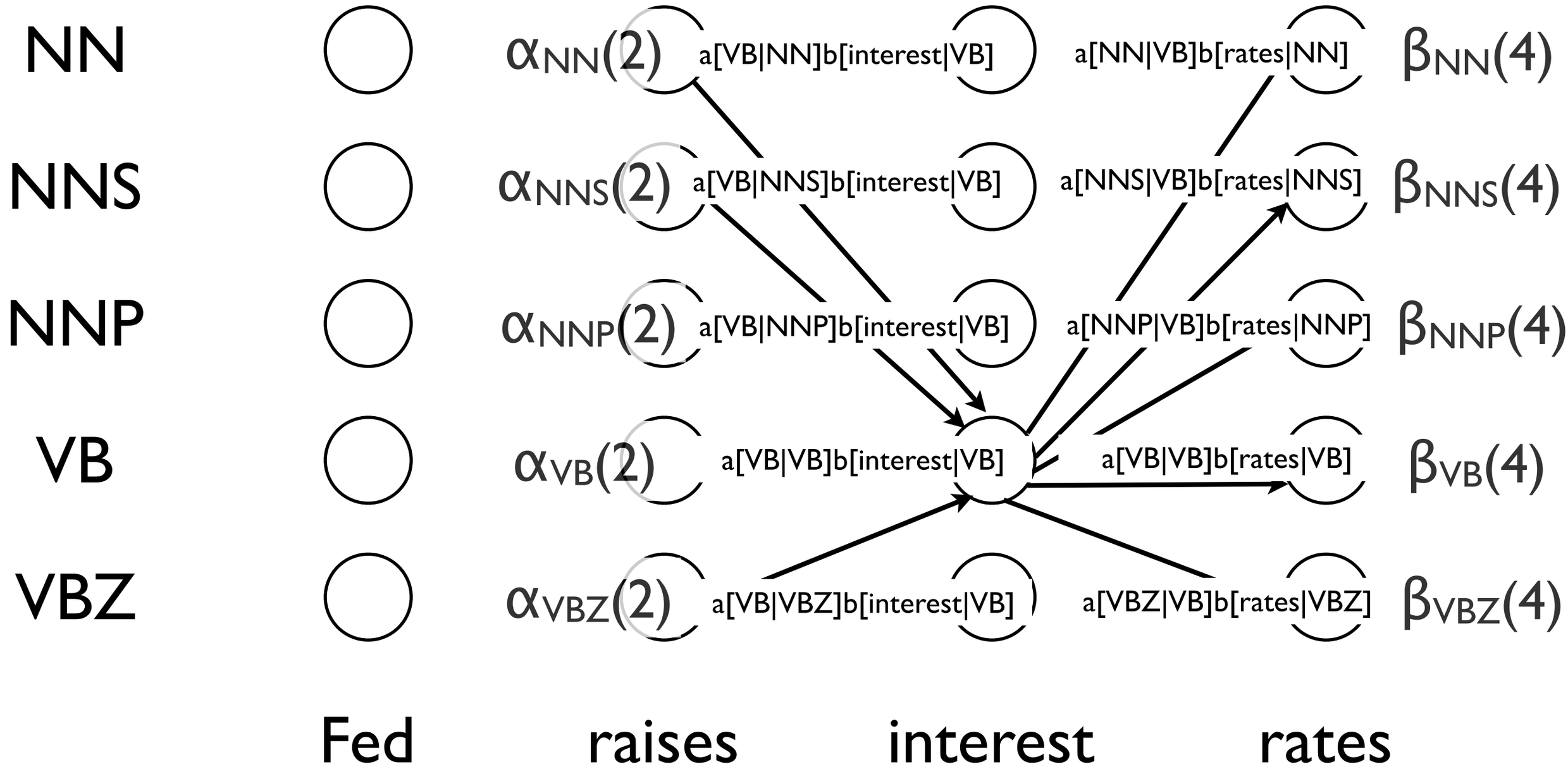
$$\beta_A(i,k) = \sum_{B,C,j} \beta_B(i,j) \cdot \beta_C(j,k) \cdot p(A \rightarrow B\ C)$$

Let $\delta_A(i,j) = p_{best}(constit(A,i,j))$

$$\delta_A(i,k) = \max_{B,C,j} \delta_B(i,j)) \cdot \delta_C(j,k) \cdot p(A \rightarrow B\ C)$$

$\beta_S(0,n) = ?$ $\qquad$ $\delta_S(0,n) = ?$

Forward-Backward Algorithm



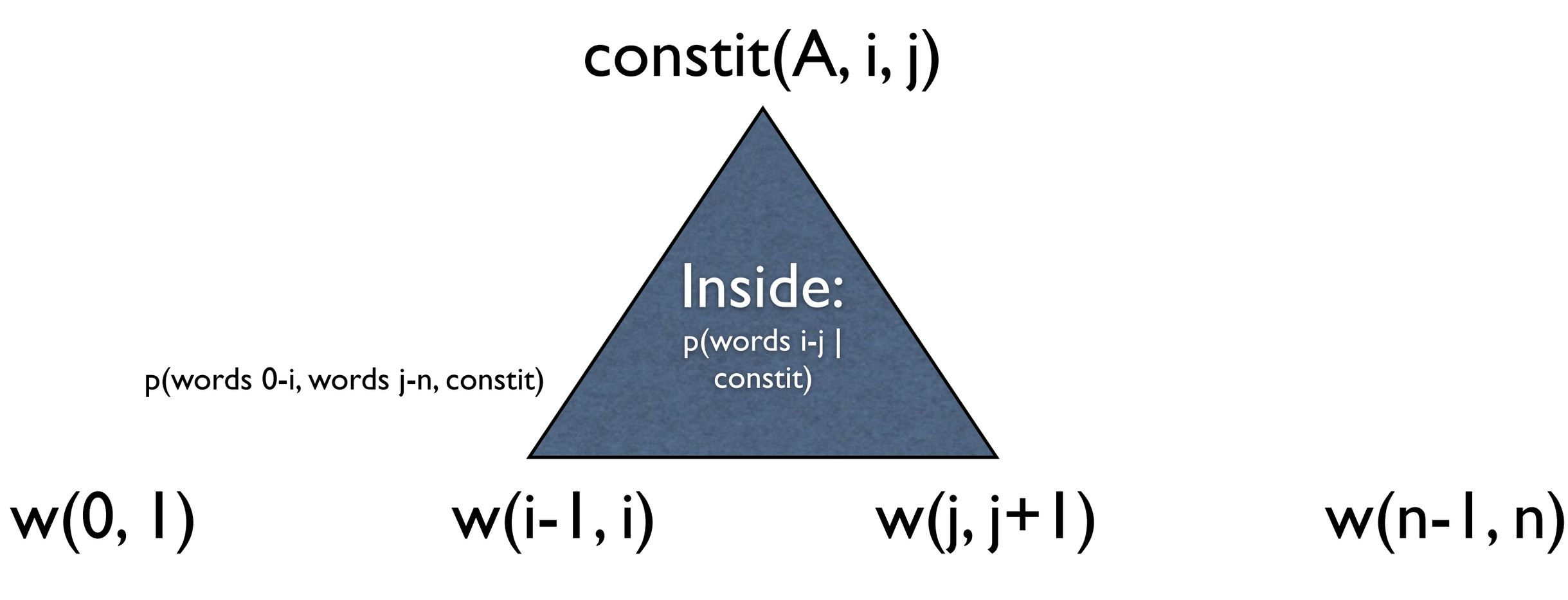
Inside & Outside

constit(A, i, j)

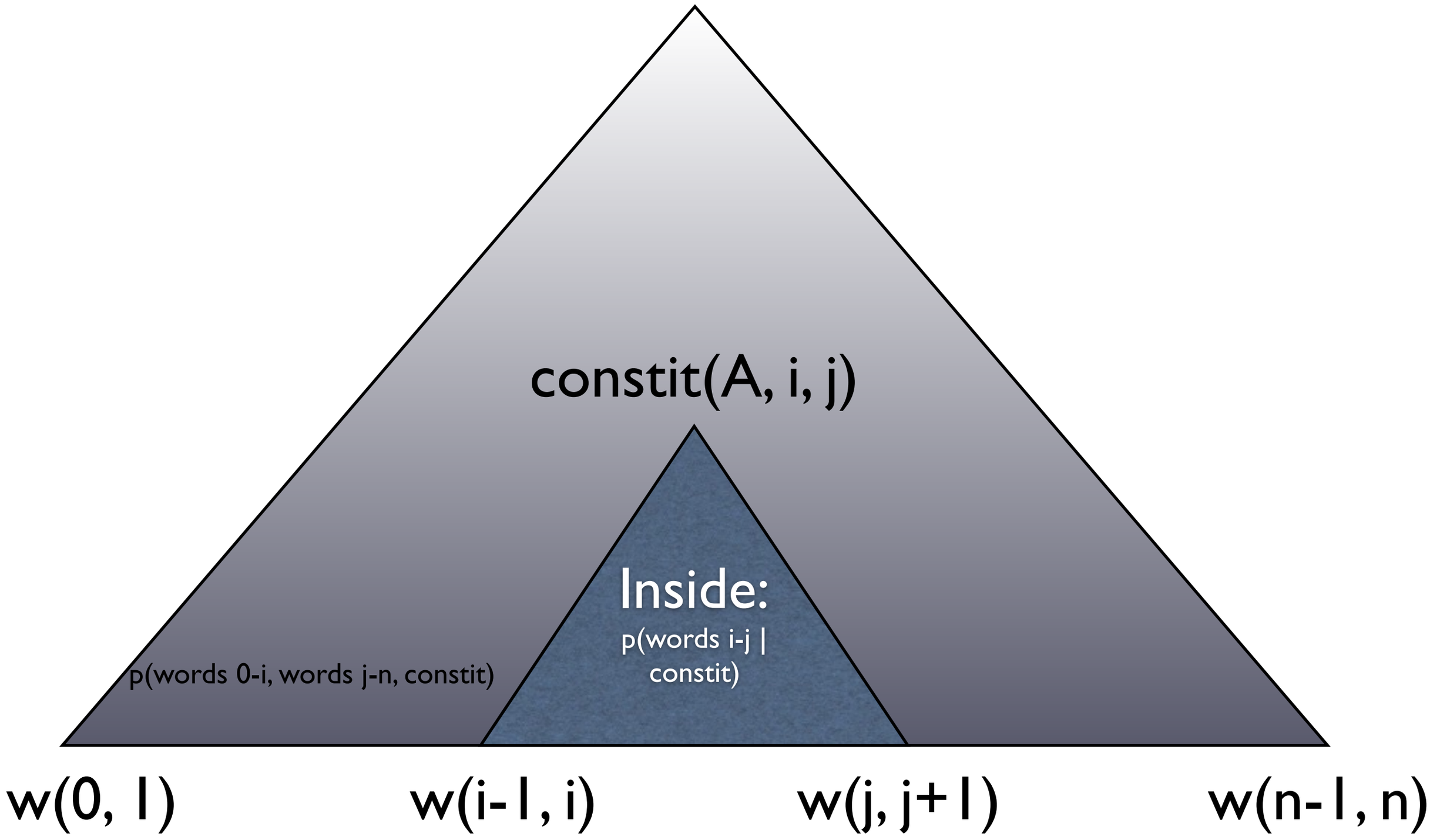
p(words 0-i, words j-n, constit)

w(0, 1) w(i-1, i) w(j, j+1) w(n-1, n)

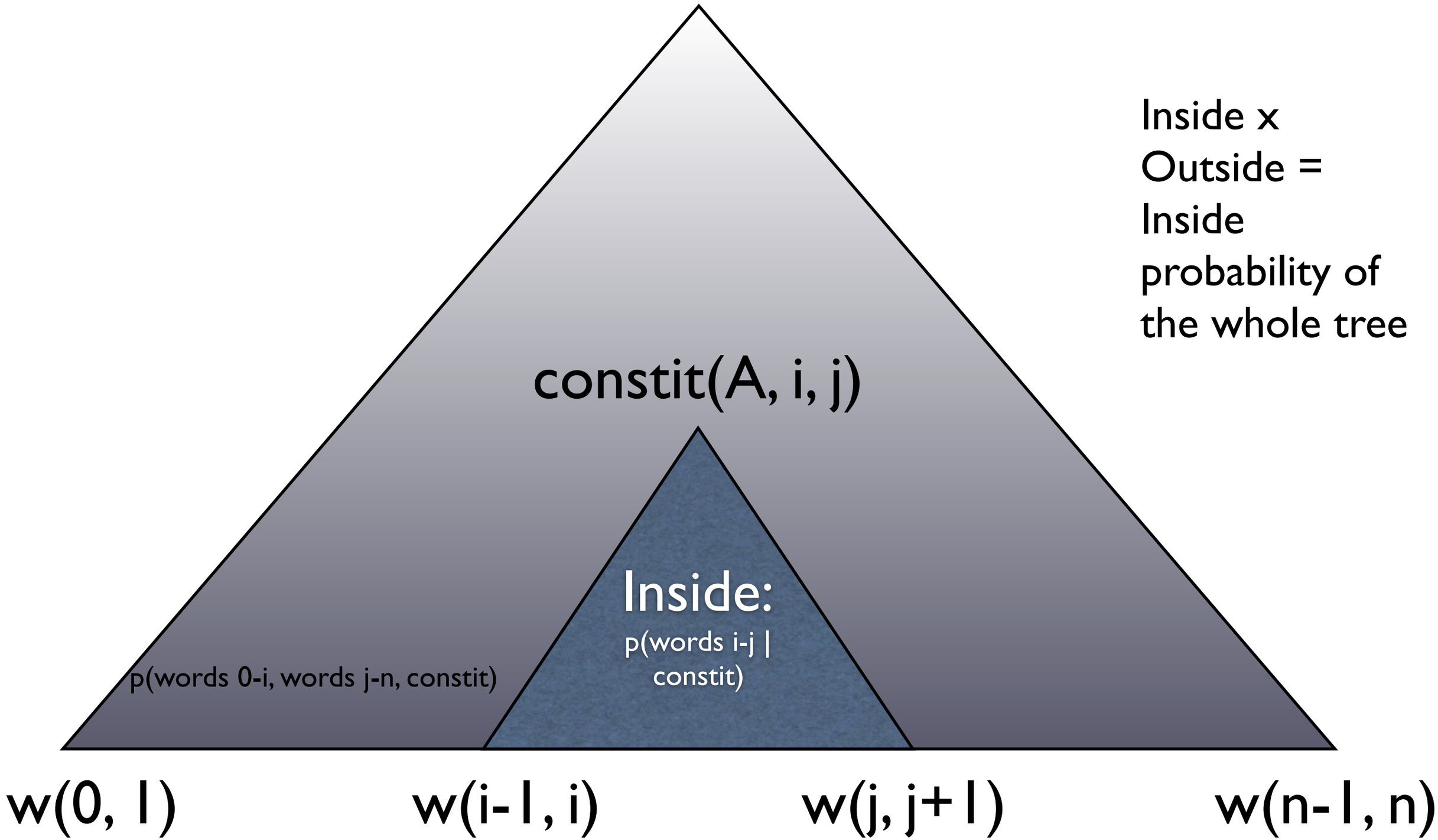
Inside & Outside



Inside & Outside



Inside & Outside



Inside x Outside = Inside probability of the whole tree

Outside Algorithm

$$\alpha_A(i,j) = p(w_{0,i}, A_{i,j}, w_{j,n})$$

Uses inside probs.

$$\alpha_A(i,j) = \sum_{B,C,k=j}^{n} \alpha_B(i,k) \cdot \beta_C(j,k) \cdot p(B \rightarrow A\ C)$$

$$+ \sum_{B,C,k=0}^{i} \alpha_B(k,j) \cdot \beta_C(k,i) \cdot p(B \rightarrow C\ A)$$

$$\alpha_S(0,n) = ?$$

$$\alpha_{PP}(0,n) = ?$$

Some resemblance to derivative product rule

Problems with Inside-Outside EM

- Each sentence at each iteration takes $O(m^3n^3)$
- Local maxima even more problematic than for HMMs: Charniak (1993) found a different maximum for each of 300 trials
- More NTs needed to learn a good model
- NTs don't correspond to intuitions: HMMs are easier to constrain with tag dictionaries

Top-Down/Bottom-Up

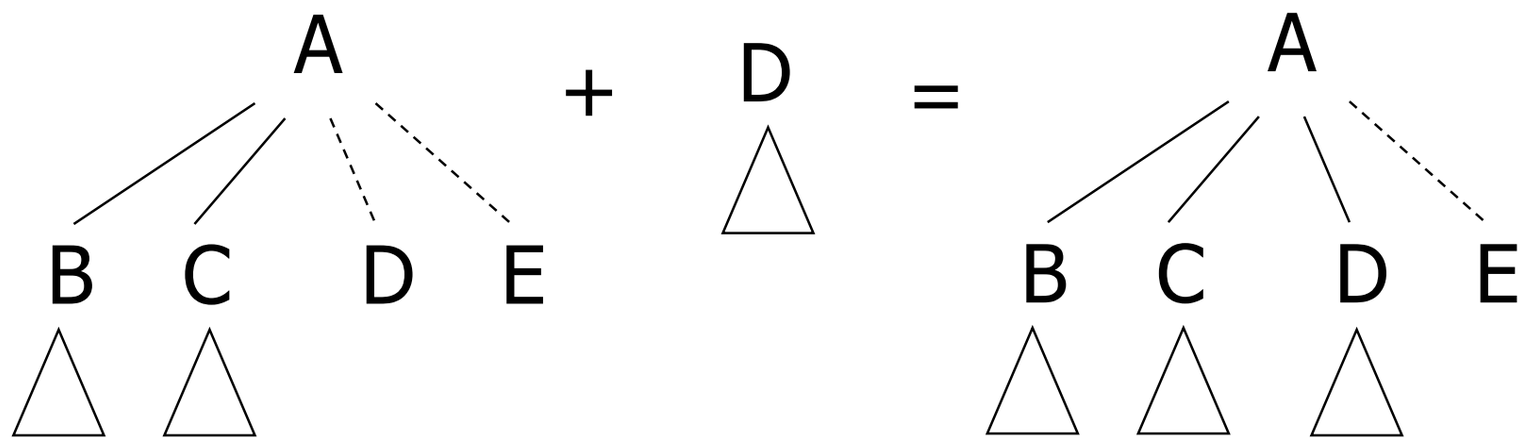
- Top-down parsers
  - Can get caught in infinite loops
  - Take exponential time backtracking
- CKY
  - Needs Chomsky normal form
  - Builds all possible constituents

Earley Parser (1970)

- Nice combination of
  - dynamic programming
  - incremental interpretation
  - avoids infinite loops
  - no restrictions on the form of the context-free grammar.
    A → B C the D of causes no problems
  - $O(n^3)$ worst case, but faster for many grammars
  - Uses left context and optionally right context to constrain search.

Earley's Overview

- Finds constituents and partial constituents in input
  - A → B C . D E is partial: only the first half of the A



Earley's Overview

- Proceeds incrementally left-to-right
  - Before it reads word 5, it has already built all hypotheses that are consistent with first 4 words
  - Reads word 5 & attaches it to immediately preceding hypotheses. Might yield new constituents that are then attached to hypotheses immediately preceding *them …*
  - E.g., attaching D to A → B C . D E gives A → B C D . E
  - Attaching E to that gives A → B C D E .
  - Now we have a complete A that we can attach to hypotheses immediately preceding the A, etc.

The Parse Table

- Columns 0 through n corresponding to the gaps between words
- Entries in column 5 look like (3, NP → NP . PP)

  (but we'll omit the → etc. to save space)
  - Built while processing word 5
  - Means that the input substring from 3 to 5 matches the initial NP portion of a **NP → NP PP** rule
  - Dot shows how much we've matched as of column 5
  - Perfectly fine to have entries like **(3, VP → is it . true that S)**

The Parse Table

- Entries in column 5 look like (3, NP → NP . PP)
- What will it mean that we have this entry?
  - *Unknown right context: Doesn't* mean we'll necessarily be able to find a VP starting at column 5 to complete the S.
  - *Known left context: Does* mean that some dotted rule back in column 3 is looking for an S that starts at 3.
    - So if we actually do find a VP starting at column 5, allowing us to complete the S, then we'll be able to attach the S to something.
    - And when that something is complete, it too will have a customer to *its* left …
    - In short, a top-down (i.e., goal-directed) parser: it chooses to start building a constituent not because of the input but because that's what the left context needs. In **the spoon**, won't build **spoon** as a verb because there's no way to use a verb there.
    - So any hypothesis in column 5 *could* get used in the correct parse, if words 1-5 are continued in just the right way by words 6-n.

Earley's as a Recognizer

- Add **ROOT → . S** to column 0.
- For each j from 0 to n:
  - For each dotted rule in column j, (including those we add as we go!) look at what's after the dot:
    - If it's a word w, SCAN:
      - If w matches the input word between j and j+1, advance the dot and add the resulting rule to column j+1
    - If it's a non-terminal X, PREDICT:
      - Add all rules for X to the bottom of column j, wth the dot at the start: e.g. **X → . Y Z**
    - If there's nothing after the dot, ATTACH:
      - We've finished some constituent, A, that started in column I<j. So for each rule in column j that has A after the dot: Advance the dot and add the result to the bottom of column j.
- Output "yes" just if last column has **ROOT → S .**
- **NOTE: Don't add an entry to a column if it's already there!**

Earley's Summary

- Process all hypotheses one at a time in order. (Current hypothesis is shown in blue.)
- This may add new hypotheses to the end of the to-do list, or try to add old hypotheses again.

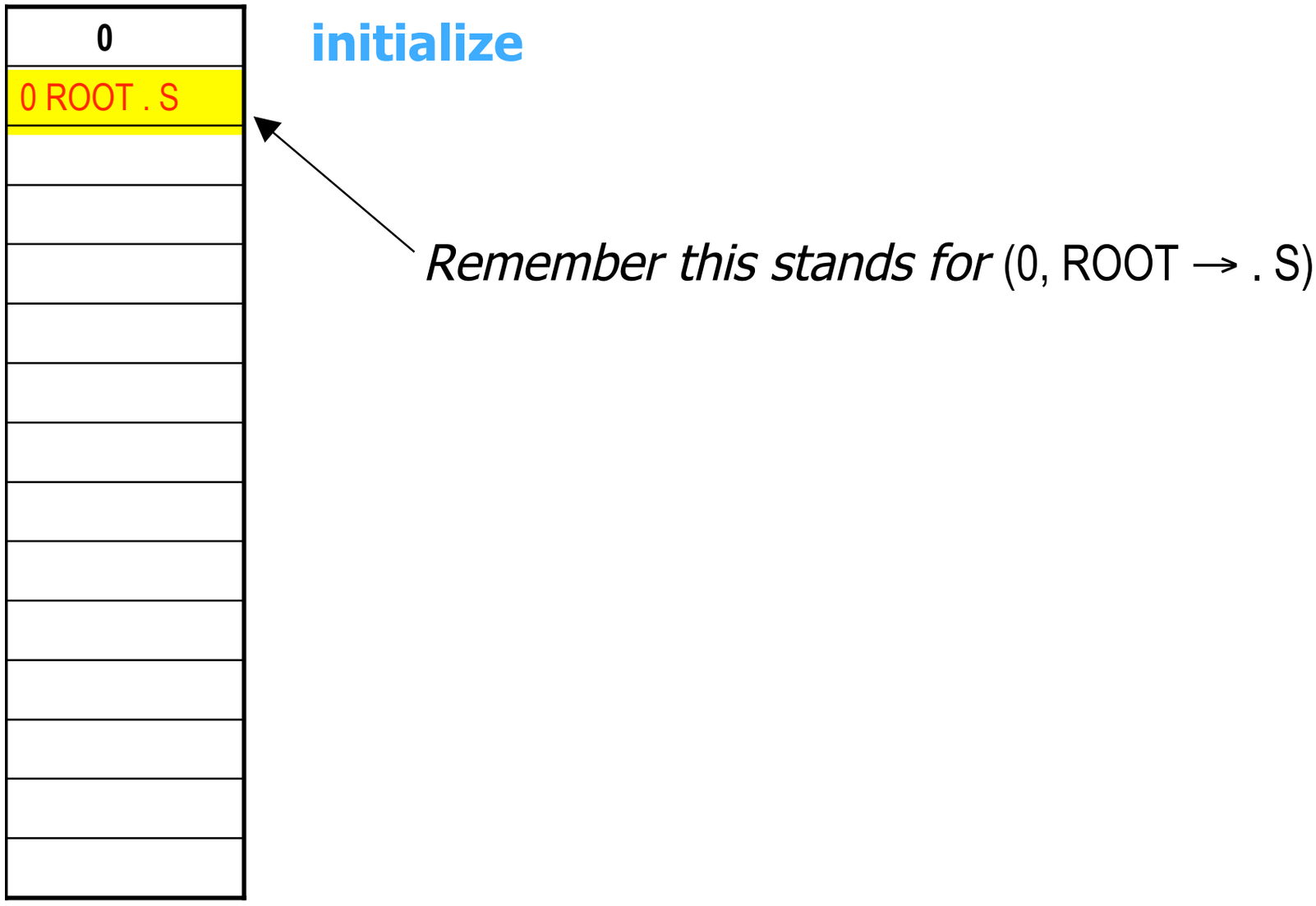
- Process a hypothesis according to what follows the dot:
  - If a word, **scan** input and see if it matches
  - If a nonterminal, **predict** ways to match it
    - (we'll predict blindly, but could reduce # of predictions by *looking ahead* k symbols in the input and only making predictions that are compatible with this limited *right context*)
  - If nothing, then we have a complete constituent, so **attach** it to all its customers

A (Whimsical) Grammar

S	→ NP VP	NP	→ Papa
NP	→ Det N	N	→ caviar
NP	→ NP PP	N	→ spoon
VP	→ V NP	V	→ ate
VP	→ VP PP	P	→ with
PP	→ P NP	Det	→ the
		Det	→ a

An Input Sentence

Papa ate the caviar with a spoon.


0
0 ROOT . S
initialize
Remember this stands for (0, ROOT → . S)

predict the kind of S we are looking for

Remember this stands for (0, S → . NP VP)

0
0 ROOT . S
0 S . NP VP
0 NP . Det N
0 NP . NP PP
0 NP . Papa

predict the kind of NP we are looking for
(actually we'll look for 3 kinds: any of the 3 will do)

0
0 ROOT . S
0 S . NP VP
0 NP . Det N
0 NP . NP PP
0 NP . Papa
0 Det . the
0 Det . a

predict the kind of Det we are looking for *(2 kinds)*

0
0 ROOT . S
0 S . NP VP
0 NP . Det N
0 NP . NP PP
0 NP . Papa
0 Det . the
0 Det . a

predict the kind of NP we're looking for

but we were already looking for these so don't add duplicate goals! Note that this happened when we were processing a left-recursive rule.

0 Papa 1	
0 ROOT . S	0 NP Papa .
0 S . NP VP	
0 NP . Det N	
0 NP . NP PP	
0 NP . Papa	
0 Det . the	
0 Det . a	

scan: the desired word is in the input!

0 Papa 1	
0 ROOT . S	0 NP Papa .
0 S . NP VP	
0 NP . Det N	
0 NP . NP PP	
0 NP . Papa	
0 Det . the	
0 Det . a	

scan: failure

0 Papa 1	
0 ROOT . S	0 NP Papa .
0 S . NP VP	
0 NP . Det N	
0 NP . NP PP	
0 NP . Papa	
0 Det . the	
0 Det . a	

scan: failure

0 Papa 1	
0 ROOT . S	0 NP Papa .
0 S . NP VP	0 S NP . VP
0 NP . Det N	0 NP NP . PP
0 NP . NP PP	
0 NP . Papa	
0 Det . the	
0 Det . a	

attach the newly created NP
(which starts at 0) to its customers
(incomplete constituents that *end* at 0
and have NP after the dot)

0 Papa 1	
0 ROOT . S	0 NP Papa .
0 S . NP VP	0 S NP . VP
0 NP . Det N	0 NP NP . PP
0 NP . NP PP	1 VP . V NP
0 NP . Papa	1 VP . VP PP
0 Det . the	
0 Det . a	

predict

0 Papa 1	
0 ROOT . S	0 NP Papa .
0 S . NP VP	0 S NP . VP
0 NP . Det N	0 NP NP . PP
0 NP . NP PP	1 VP . V NP
0 NP . Papa	1 VP . VP PP
0 Det . the	1 PP . P NP
0 Det . a	

predict

0 Papa 1	
0 ROOT . S	0 NP Papa .
0 S . NP VP	0 S NP . VP
0 NP . Det N	0 NP NP . PP
0 NP . NP PP	1 VP . V NP
0 NP . Papa	1 VP . VP PP
0 Det . the	1 PP . P NP
0 Det . a	1 V . ate

predict

0 Papa 1	
0 ROOT . S	0 NP Papa .
0 S . NP VP	0 S NP . VP
0 NP . Det N	0 NP NP . PP
0 NP . NP PP	1 VP . V NP
0 NP . Papa	1 VP . VP PP
0 Det . the	1 PP . P NP
0 Det . a	1 V . ate

predict

0 Papa 1	
0 ROOT . S	0 NP Papa .
0 S . NP VP	0 S NP . VP
0 NP . Det N	0 NP NP . PP
0 NP . NP PP	1 VP . V NP
0 NP . Papa	1 VP . VP PP
0 Det . the	1 PP . P NP
0 Det . a	1 V . ate
	1 P . with

predict

predict

0 Papa 1 ate 2		
0 ROOT . S	0 NP Papa .	1 V ate .
0 S . NP VP	0 S NP . VP	
0 NP . Det N	0 NP NP . PP	
0 NP . NP PP	1 VP . V NP	
0 NP . Papa	1 VP . VP PP	
0 Det . the	1 PP . P NP	
0 Det . a	1 V . ate	
	1 P . with	

scan: success!

0 Papa 1 ate 2		
0 ROOT . S	0 NP Papa .	1 V ate .
0 S . NP VP	0 S NP . VP	
0 NP . Det N	0 NP NP . PP	
0 NP . NP PP	1 VP . V NP	
0 NP . Papa	1 VP . VP PP	
0 Det . the	1 PP . P NP	
0 Det . a	1 V . ate	
	1 P . with	

scan: failure

0 Papa 1 ate 2		
0 ROOT . S	0 NP Papa .	1 V ate .
0 S . NP VP	0 S NP . VP	1 VP V . NP
0 NP . Det N	0 NP NP . PP	
0 NP . NP PP	1 VP . V NP	
0 NP . Papa	1 VP . VP PP	
0 Det . the	1 PP . P NP	
0 Det . a	1 V . ate	
	1 P . with	

attach

0 Papa 1 ate 2		
0 ROOT . S	0 NP Papa .	1 V ate .
0 S . NP VP	0 S NP . VP	1 VP V . NP
0 NP . Det N	0 NP NP . PP	2 NP . Det N
0 NP . NP PP	1 VP . V NP	2 NP . NP PP
0 NP . Papa	1 VP . VP PP	2 NP . Papa
0 Det . the	1 PP . P NP	
0 Det . a	1 V . ate	
	1 P . with	

predict

0 Papa 1 ate 2		
0 ROOT . S	0 NP Papa .	1 V ate .
0 S . NP VP	0 S NP . VP	1 VP V . NP
0 NP . Det N	0 NP NP . PP	2 NP . Det N
0 NP . NP PP	1 VP . V NP	2 NP . NP PP
0 NP . Papa	1 VP . VP PP	2 NP . Papa
0 Det . the	1 PP . P NP	2 Det . the
0 Det . a	1 V . ate	2 Det . a
	1 P . with	

predict *(these next few steps should look familiar)*

0 Papa 1 ate 2		
0 ROOT . S	0 NP Papa .	1 V ate .
0 S . NP VP	0 S NP . VP	1 VP V . NP
0 NP . Det N	0 NP NP . PP	2 NP . Det N
0 NP . NP PP	1 VP . V NP	2 NP . NP PP
0 NP . Papa	1 VP . VP PP	2 NP . Papa
0 Det . the	1 PP . P NP	2 Det . the
0 Det . a	1 V . ate	2 Det . a
	1 P . with	

predict

0 Papa 1 ate 2		
0 ROOT . S	0 NP Papa .	1 V ate .
0 S . NP VP	0 S NP . VP	1 VP V . NP
0 NP . Det N	0 NP NP . PP	2 NP . Det N
0 NP . NP PP	1 VP . V NP	2 NP . NP PP
0 NP . Papa	1 VP . VP PP	2 NP . Papa
0 Det . the	1 PP . P NP	2 Det . the
0 Det . a	1 V . ate	2 Det . a
	1 P . with	

scan *(this time we fail since Papa is not the next word)*

0 Papa 1 ate 2 the 3			
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .
0 S . NP VP	0 S NP . VP	1 VP V . NP	
0 NP . Det N	0 NP NP . PP	2 NP . Det N	
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	
0 NP . Papa	1 VP . VP PP	2 NP . Papa	
0 Det . the	1 PP . P NP	2 Det . the	
0 Det . a	1 V . ate	2 Det . a	
	1 P . with		

scan: success!

0 Papa 1 ate 2 the 3			
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .
0 S . NP VP	0 S NP . VP	1 VP V . NP	
0 NP . Det N	0 NP NP . PP	2 NP . Det N	
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	
0 NP . Papa	1 VP . VP PP	2 NP . Papa	
0 Det . the	1 PP . P NP	2 Det . the	
0 Det . a	1 V . ate	2 Det . a	
	1 P . with		

0 Papa 1 ate 2 the 3			
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N
0 NP . Det N	0 NP NP . PP	2 NP . Det N	
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	
0 NP . Papa	1 VP . VP PP	2 NP . Papa	
0 Det . the	1 PP . P NP	2 Det . the	
0 Det . a	1 V . ate	2 Det . a	
	1 P . with		

0 Papa 1 ate 2 the 3			
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon
0 NP . Papa	1 VP . VP PP	2 NP . Papa	
0 Det . the	1 PP . P NP	2 Det . the	
0 Det . a	1 V . ate	2 Det . a	
	1 P . with		

0 Papa 1	ate 2	the 3	caviar 4	
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	
0 NP . Papa	1 VP . VP PP	2 NP . Papa		
0 Det . the	1 PP . P NP	2 Det . the		
0 Det . a	1 V . ate	2 Det . a		
	1 P . with			

0 Papa 1 ate 2 the 3 caviar 4				
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	
0 NP . Papa	1 VP . VP PP	2 NP . Papa		
0 Det . the	1 PP . P NP	2 Det . the		
0 Det . a	1 V . ate	2 Det . a		
	1 P . with			

0 Papa 1 ate 2 the 3 caviar 4				
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	
0 NP . Papa	1 VP . VP PP	2 NP . Papa		
0 Det . the	1 PP . P NP	2 Det . the		
0 Det . a	1 V . ate	2 Det . a		
	1 P . with			

attach

0 Papa 1 ate 2 the 3 caviar 4				
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	1 VP V NP .
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	2 NP NP . PP
0 NP . Papa	1 VP . VP PP	2 NP . Papa		
0 Det . the	1 PP . P NP	2 Det . the		
0 Det . a	1 V . ate	2 Det . a		
	1 P . with			

attach
(again!)

0 Papa 1 ate 2 the 3 caviar 4				
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	1 VP V NP .
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	2 NP NP . PP
0 NP . Papa	1 VP . VP PP	2 NP . Papa		0 S NP VP .
0 Det . the	1 PP . P NP	2 Det . the		1 VP VP . PP
0 Det . a	1 V . ate	2 Det . a		
	1 P . with			

attach
(again!)

0 Papa 1 ate 2 the 3 caviar 4				
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	1 VP V NP .
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	2 NP NP . PP
0 NP . Papa	1 VP . VP PP	2 NP . Papa		0 S NP VP .
0 Det . the	1 PP . P NP	2 Det . the		1 VP VP . PP
0 Det . a	1 V . ate	2 Det . a		4 PP . P NP
	1 P . with			

0 Papa 1 ate 2 the 3 caviar 4				
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	1 VP V NP .
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	2 NP NP . PP
0 NP . Papa	1 VP . VP PP	2 NP . Papa		0 S NP VP .
0 Det . the	1 PP . P NP	2 Det . the		1 VP VP . PP
0 Det . a	1 V . ate	2 Det . a		4 PP . P NP
	1 P . with			0 ROOT S .

attach *(again!)*

0 Papa	1 ate	2 the	3 caviar	4
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	1 VP V NP .
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	2 NP NP . PP
0 NP . Papa	1 VP . VP PP	2 NP . Papa		0 S NP VP .
0 Det . the	1 PP . P NP	2 Det . the		1 VP VP . PP
0 Det . a	1 V . ate	2 Det . a		4 PP . P NP
	1 P . with			0 ROOT S .

0 Papa 1 ate 2 the 3 caviar 4				
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	1 VP V NP .
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	2 NP NP . PP
0 NP . Papa	1 VP . VP PP	2 NP . Papa		0 S NP VP .
0 Det . the	1 PP . P NP	2 Det . the		1 VP VP . PP
0 Det . a	1 V . ate	2 Det . a		4 PP . P NP
	1 P . with			0 ROOT S .
				4 P . with

0 Papa 1 ate 2 the 3 caviar 4				
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	1 VP V NP .
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	2 NP NP . PP
0 NP . Papa	1 VP . VP PP	2 NP . Papa		0 S NP VP .
0 Det . the	1 PP . P NP	2 Det . the		1 VP VP . PP
0 Det . a	1 V . ate	2 Det . a		4 PP . P NP
	1 P . with			0 ROOT S .
				4 P . with

0 Papa	1 ate	2 the	3 caviar	4 with	5
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .	4 P with .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .	
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	1 VP V NP .	
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	2 NP NP . PP	
0 NP . Papa	1 VP . VP PP	2 NP . Papa		0 S NP VP .	
0 Det . the	1 PP . P NP	2 Det . the		1 VP VP . PP	
0 Det . a	1 V . ate	2 Det . a		4 PP . P NP	
	1 P . with			0 ROOT S .	
				4 P . with	

0 Papa 1 ate 2 the 3 caviar 4 with 5					
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .	4 P with .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .	4 PP P . NP
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	1 VP V NP .	
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	2 NP NP . PP	
0 NP . Papa	1 VP . VP PP	2 NP . Papa		0 S NP VP .	
0 Det . the	1 PP . P NP	2 Det . the		1 VP VP . PP	
0 Det . a	1 V . ate	2 Det . a		4 PP . P NP	
	1 P . with			0 ROOT S .	
				4 P . with	

0 Papa 1 ate 2 the 3 caviar 4 with 5					
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .	4 P with .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .	4 PP P . NP
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	1 VP V NP .	5 NP . Det N
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	2 NP NP . PP	5 NP . NP PP
0 NP . Papa	1 VP . VP PP	2 NP . Papa		0 S NP VP .	5 NP . Papa
0 Det . the	1 PP . P NP	2 Det . the		1 VP VP . PP	
0 Det . a	1 V . ate	2 Det . a		4 PP . P NP	
	1 P . with			0 ROOT S .	
				4 P . with	

0 Papa 1 ate 2 the 3 caviar 4 with 5					
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .	4 P with .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .	4 PP P . NP
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	1 VP V NP .	5 NP . Det N
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	2 NP NP . PP	5 NP . NP PP
0 NP . Papa	1 VP . VP PP	2 NP . Papa		0 S NP VP .	5 NP . Papa
0 Det . the	1 PP . P NP	2 Det . the		1 VP VP . PP	5 Det . the
0 Det . a	1 V . ate	2 Det . a		4 PP . P NP	5 Det . a
	1 P . with			0 ROOT S .	
				4 P . with	

0 Papa 1 ate 2 the 3 caviar 4 with 5					
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .	4 P with .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .	4 PP P . NP
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	1 VP V NP .	5 NP . Det N
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	2 NP NP . PP	5 NP . NP PP
0 NP . Papa	1 VP . VP PP	2 NP . Papa		0 S NP VP .	5 NP . Papa
0 Det . the	1 PP . P NP	2 Det . the		1 VP VP . PP	5 Det . the
0 Det . a	1 V . ate	2 Det . a		4 PP . P NP	5 Det . a
	1 P . with			0 ROOT S .	
				4 P . with	

0 Papa 1 ate 2 the 3 caviar 4 with 5					
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .	4 P with .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .	4 PP P . NP
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	1 VP V NP .	5 NP . Det N
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	2 NP NP . PP	5 NP . NP PP
0 NP . Papa	1 VP . VP PP	2 NP . Papa		0 S NP VP .	5 NP . Papa
0 Det . the	1 PP . P NP	2 Det . the		1 VP VP . PP	5 Det . the
0 Det . a	1 V . ate	2 Det . a		4 PP . P NP	5 Det . a
	1 P . with			0 ROOT S .	
				4 P . with	

0 Papa 1 ate 2 the 3 caviar 4 with 5					
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .	4 P with .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .	4 PP P . NP
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	1 VP V NP .	5 NP . Det N
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	2 NP NP . PP	5 NP . NP PP
0 NP . Papa	1 VP . VP PP	2 NP . Papa		0 S NP VP .	5 NP . Papa
0 Det . the	1 PP . P NP	2 Det . the		1 VP VP . PP	5 Det . the
0 Det . a	1 V . ate	2 Det . a		4 PP . P NP	5 Det . a
	1 P . with			0 ROOT S .	
				4 P . with	

e	2 the	3 caviar	4 with	5 a	6
	1 V ate .	2 Det the .	3 N caviar .	4 P with .	5 Det a .
	1 VP V . NP	2 NP Det . N	2 NP Det N .	4 PP P . NP	
P	2 NP . Det N	3 N . caviar	1 VP V NP .	5 NP . Det N	
	2 NP . NP PP	3 N . spoon	2 NP NP . PP	5 NP . NP PP	
P	2 NP . Papa		0 S NP VP .	5 NP . Papa	
	2 Det . the		1 VP VP . PP	5 Det . the	
	2 Det . a		4 PP . P NP	5 Det . a	
			0 ROOT S .		
			4 P . with		

e	2	the	3	caviar	4	with	5	a	6	
	1 V ate .		2 Det the .		3 N caviar .		4 P with .		5 Det a .	
	1 VP V . NP		2 NP Det . N		2 NP Det N .		4 PP P . NP		5 NP Det . N	
P	2 NP . Det N		3 N . caviar		1 VP V NP .		5 NP . Det N			
	2 NP . NP PP		3 N . spoon		2 NP NP . PP		5 NP . NP PP			
P	2 NP . Papa				0 S NP VP .		5 NP . Papa			
	2 Det . the				1 VP VP . PP		5 Det . the			
	2 Det . a				4 PP . P NP		5 Det . a			
					0 ROOT S .					
					4 P . with					

e	2 the	3 caviar	4 with	5 a	6
	1 V ate .	2 Det the .	3 N caviar .	4 P with .	5 Det a .
	1 VP V . NP	2 NP Det . N	2 NP Det N .	4 PP P . NP	5 NP Det . N
P	2 NP . Det N	3 N . caviar	1 VP V NP .	5 NP . Det N	6 N . caviar
	2 NP . NP PP	3 N . spoon	2 NP NP . PP	5 NP . NP PP	6 N . spoon
P	2 NP . Papa		0 S NP VP .	5 NP . Papa	
	2 Det . the		1 VP VP . PP	5 Det . the	
	2 Det . a		4 PP . P NP	5 Det . a	
			0 ROOT S .		
			4 P . with		

e	2	the	3	caviar	4	with	5	a	6
	1 V ate .		2 Det the .		3 N caviar .		4 P with .		5 Det a .
	1 VP V . NP		2 NP Det . N		2 NP Det N .		4 PP P . NP		5 NP Det . N
P	2 NP . Det N		3 N . caviar		1 VP V NP .		5 NP . Det N		6 N . caviar
	2 NP . NP PP		3 N . spoon		2 NP NP . PP		5 NP . NP PP		6 N . spoon
P	2 NP . Papa				0 S NP VP .		5 NP . Papa		
	2 Det . the				1 VP VP . PP		5 Det . the		
	2 Det . a				4 PP . P NP		5 Det . a		
					0 ROOT S .				
					4 P . with				

e	2 the	3 caviar	4 with	5 a	6 spoon	7
	1 V ate .	2 Det the .	3 N caviar .	4 P with .	5 Det a .	6 N spoon .
	1 VP V . NP	2 NP Det . N	2 NP Det N .	4 PP P . NP	5 NP Det . N	
P	2 NP . Det N	3 N . caviar	1 VP V NP .	5 NP . Det N	6 N . caviar	
	2 NP . NP PP	3 N . spoon	2 NP NP . PP	5 NP . NP PP	6 N . spoon	
P	2 NP . Papa		0 S NP VP .	5 NP . Papa		
	2 Det . the		1 VP VP . PP	5 Det . the		
	2 Det . a		4 PP . P NP	5 Det . a		
			0 ROOT S .			
			4 P . with			

e	2 the	3 caviar	4 with	5 a	6 spoon	7
	1 V ate .	2 Det the .	3 N caviar .	4 P with .	5 Det a .	6 N spoon .
	1 VP V . NP	2 NP Det . N	2 NP Det N .	4 PP P . NP	5 NP Det . N	5 NP Det N .
P	2 NP . Det N	3 N . caviar	1 VP V NP .	5 NP . Det N	6 N . caviar	
	2 NP . NP PP	3 N . spoon	2 NP NP . PP	5 NP . NP PP	6 N . spoon	
P	2 NP . Papa		0 S NP VP .	5 NP . Papa		
	2 Det . the		1 VP VP . PP	5 Det . the		
	2 Det . a		4 PP . P NP	5 Det . a		
			0 ROOT S .			
			4 P . with			

e	2	the	3	caviar	4	with	5	a	6	spoon	7	
	1 V ate .		2 Det the .		3 N caviar .		4 P with .		5 Det a .		6 N spoon .	
	1 VP V . NP		2 NP Det . N		2 NP Det N .		4 PP P . NP		5 NP Det . N		5 NP Det N .	
P	2 NP . Det N		3 N . caviar		1 VP V NP .		5 NP . Det N		6 N . caviar		4 PP P NP .	
	2 NP . NP PP		3 N . spoon		2 NP NP . PP		5 NP . NP PP		6 N . spoon		5 NP NP . PP	
P	2 NP . Papa				0 S NP VP .		5 NP . Papa					
	2 Det . the				1 VP VP . PP		5 Det . the					
	2 Det . a				4 PP . P NP		5 Det . a					
					0 ROOT S .							
					4 P . with							

0 Papa 1 ate 2 the 3 caviar 4 with a spoon 7						
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .	...	6 N spoon .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .		5 NP Det N .
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	1 VP V NP .		4 PP P NP .
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	2 NP NP . PP		5 NP NP . PP
0 NP . Papa	1 VP . VP PP	2 NP . Papa		0 S NP VP .		2 NP NP PP .
0 Det . the	1 PP . P NP	2 Det . the		1 VP VP . PP		1 VP VP PP .
0 Det . a	1 V . ate	2 Det . a		4 PP . P NP		
	1 P . with			0 ROOT S .		
				4 P . with		

0 Papa 1 ate 2 the 3 caviar 4 with a spoon 7						
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .	...	6 N spoon .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .		5 NP Det N .
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	1 VP V NP .		4 PP P NP .
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	2 NP NP . PP		5 NP NP . PP
0 NP . Papa	1 VP . VP PP	2 NP . Papa		0 S NP VP .		2 NP NP PP .
0 Det . the	1 PP . P NP	2 Det . the		1 VP VP . PP		1 VP VP PP .
0 Det . a	1 V . ate	2 Det . a		4 PP . P NP		7 PP . P NP
	1 P . with			0 ROOT S .		
				4 P . with		

0 Papa 1 ate 2 the 3 caviar 4 with a spoon 7						
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .	...	6 N spoon .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .		5 NP Det N .
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	1 VP V NP .		4 PP P NP .
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	2 NP NP . PP		5 NP NP . PP
0 NP . Papa	1 VP . VP PP	2 NP . Papa		0 S NP VP .		2 NP NP PP .
0 Det . the	1 PP . P NP	2 Det . the		1 VP VP . PP		1 VP VP PP .
0 Det . a	1 V . ate	2 Det . a		4 PP . P NP		7 PP . P NP
	1 P . with			0 ROOT S .		1 VP V NP .
				4 P . with		2 NP NP . PP

0 Papa 1 ate 2 the 3 caviar 4 with a spoon 7						
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .	...	6 N spoon .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .		5 NP Det N .
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	1 VP V NP .		4 PP P NP .
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	2 NP NP . PP		5 NP NP . PP
0 NP . Papa	1 VP . VP PP	2 NP . Papa		0 S NP VP .		2 NP NP PP .
0 Det . the	1 PP . P NP	2 Det . the		1 VP VP . PP		1 VP VP PP .
0 Det . a	1 V . ate	2 Det . a		4 PP . P NP		7 PP . P NP
	1 P . with			0 ROOT S .		1 VP V NP .
				4 P . with		2 NP NP . PP
						0 S NP VP .
						1 VP VP . PP

0 Papa 1 ate 2 the 3 caviar 4 with a spoon 7						
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .	...	6 N spoon .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .		5 NP Det N .
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	1 VP V NP .		4 PP P NP .
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	2 NP NP . PP		5 NP NP . PP
0 NP . Papa	1 VP . VP PP	2 NP . Papa		0 S NP VP .		2 NP NP PP .
0 Det . the	1 PP . P NP	2 Det . the		1 VP VP . PP		1 VP VP PP .
0 Det . a	1 V . ate	2 Det . a		4 PP . P NP		7 PP . P NP
	1 P . with			0 ROOT S .		1 VP V NP .
				4 P . with		2 NP NP . PP
						0 S NP VP .
						1 VP VP . PP
						7 P . with

0 Papa	1 ate	2 the	3 caviar	4 with a spoon 7		
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .	...	6 N spoon .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .		5 NP Det N .
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	1 VP V NP .		4 PP P NP .
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	2 NP NP . PP		5 NP NP . PP
0 NP . Papa	1 VP . VP PP	2 NP . Papa		0 S NP VP .		2 NP NP PP .
0 Det . the	1 PP . P NP	2 Det . the		1 VP VP . PP		1 VP VP PP .
0 Det . a	1 V . ate	2 Det . a		4 PP . P NP		7 PP . P NP
	1 P . with			0 ROOT S .		1 VP V NP .
				4 P . with		2 NP NP . PP
						0 S NP VP .
						1 VP VP . PP
						7 P . with

0 Papa 1 ate	2 the	3 caviar	4 with a spoon 7			
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .	...	6 N spoon .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .		5 NP Det N .
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	1 VP V NP .		4 PP P NP .
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	2 NP NP . PP		5 NP NP . PP
0 NP . Papa	1 VP . VP PP	2 NP . Papa		0 S NP VP .		2 NP NP PP .
0 Det . the	1 PP . P NP	2 Det . the		1 VP VP . PP		1 VP VP PP .
0 Det . a	1 V . ate	2 Det . a		4 PP . P NP		7 PP . P NP
	1 P . with			0 ROOT S .		1 VP V NP .
				4 P . with		2 NP NP . PP
						0 S NP VP .
						1 VP VP . PP
						7 P . with

0 Papa 1 ate 2 the 3 caviar 4 with a spoon 7						
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .	...	6 N spoon .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .		5 NP Det N .
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	1 VP V NP .		4 PP P NP .
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	2 NP NP . PP		5 NP NP . PP
0 NP . Papa	1 VP . VP PP	2 NP . Papa		0 S NP VP .		2 NP NP PP .
0 Det . the	1 PP . P NP	2 Det . the		1 VP VP . PP		1 VP VP PP .
0 Det . a	1 V . ate	2 Det . a		4 PP . P NP		7 PP . P NP
	1 P . with			0 ROOT S .		1 VP V NP .
				4 P . with		2 NP NP . PP
						0 S NP VP .
						1 VP VP . PP
						7 P . with
						0 ROOT S .

0 Papa	1 ate	2 the	3 caviar	4 with a spoon 7		
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .	...	6 N spoon .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .		5 NP Det N .
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	1 VP V NP .		4 PP P NP .
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	2 NP NP . PP		5 NP NP . PP
0 NP . Papa	1 VP . VP PP	2 NP . Papa		0 S NP VP .		2 NP NP PP .
0 Det . the	1 PP . P NP	2 Det . the		1 VP VP . PP		1 VP VP PP .
0 Det . a	1 V . ate	2 Det . a		4 PP . P NP		7 PP . P NP
	1 P . with			0 ROOT S .		1 VP V NP .
				4 P . with		2 NP NP . PP
						0 S NP VP .
						1 VP VP . PP
						7 P . with
						0 ROOT S .

0 Papa 1 ate 2 the 3 caviar 4 with a spoon 7						
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .	...	6 N spoon .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .		5 NP Det N .
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	1 VP V NP .		4 PP P NP .
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	2 NP NP . PP		5 NP NP . PP
0 NP . Papa	1 VP . VP PP	2 NP . Papa		0 S NP VP .		2 NP NP PP .
0 Det . the	1 PP . P NP	2 Det . the		1 VP VP . PP		1 VP VP PP .
0 Det . a	1 V . ate	2 Det . a		4 PP . P NP		7 PP . P NP
	1 P . with			0 ROOT S .		1 VP V NP .
				4 P . with		2 NP NP . PP
						0 S NP VP .
						1 VP VP . PP
						7 P . with
						0 ROOT S .

0 Papa 1 ate 2 the 3 caviar 4 with a spoon 7						
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .	...	6 N spoon .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .		5 NP Det N .
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	1 VP V NP .		4 PP P NP .
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	2 NP NP . PP		5 NP NP . PP
0 NP . Papa	1 VP . VP PP	2 NP . Papa		0 S NP VP .		2 NP NP PP .
0 Det . the	1 PP . P NP	2 Det . the		1 VP VP . PP		1 VP VP PP .
0 Det . a	1 V . ate	2 Det . a		4 PP . P NP		7 PP . P NP
	1 P . with			0 ROOT S .		1 VP V NP .
				4 P . with		2 NP NP . PP
						0 S NP VP .
						1 VP VP . PP
						7 P . with
						0 ROOT S .

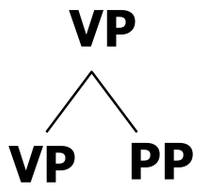
0 Papa 1 ate 2 the 3 caviar 4 with a spoon 7						
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .	...	6 N spoon .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .		5 NP Det N .
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	1 VP V NP .		4 PP P NP .
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	2 NP NP . PP		5 NP NP . PP
0 NP . Papa	1 VP . VP PP	2 NP . Papa		0 S NP VP .		2 NP NP PP .
0 Det . the	1 PP . P NP	2 Det . the		1 VP VP . PP		1 VP VP PP .
0 Det . a	1 V . ate	2 Det . a		4 PP . P NP		7 PP . P NP
	1 P . with			0 ROOT S .		1 VP V NP .
				4 P . with		2 NP NP . PP
						0 S NP VP .
						1 VP VP . PP
						7 P . with
						0 ROOT S .

Left Recursion Kills Pure Top-Down Parsing …

VP

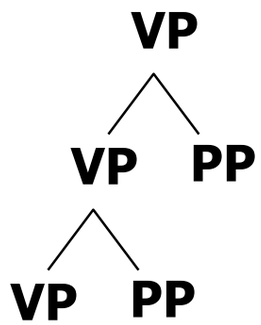
Andrew McCallum, UMass Amherst

Left Recursion Kills Pure Top-Down Parsing …

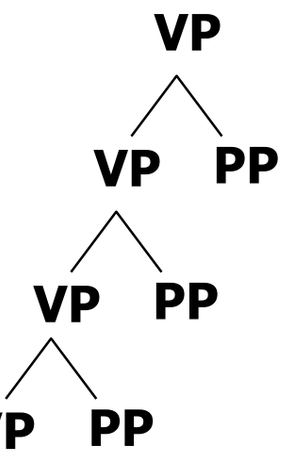


Andrew McCallum, UMass Amherst

Left Recursion Kills Pure Top-Down Parsing …



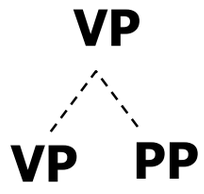
Left Recursion Kills Pure Top-Down Parsing …



makes new hypotheses ad infinitum before we've seen the PPs at all

hypotheses try to predict in advance how many PP's will arrive in input

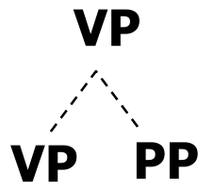
… but Earley's Alg is Okay!



1 VP → . VP PP

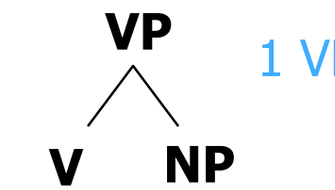
(in column 1)

… but Earley's Alg is Okay!



1 VP → . VP PP

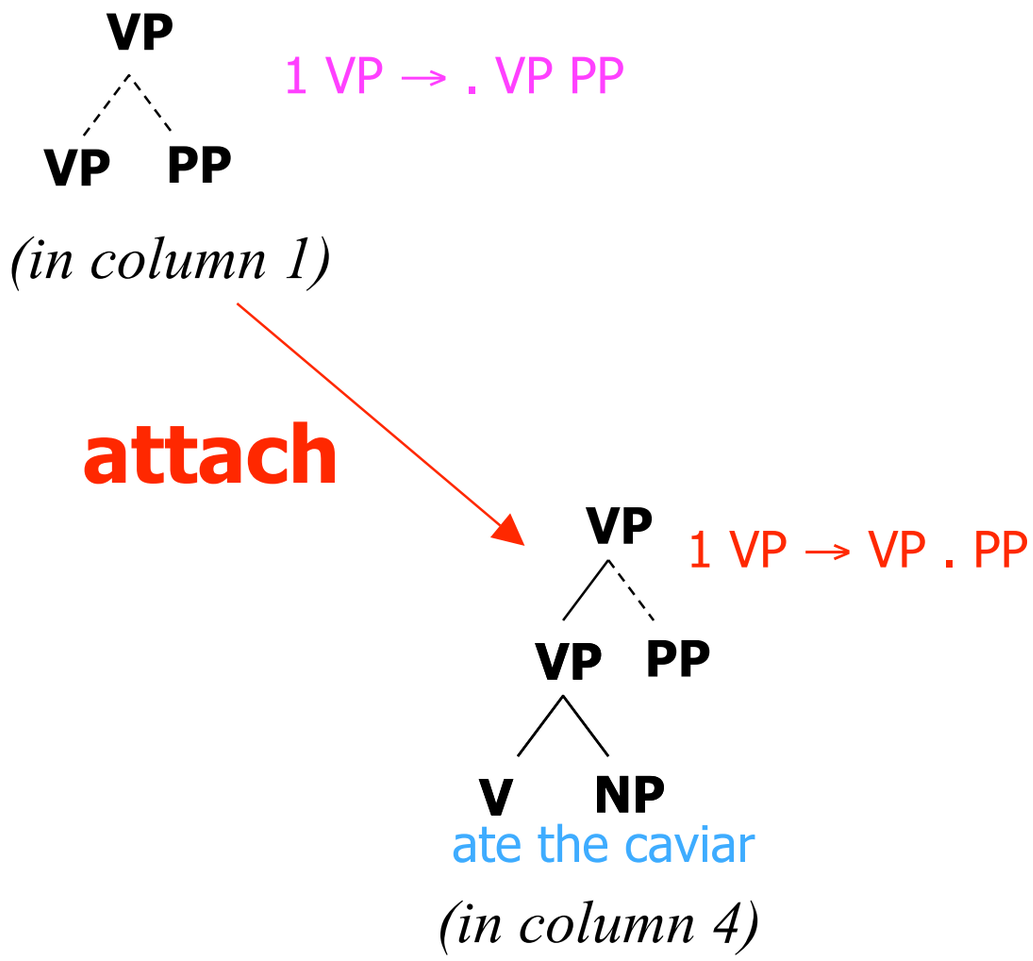
(in column 1)



1 VP → V NP .

(in column 4)

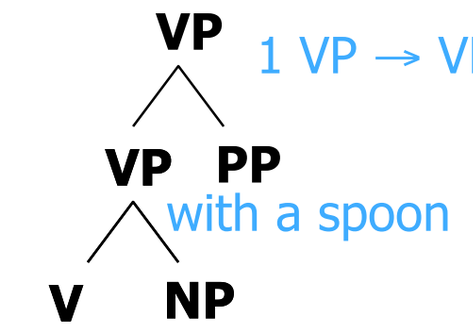
… but Earley's Alg is Okay!



… but Earley's Alg is Okay!

1 VP → . VP PP

(in column 1)



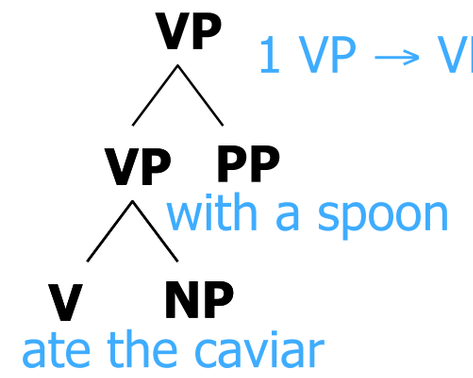
(in column 7)

… but Earley's Alg is Okay!

1 VP → . VP PP

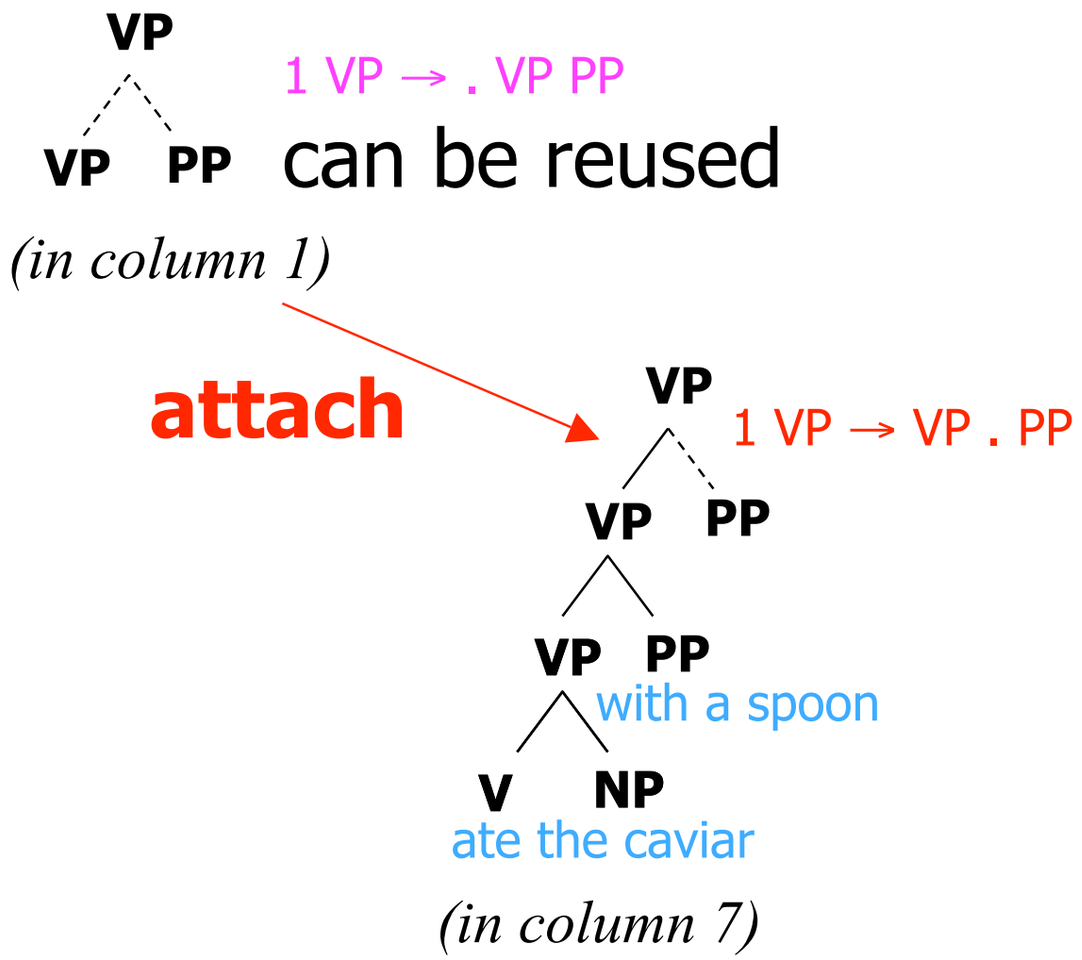
can be reused

(in column 1)

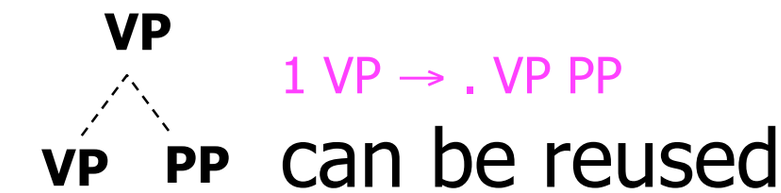


(in column 7)

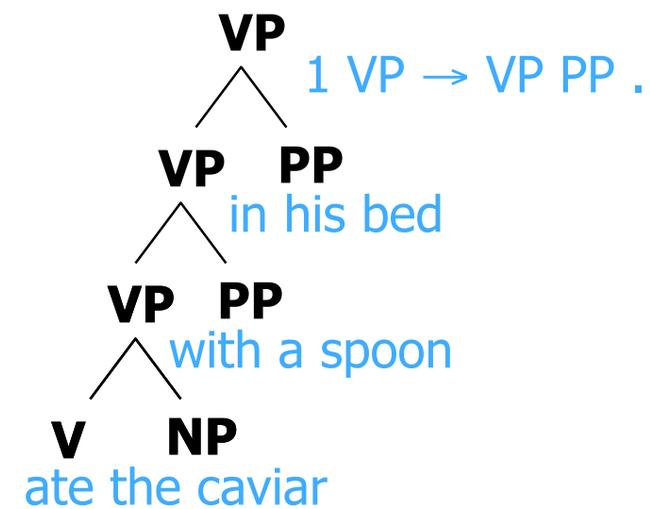
… but Earley's Alg is Okay!



… but Earley's Alg is Okay!



(in column 1)



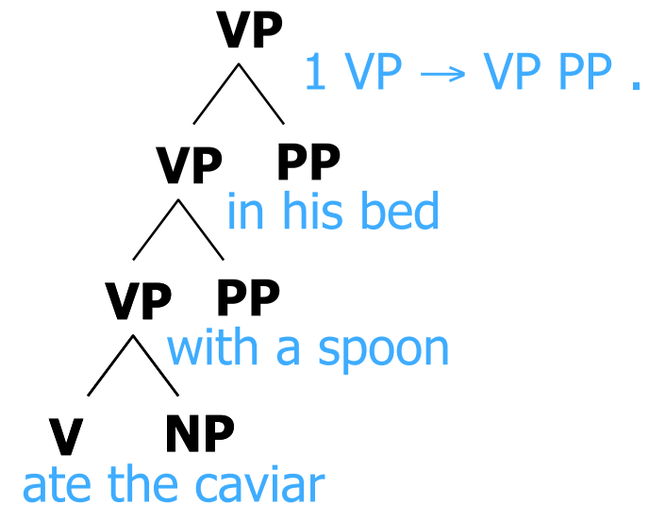
(in column 10)

… but Earley's Alg is Okay!

1 VP → . VP PP

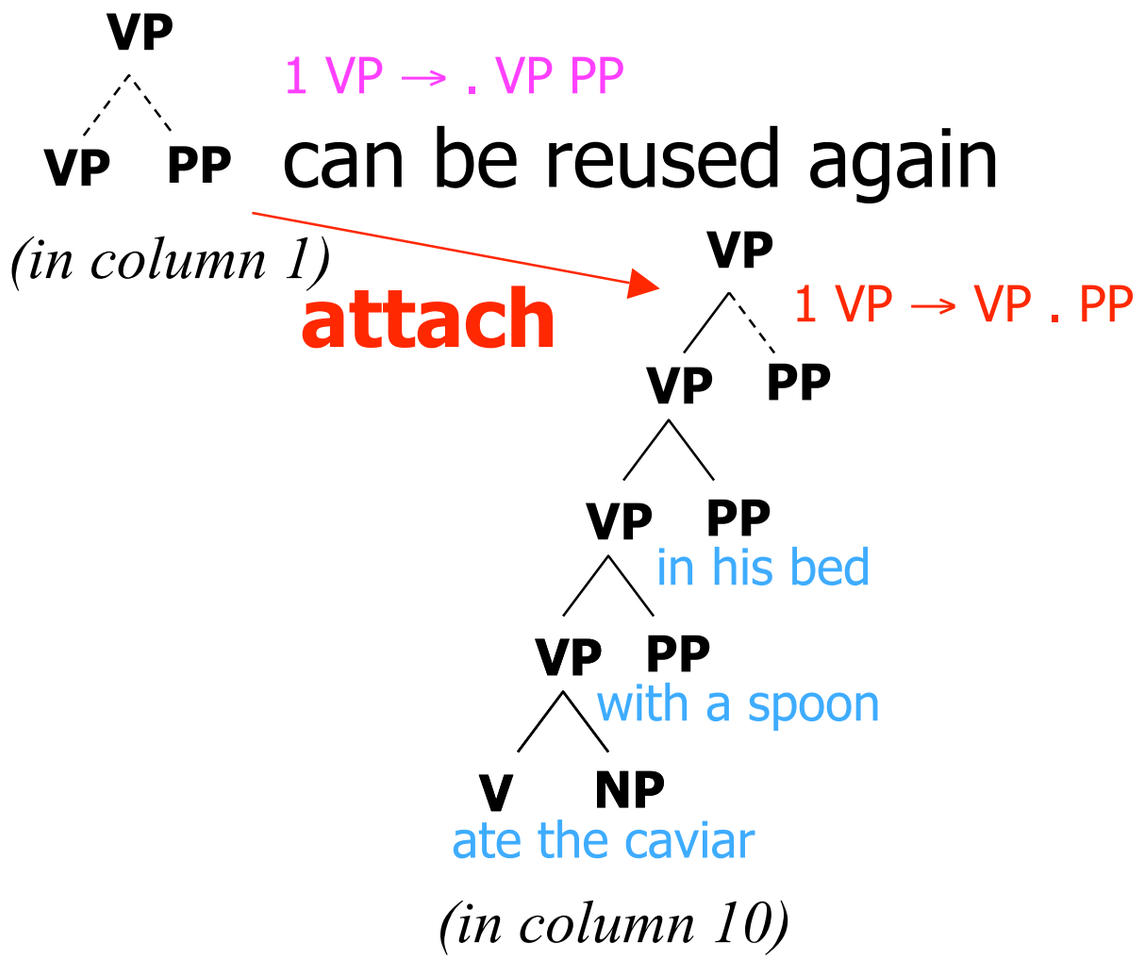
can be reused again

(in column 1)



(in column 10)

… but Earley's Alg is Okay!



0 Papa 1 ate 2 the 3 caviar 4 with a spoon 7						
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .	...	6 N spoon .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .		5 NP Det N .
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	1 VP V NP .		4 PP P NP .
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	2 NP NP . PP		5 NP NP . PP
0 NP . Papa	**1 VP . VP PP**	2 NP . Papa		0 S NP VP .		2 NP NP PP .
0 Det . the	1 PP . P NP	2 Det . the		**1 VP VP . PP**		1 VP VP PP .
0 Det . a	1 V . ate	2 Det . a		4 PP . P NP		7 PP . P NP
	1 P . with			0 ROOT S .		1 VP V NP .
				4 P . with		2 NP NP . PP
						0 S NP VP .
						1 VP VP . PP
						7 P . with
						0 ROOT S .

completed a VP in col 4
col 1 lets us use it in a VP PP structure

0 Papa	1 ate	2 the	3 caviar	4 with a spoon	7
0 ROOT . S	0 NP Papa .	1 V ate .	2 Det the .	3 N caviar .	... 6 N spoon .
0 S . NP VP	0 S NP . VP	1 VP V . NP	2 NP Det . N	2 NP Det N .	5 NP Det N .
0 NP . Det N	0 NP NP . PP	2 NP . Det N	3 N . caviar	1 VP V NP .	4 PP P NP .
0 NP . NP PP	1 VP . V NP	2 NP . NP PP	3 N . spoon	2 NP NP . PP	5 NP NP . PP
0 NP . Papa	**1 VP . VP PP**	2 NP . Papa		0 S NP VP .	2 NP NP PP .
0 Det . the	1 PP . P NP	2 Det . the		1 VP VP . PP	1 VP VP PP .
0 Det . a	1 V . ate	2 Det . a		4 PP . P NP	7 PP . P NP
	1 P . with			0 ROOT S .	1 VP V NP .
				4 P . with	2 NP NP . PP
					0 S NP VP .
					1 VP VP . PP
					7 P . with
					0 ROOT S .

completed that VP = VP PP in col 7
col 1 would let us use *it* in a VP PP structure
can reuse col 1 as often as we need

Beyond Recognition

- So far, we've described an Earley *recognizer*
- Note what we did when we tried to create entries that already existed
- What should we do when combining items?
- How to derive outside algorithm?

Parsing Tricks

Left-Corner Parsing

- Technique for 1 word of lookahead in algorithms like Earley's
- (can also do multi-word lookahead but it's harder)

Basic Earley's Algorithm

0 Papa 1	
0 ROOT . S	0 NP Papa .
0 S . NP VP	0 S NP . VP
0 NP . Det N	0 NP NP . PP
0 NP . NP PP	
0 NP . Papa	
0 Det . the	
0 Det . a	

attach

0 Papa 1	
0 ROOT . S	0 NP Papa .
0 S . NP VP	0 S NP . VP
0 NP . Det N	0 NP NP . PP
0 NP . NP PP	1 VP . V NP
0 NP . Papa	1 VP . VP PP
0 Det . the	
0 Det . a	

predict

0 Papa 1	
0 ROOT . S	0 NP Papa .
0 S . NP VP	0 S NP . VP
0 NP . Det N	0 NP NP . PP
0 NP . NP PP	1 VP . V NP
0 NP . Papa	1 VP . VP PP
0 Det . the	1 PP . P NP
0 Det . a	

predict

0 Papa 1	
0 ROOT . S	0 NP Papa .
0 S . NP VP	0 S NP . VP
0 NP . Det N	0 NP NP . PP
0 NP . NP PP	1 VP . V NP
0 NP . Papa	1 VP . VP PP
0 Det . the	1 PP . P NP
0 Det . a	1 V . ate
	1 V . drank
	1 V . snorted

predict

0 Papa 1	
0 ROOT . S	0 NP Papa .
0 S . NP VP	0 S NP . VP
0 NP . Det N	0 NP NP . PP
0 NP . NP PP	1 VP . V NP
0 NP . Papa	1 VP . VP PP
0 Det . the	1 PP . P NP
0 Det . a	1 V . ate
	1 V . drank
	1 V . snorted

predict

0 Papa 1	
0 ROOT . S	0 NP Papa .
0 S . NP VP	0 S NP . VP
0 NP . Det N	0 NP NP . PP
0 NP . NP PP	1 VP . V NP
0 NP . Papa	1 VP . VP PP
0 Det . the	1 PP . P NP
0 Det . a	1 V . ate
	1 V . drank
	1 V . snorted

predict

- .V makes us add all the verbs in the vocabulary!
- **Slow** – we'd like a shortcut.

0 Papa 1	
0 ROOT . S	0 NP Papa .
0 S . NP VP	0 S NP . VP
0 NP . Det N	0 NP NP . PP
0 NP . NP PP	1 VP . V NP
0 NP . Papa	1 VP . VP PP
0 Det . the	1 PP . P NP
0 Det . a	1 V . ate
	1 V . drank
	1 V . snorted

predict

0 Papa 1	
0 ROOT . S	0 NP Papa .
0 S . NP VP	0 S NP . VP
0 NP . Det N	0 NP NP . PP
0 NP . NP PP	1 VP . V NP
0 NP . Papa	1 VP . VP PP
0 Det . the	1 PP . P NP
0 Det . a	1 V . ate
	1 V . drank
	1 V . snorted

predict

0 Papa 1	
0 ROOT . S	0 NP Papa .
0 S . NP VP	0 S NP . VP
0 NP . Det N	0 NP NP . PP
0 NP . NP PP	1 VP . V NP
0 NP . Papa	1 VP . VP PP
0 Det . the	1 PP . P NP
0 Det . a	1 V . ate
	1 V . drank
	1 V . snorted

predict

- Every .VP adds all VP → … rules again.
- Before adding a rule, check it's not a duplicate.
- **Slow** if there are > 700 VP → … rules

0 Papa 1	
0 ROOT . S	0 NP Papa .
0 S . NP VP	0 S NP . VP
0 NP . Det N	0 NP NP . PP
0 NP . NP PP	1 VP . V NP
0 NP . Papa	1 VP . VP PP
0 Det . the	1 PP . P NP
0 Det . a	1 V . ate
	1 V . drank
	1 V . snorted
	1 P . with

predict

0	Papa	1
0 ROOT . S	0 NP Papa .	
0 S . NP VP	0 S NP . VP	
0 NP . Det N	0 NP NP . PP	
0 NP . NP PP	1 VP . V NP	
0 NP . Papa	1 VP . VP PP	
0 Det . the	1 PP . P NP	
0 Det . a	1 V . ate	
	1 V . drank	
	1 V . snorted	
	1 P . with	

predict

- .P makes us add all the prepositions ...

1-word lookahead would help

0	Papa	1	ate
0 ROOT . S		0 NP Papa .	
0 S . NP VP		0 S NP . VP	
0 NP . Det N		0 NP NP . PP	
0 NP . NP PP		1 VP . V NP	
0 NP . Papa		1 VP . VP PP	
0 Det . the		1 PP . P NP	
0 Det . a		1 V . ate	
		1 V . drank	
		1 V . snorted	
		1 P . with	

1-word lookahead would help

0	Papa	1	ate
0 ROOT . S		0 NP Papa .	
0 S . NP VP		0 S NP . VP	
0 NP . Det N		0 NP NP . PP	
0 NP . NP PP		1 VP . V NP	
0 NP . Papa		1 VP . VP PP	
0 Det . the		1 PP . P NP	
0 Det . a		1 V . ate	
		~~1 V . drank~~	
		~~1 V . snorted~~	
		~~1 P . with~~	

No point in adding words other than ate

1-word lookahead would help

0	Papa	1	ate
0 ROOT . S		0 NP Papa .	
0 S . NP VP		0 S NP . VP	
0 NP . Det N		~~0 NP NP . PP~~	
0 NP . NP PP		1 VP . V NP	
0 NP . Papa		1 VP . VP PP	
0 Det . the		~~1 PP . P NP~~	
0 Det . a		1 V . ate	
		~~1 V . drank~~	
		~~1 V . snorted~~	
		~~1 P . with~~	

In fact, no point in adding any constituent that can't start with ate

Don't bother adding PP, P, etc.

No point in adding words other than ate

With Left-Corner Filter

0 Papa 1	ate
0 ROOT . S	0 NP Papa .
0 S . NP VP	0 S NP . VP
0 NP . Det N	~~0 NP NP . PP~~
0 NP . NP PP	
0 NP . Papa	
0 Det . the	
0 Det . a	

attach

With Left-Corner Filter

0	Papa	1	ate
0 ROOT . S	0 NP Papa .		**attach**
0 S . NP VP	0 S NP . VP		
0 NP . Det N	~~0 NP NP . PP~~		PP can't start with ate
0 NP . NP PP			
0 NP . Papa			
0 Det . the			
0 Det . a			

With Left-Corner Filter

0 Papa 1	ate
0 ROOT . S	0 NP Papa .
0 S . NP VP	0 S NP . VP
0 NP . Det N	~~0 NP NP . PP~~
0 NP . NP PP	
0 NP . Papa	
0 Det . the	
0 Det . a	

attach

PP can't start with ate

Pruning– now we won't predict

1 PP . P NP

1 PP . ate

With Left-Corner Filter

0 Papa 1	ate
0 ROOT . S	0 NP Papa .
0 S . NP VP	0 S NP . VP
0 NP . Det N	~~0 NP NP . PP~~
0 NP . NP PP	
0 NP . Papa	
0 Det . the	
0 Det . a	

attach

PP can't start with ate

Pruning– now we won't predict

1 PP . P NP

1 PP . ate

either!

With Left-Corner Filter

0 Papa 1	ate
0 ROOT . S	0 NP Papa .
0 S . NP VP	0 S NP . VP
0 NP . Det N	~~0 NP NP . PP~~
0 NP . NP PP	
0 NP . Papa	
0 Det . the	
0 Det . a	

attach

PP can't start with ate

Pruning– now we won't predict

1 PP . P NP

1 PP . ate

either!

0	Papa	1	ate
0 ROOT . S	0 NP Papa .		
0 S . NP VP	0 S NP . VP		**predict**
0 NP . Det N	~~0 NP NP . PP~~		
0 NP . NP PP	1 VP . V NP		
0 NP . Papa	1 VP . VP PP		
0 Det . the			
0 Det . a			

0	Papa	1	ate
0 ROOT . S		0 NP Papa .	
0 S . NP VP		0 S NP . VP	
0 NP . Det N		~~0 NP NP . PP~~	
0 NP . NP PP		1 VP . V NP	**predict**
0 NP . Papa		1 VP . VP PP	
0 Det . the		1 V . ate	
0 Det . a		~~1 V . drank~~	
		~~1 V . snorted~~	

0	Papa	1	ate
0 ROOT . S	0 NP Papa .		
0 S . NP VP	0 S NP . VP		
0 NP . Det N	~~0 NP NP . PP~~		
0 NP . NP PP	1 VP . V NP	**predict**	
0 NP . Papa	1 VP . VP PP		
0 Det . the	1 V . ate		
0 Det . a	~~1 V . drank~~		
	~~1 V . snorted~~		

0	Papa	1	ate
0 ROOT . S		0 NP Papa .	
0 S . NP VP		0 S NP . VP	
0 NP . Det N		~~0 NP NP . PP~~	
0 NP . NP PP		1 VP . V NP	
0 NP . Papa		1 VP . VP PP	
0 Det . the		1 V . ate	
0 Det . a		~~1 V . drank~~	
		~~1 V . snorted~~	

predict

Merging Right-Hand Sides

- Grammar might have rules

  X → A G H P

  X → B G H P

- Could end up with both of these in chart:

  (2, X → A . G H P) in column 5

  (2, X → B . G H P) in column 5

- But these are now interchangeable: if one produces X then so will the other
- To avoid this redundancy, can always use dotted rules of this form: **X → ... G H P**

Merging Right-Hand Sides

- Similarly, grammar might have rules

  X → A G H P

  X → A G H Q

- Could end up with both of these in chart:

  (2, X → A . G H P) in column 5

  (2, X → A . G H Q) in column 5

- Not interchangeable, but we'll be processing them in parallel for a while …
- Solution: write grammar as **X → A G H (P|Q)**

Merging Right-Hand Sides

- Combining the two previous cases:

  X → A G H P

  X → A G H Q

  X → B G H P

  X → B G H Q

  becomes

  X → (A | B) G H (P | Q)

- And often nice to write stuff like

  NP → (Det | ε) Adj* N

Merging Right-Hand Sides

Merging Right-Hand Sides

X → (A | B) G H (P | Q)

NP → (Det | ε) Adj* N

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- These are regular expressions!

Merging Right-Hand Sides

X → (A | B) G H (P | Q)

NP → (Det | ε) Adj* N

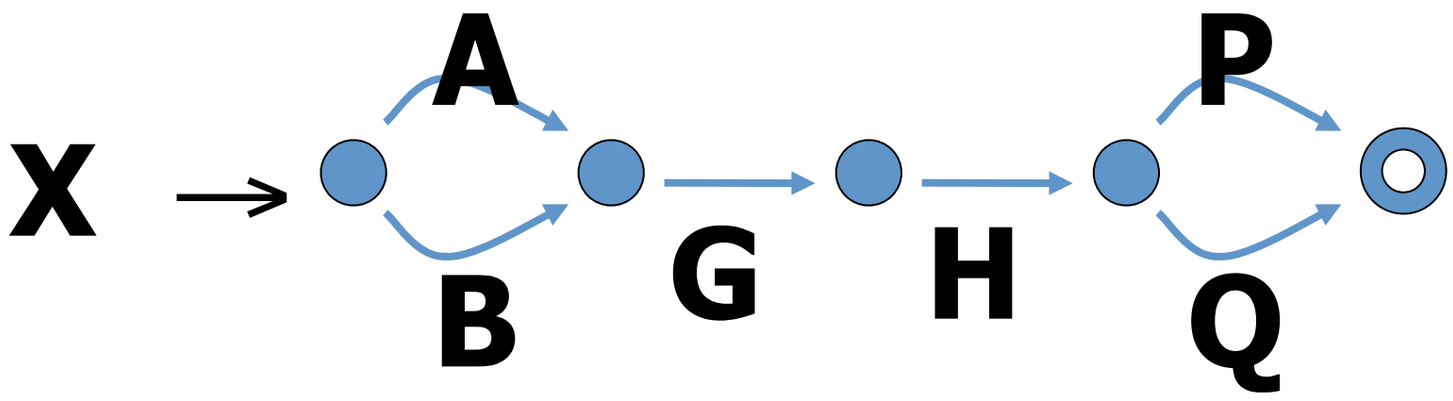
- These are regular expressions!
- Build their minimal DFAs:

Merging Right-Hand Sides

X → (A | B) G H (P | Q)

NP → (Det | ε) Adj* N

- These are regular expressions!
- Build their minimal DFAs:

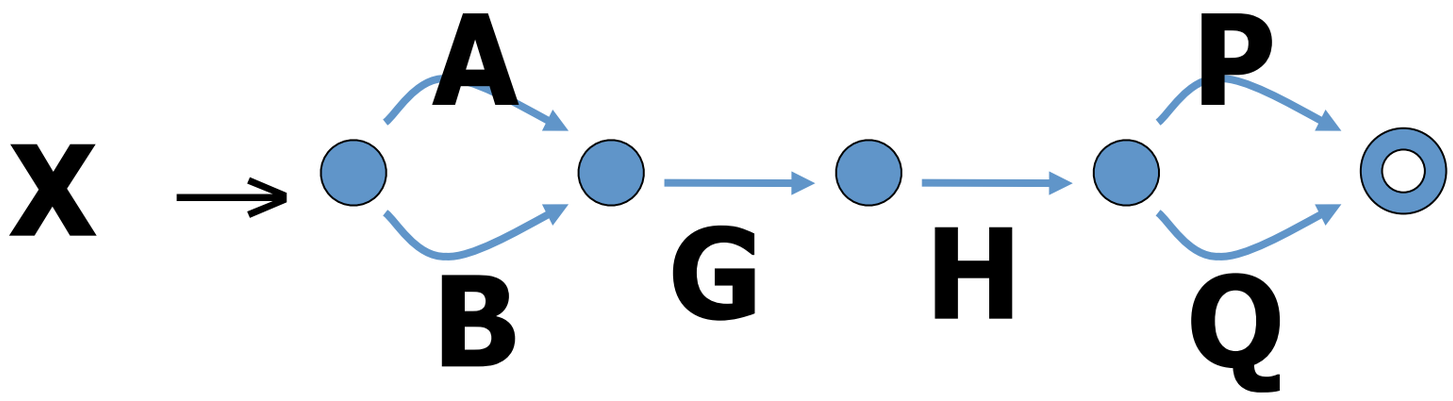


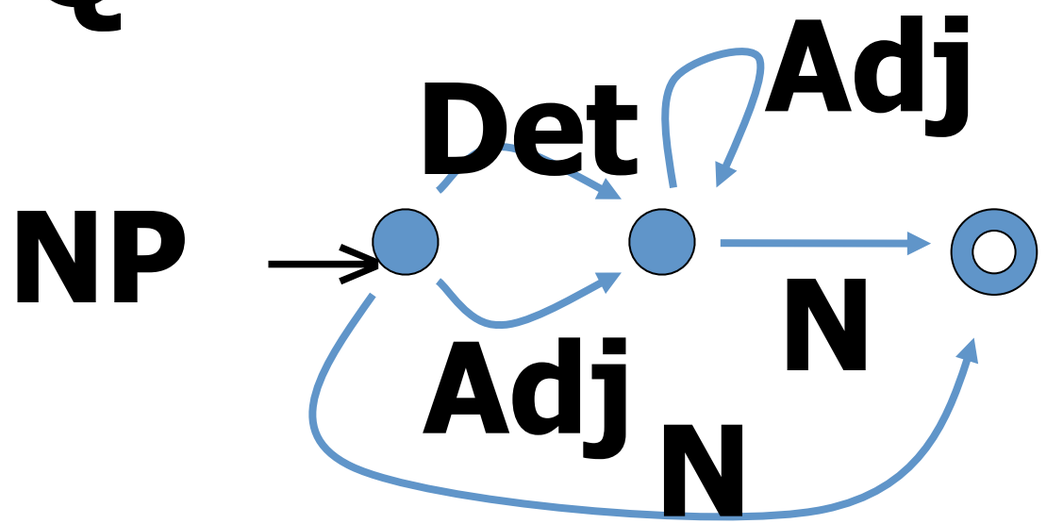
Merging Right-Hand Sides

X → (A | B) G H (P | Q)

NP → (Det | ε) Adj* N

- These are regular expressions!
- Build their minimal DFAs:





Merging Right-Hand Sides

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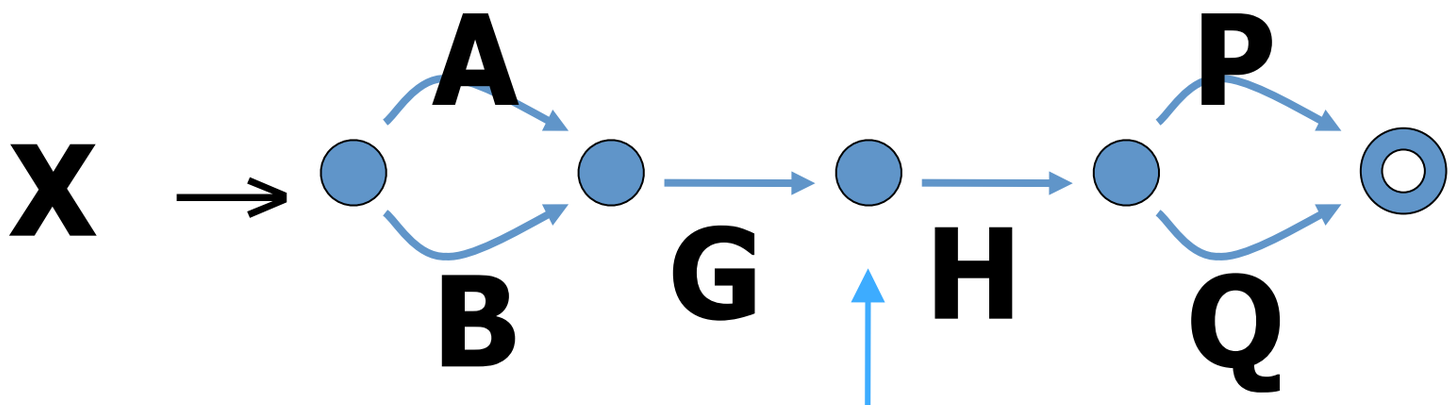
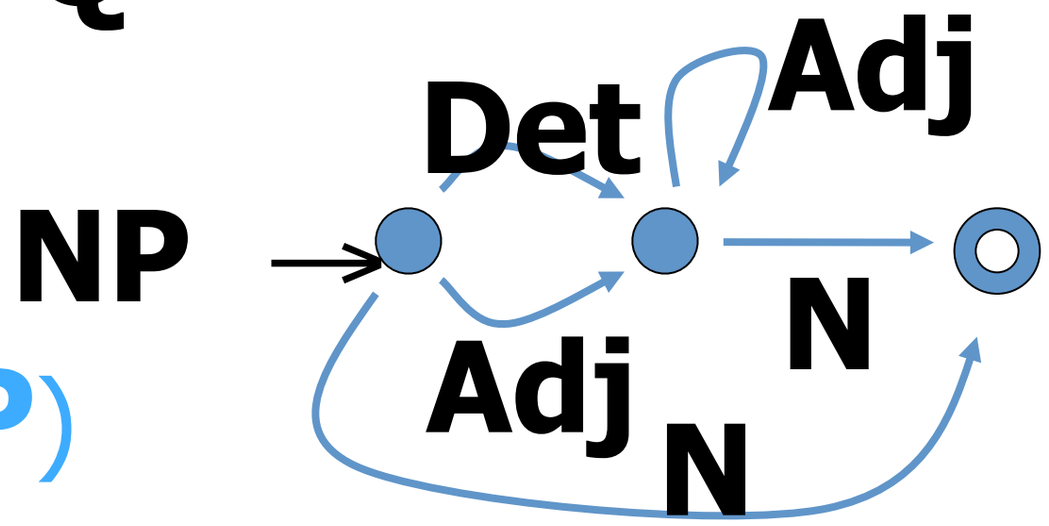


- Automaton states replace dotted rules (**X → A G . H P**)



Merging Right-Hand Sides

Indeed, *all* **NP** → rules can be unioned into a single DFA!

NP → ADJP ADJP JJ JJ NN NNS
NP → ADJP DT NN
NP → ADJP JJ NN
NP → ADJP JJ NN NNS
NP → ADJP JJ NNS
NP → ADJP NN
NP → ADJP NN NN
NP → ADJP NN NNS
NP → ADJP NNS
NP → ADJP NPR
NP → ADJP NPRS
NP → DT
NP → DT ADJP
NP → DT ADJP , JJ NN
NP → DT ADJP ADJP NN
NP → DT ADJP JJ JJ NN
NP → DT ADJP JJ NN
NP → DT ADJP JJ NN NN

ets

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Indeed, *all* **NP** → rules can be unioned into a single DFA!

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| ADJP JJ NN
| ADJP JJ NN NNS
| ADJP JJ NNS
| ADJP NN
| ADJP NN NN
| ADJP NN NNS
| ADJP NNS
| ADJP NPR
| ADJP NPRS
| DT
| DT ADJP
| DT ADJP , JJ NN
| DT ADJP ADJP NN
| DT ADJP JJ JJ NN
| DT ADJP JJ NN
| DT ADJP JJ NN NN

etc.

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Indeed, *all* **NP** → rules can be unioned into a single DFA!

NP → ADJP ADJP JJ JJ NN NNS
| ADJP DT NN
| ADJP JJ NN
| ADJP JJ NN NNS
| ADJP JJ NNS
| ADJP NN
| ADJP NN NN
| ADJP NN NNS
| ADJP NNS
| ADJP NPR
| ADJP NPRS
| DT
| DT ADJP
| DT ADJP , JJ NN
| DT ADJP ADJP NN
| DT ADJP JJ JJ NN
| DT ADJP JJ NN
| DT ADJP JJ NN NN

etc.

regular expression

Merging Right-Hand Sides

Indeed, *all* **NP** → rules can be unioned into a single DFA!

NP → ADJP ADJP JJ JJ NN NNS
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| ADJP JJ NN NNS
| ADJP JJ NNS
| ADJP NN
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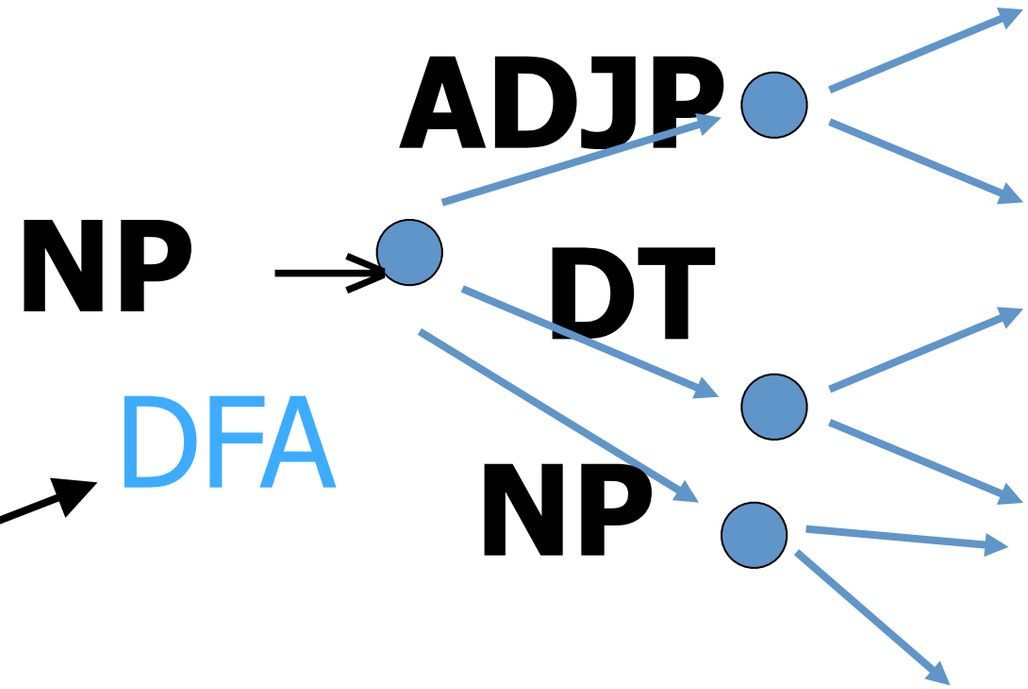
| ADJP NN NNS
| ADJP NNS
| ADJP NPR
| ADJP NPRS
| DT
| DT ADJP
| DT ADJP , JJ NN
| DT ADJP ADJP NN
| DT ADJP JJ JJ NN
| DT ADJP JJ NN
| DT ADJP JJ NN NN

etc.

regular expression → DFA



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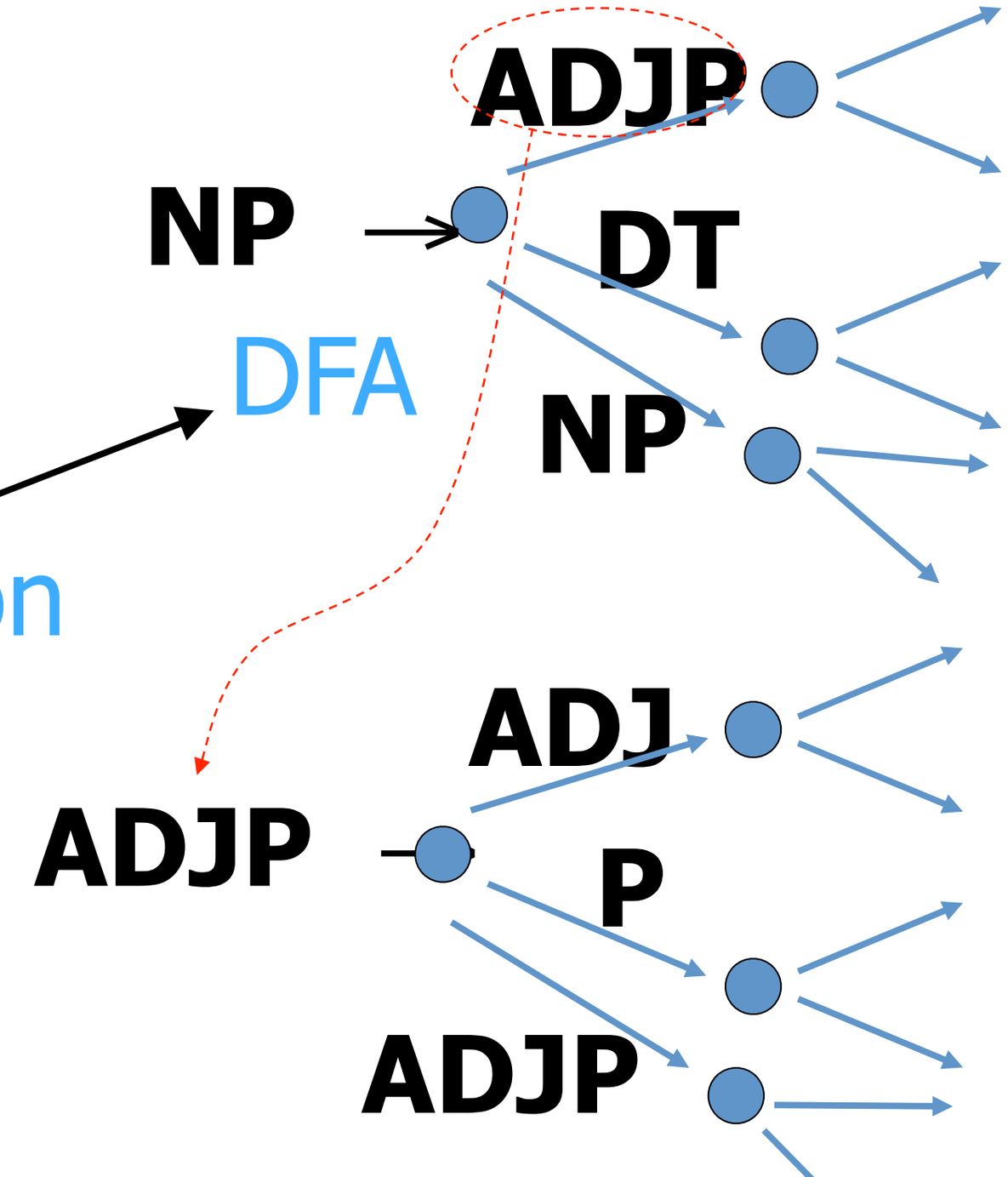
| ADJP NN NNS
| ADJP NNS
| ADJP NPR
| ADJP NPRS
| DT
| DT ADJP
| DT ADJP , JJ NN
| DT ADJP ADJP NN
| DT ADJP JJ JJ NN
| DT ADJP JJ NN
| DT ADJP JJ NN NN

etc.

regular expression → DFA



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| ADJP NPR
| ADJP NPRS
| DT
| DT ADJP
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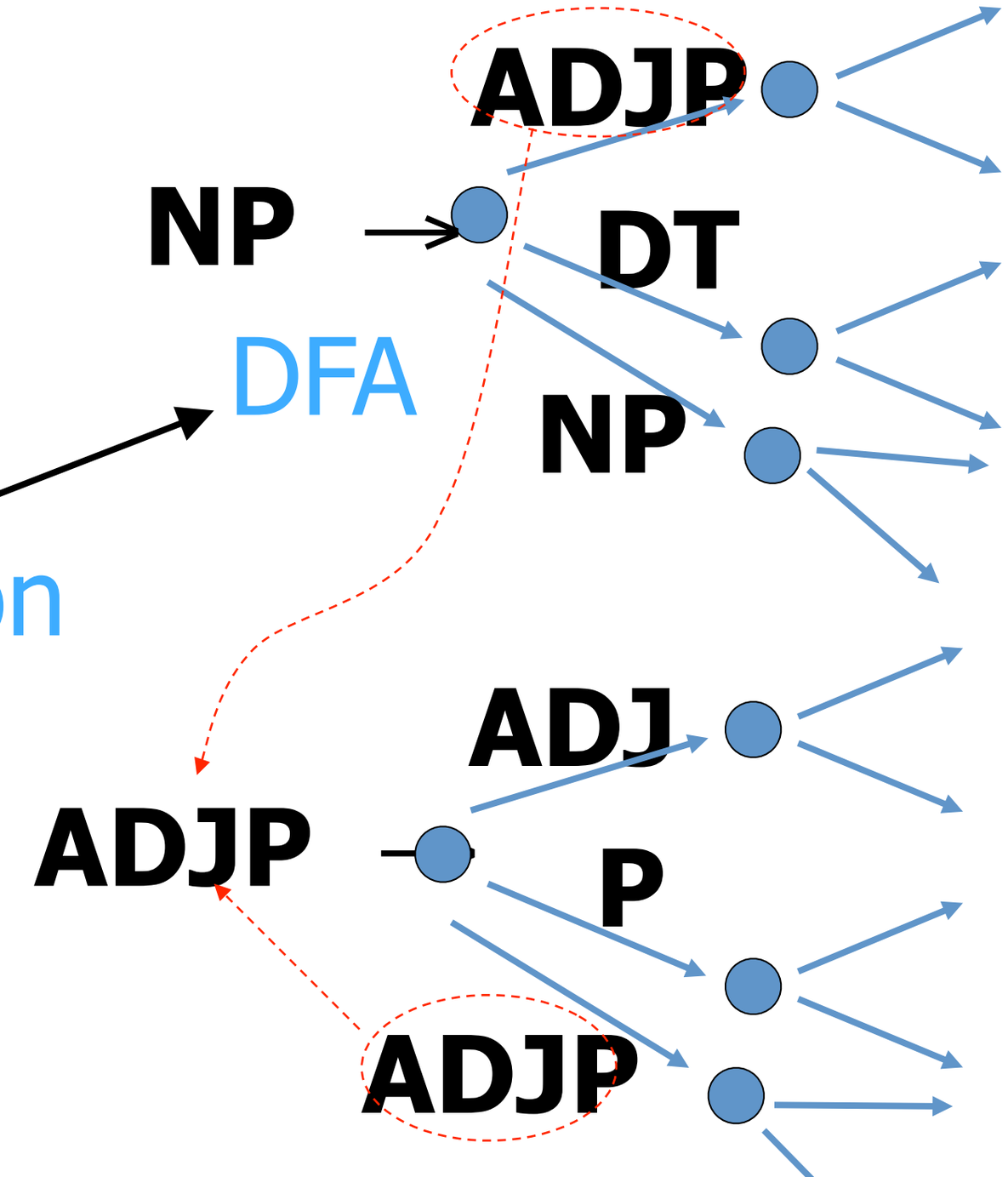
| DT ADJP ADJP NN
| DT ADJP JJ JJ NN
| DT ADJP JJ NN
| DT ADJP JJ NN NN

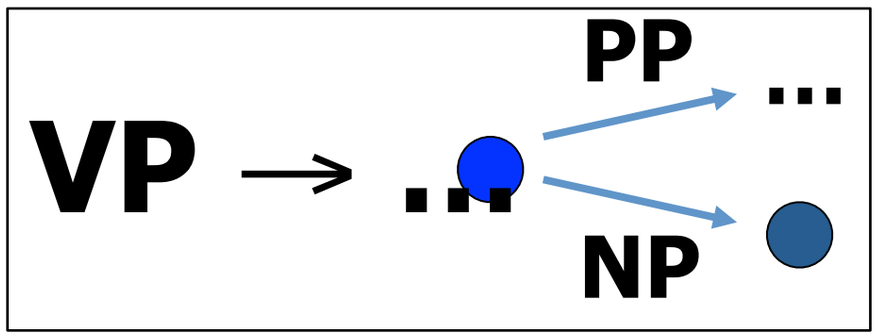
etc.

regular expression → DFA



Earley's Algorithm on DFAs

- What does Earley's algorithm now look like?

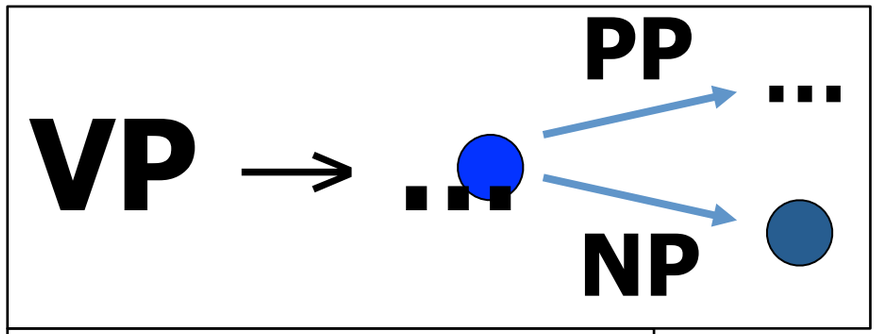


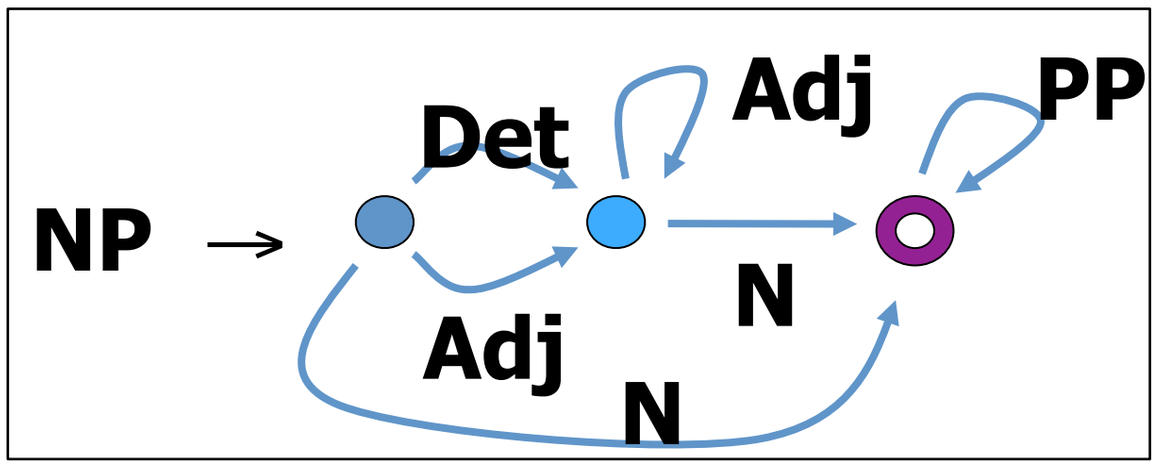
Column 4
...
(2, ●)

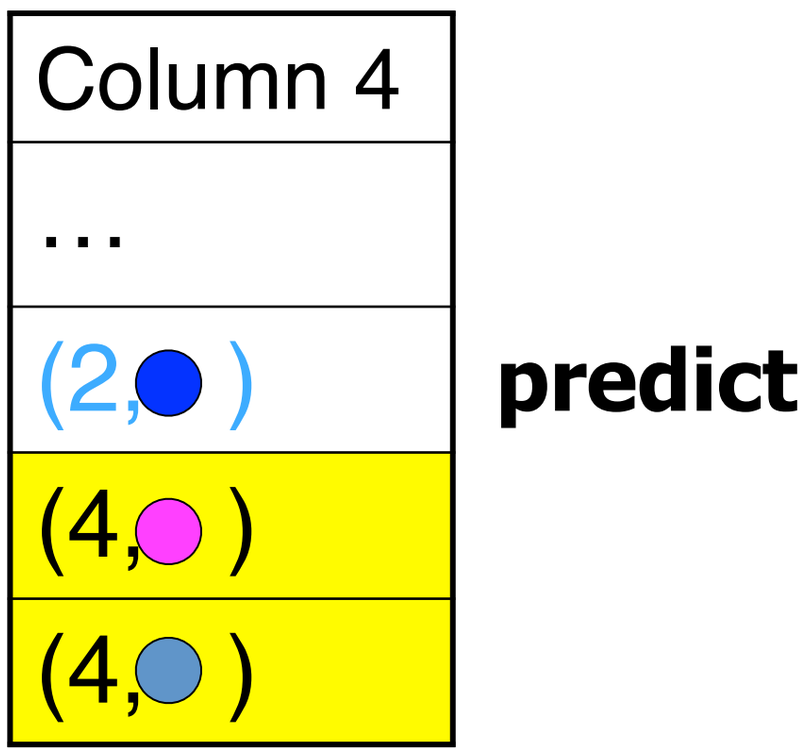
predict

Earley's Algorithm on DFAs

- What does Earley's algorithm now look like?







predict

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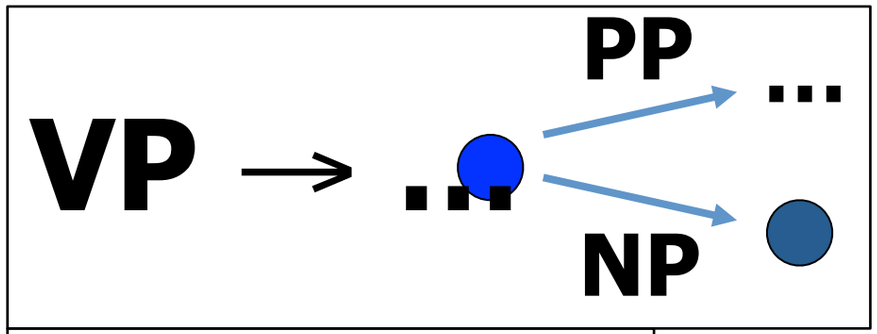

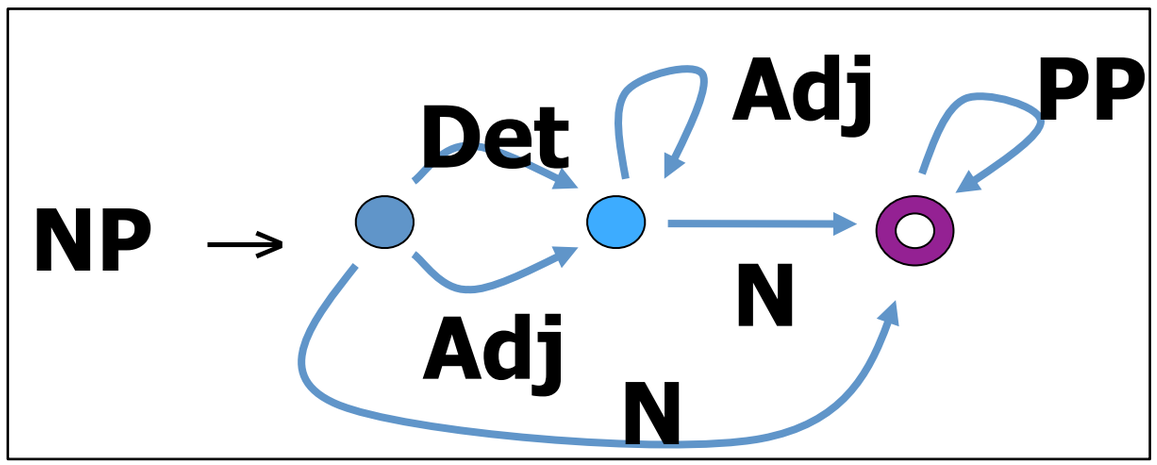

Column 4	Column 5	…	Column 7
…	…		
(2, ●)			(4, ○)
(4, ●)			
(4, ●)	(4, ●)		

predict or attach?

Earley's Algorithm on DFAs

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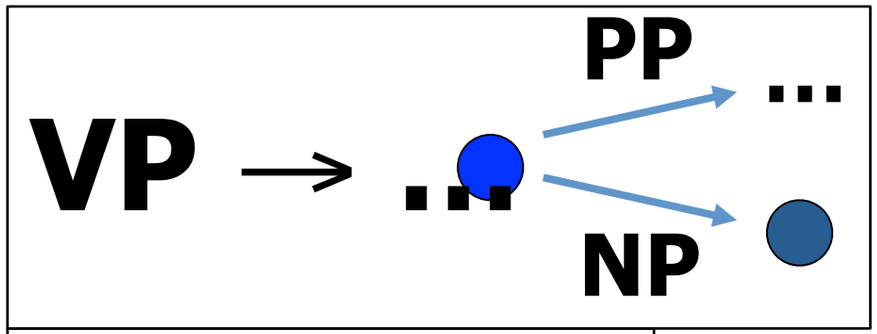

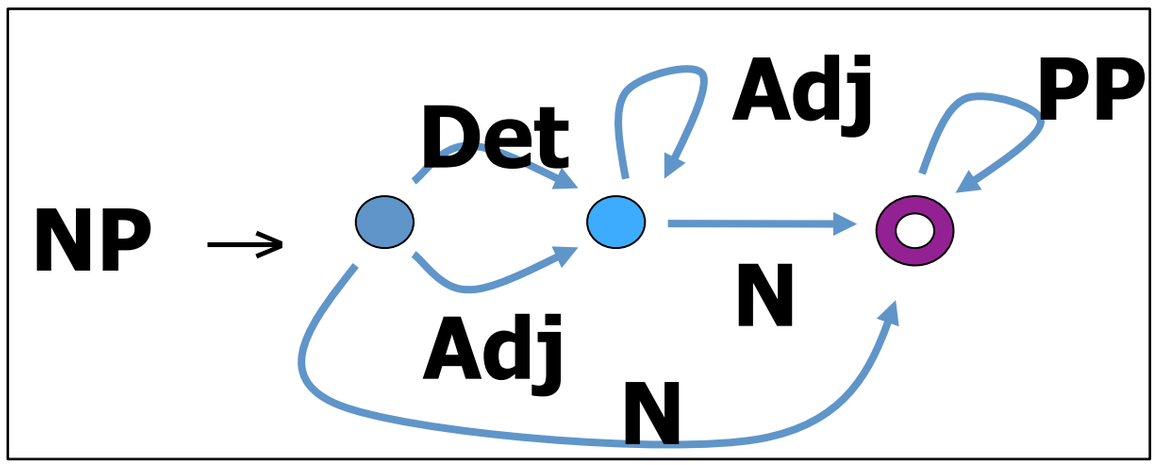

Column 4	Column 5	…	Column 7
…	…		
(2, ●)			(4, ○)
(4, ●)			
(4, ●)	(4, ●)		

predict or attach?

Both!

Pruning for Speed

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- Heuristically throw away constituents that probably won't make it into best complete parse.

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  - Throw x away if $p(x) < 10^{-200}$ (and lower this threshold if we don't get a parse)
  - Throw x away if $p(x) < 100 * p(y)$ for some y that spans the same set of words
  - Throw x away if $p(x)*q(x)$ is small, where $q(x)$ is an estimate of probability of all rules needed to combine x with the other words in the sentence

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  - if priorities are defined carefully, obtain an A* algorithm
- Put each constit on a priority queue (heap)
- Repeatedly pop and process best constituent.
  - CKY style: combine w/ previously popped neighbors.
  - Earley style: scan/predict/attach as usual. What else?

Preprocessing

Preprocessing

- First “tag” the input with parts of speech:
  - Guess the correct preterminal for each word, using faster methods we’ll learn later
  - Now only allow one part of speech per word
  - This eliminates a lot of crazy constituents!
  - But if you tagged wrong you could be hosed

- Raise the stakes:
  - What if tag says not just “verb” but “transitive verb”? Or “verb with a direct object and 2 PPs attached”? (“supertagging”)

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- Safer to allow a few possible tags per word, not just one …

Center-Embedding

```
if x
then
    if y
    then
    if a
    then b
    endif
    else b
    endif
else b
endif
```

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STATEMENT → if EXPR then
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STATEMENT → if EXPR then
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STATEMENT → if EXPR then STATEMENT
else STATEMENT endif

Center-Embedding

Center-Embedding

- This is the rat that ate the malt.

Center-Embedding

- This is the rat that ate the malt.
- This is the malt that the rat ate.

Center-Embedding

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Center-Embedding

- This is the rat that ate the malt.
- This is the malt that the rat ate.

- This is the cat that bit the rat that ate the malt.

Center-Embedding

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- This is the cat that bit the rat that ate the malt.
- This is the malt that the rat that the cat bit ate.

- This is the dog that chased the cat that bit the rat that ate the malt.

Center-Embedding

- This is the rat that ate the malt.
- This is the malt that the rat ate.

- This is the cat that bit the rat that ate the malt.
- This is the malt that the rat that the cat bit ate.

- This is the dog that chased the cat that bit the rat that ate the malt.
- This is the malt that [the rat that [the cat that [the dog chased] bit] ate].

More Center-Embedding

[What did you disguise
[those handshakes that
you greeted
[the people we bought
[the bench
[Billy was read to]
on]
with]
with]
for]?

More Center-Embedding

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[the people we bought
[the bench
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on]
with]
with]
for]?

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[the idol I sacrificed
[the fellow we sold
[the bridge you threw
[the bench
[Billy was read to]

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n]
for]?

[Which mantelpiece did you
put
[the idol I sacrificed
[the fellow we sold
[the bridge you threw
[the bench
[Billy was read to]
on]
off]
to]
on]?

Take that, English teachers!

Center Recursion vs. Tail Recursion

[What did you disguise

[those handshakes that

you greeted

[the people we bought

[the bench

[Billy was read to]

on]

with]

with]

for]?

[For what did you disguise

[those handshakes with which

you greeted

[the people with which we bought

[the bench on which

[Billy was read to]?

"pied piping" –
NP moves leftward,
preposition follows along

Disallow Center-Embedding?

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- Center-embedding seems to be in the grammar, but people have trouble processing more than 1 level of it.

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- You can limit # levels of center-embedding via features: e.g., S[S_DEPTH=n+1] → A S[S_DEPTH=n] B

Disallow Center-Embedding?

- Center-embedding seems to be in the grammar, but people have trouble processing more than 1 level of it.
- You can limit # levels of center-embedding via features: e.g., S[S_DEPTH=n+1] → A S[S_DEPTH=n] B

- If a CFG limits # levels of embedding, then it can be compiled into a finite-state machine – we don't need a stack at all!
  - Finite-state recognizers run in linear time.
  - However, it's tricky to turn them into parsers for the original CFG from which the recognizer was compiled.

Finally

- Treebanks and evaluation
- Lexicalized parsing (with heads)
- Towards dependency parsing

Treebanks

- Pure Grammar Induction Approaches tend not to produce the parse trees that people want

- Solution
  - Give a some example of parse trees that we want
  - Make a learning tool learn a grammar

- Treebank
  - A collection of such example parses
  - PennTreebank is most widely used

Treebanks

- Penn Treebank
  - Trees are represented via bracketing
  - Fairly flat structures for Noun Phrases
    (NP Arizona real estate loans)
  - Tagged with grammatical and semantic functions
    (-SBJ , –LOC, …)
  - Use empty nodes(*) to indicate understood subjects and extraction gaps

```
(  ( S ( NP-SBJ  The move)
        ( VP  followed
                ( NP  ( NP a round )
                        ( PP  of
                                (NP  ( NP similar increases )
                                        ( PP by
                                                ( NP other lenders ) )
                                        ( PP against
                                                ( NP Arizona real estate loans )))))
                ,
                ( S-ADV ( NP-SBJ * )
                        ( VP  reflecting
                                ( NP a continuing decline )
                                ( PP-LOC  in
                                                (NP  that market )))))))
        . )
```

Treebanks

- Many people have argued that it is better to have linguists constructing treebanks than grammars

- Because it is easier
  - to work out the correct parse of sentences
- than
  - to try to determine what all possible manifestations of a certain rule or grammatical construct are

Parser Evaluation

Evaluation

Ultimate goal is to build system for IE, QA, MT

- People are rarely interested in syntactic analysis for its own sake
- Evaluate the system for evaluate the parser

For Simplicity and modularization, and Convenience

- Compare parses from a parser with the result of hand parsing of a sentence(gold standard)

What is objective criterion that we are trying to maximize?

Evaluation

Tree Accuracy (Exact match)

- It is a very tough standard!!!
- But in many ways it is a sensible one to use

PARSEVAL Measures

- For some purposes, partially correct parses can be useful
- Originally for non-statistical parsers
- Evaluate the component pieces of a parse
- Measures : Precision, Recall, Crossing brackets

Evaluation

(Labeled) Precision

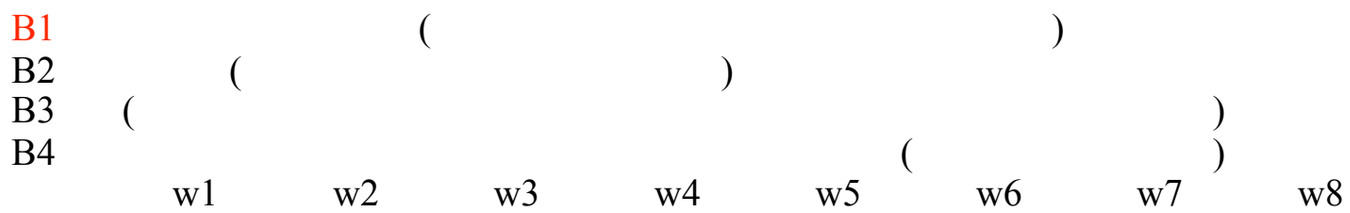
How many brackets in the parse match those in the correct tree (Gold standard)?

(Labeled) Recall

How many of the brackets in the correct tree are in the parse?

Crossing brackets

Average of how many constituents in one tree cross over constituent boundaries in the other tree



Problems with PARSEVAL

Even vanilla PCFG performs quite well

It measures success at the level of individual decisions

You must make many consecutive decisions correctly to be correct on the entire tree.

Problems with PARSEVAL (2)

Behind story

The structure of Penn Treebank

Flat → Few brackets → Low Crossing brackets

Troublesome brackets are avoided

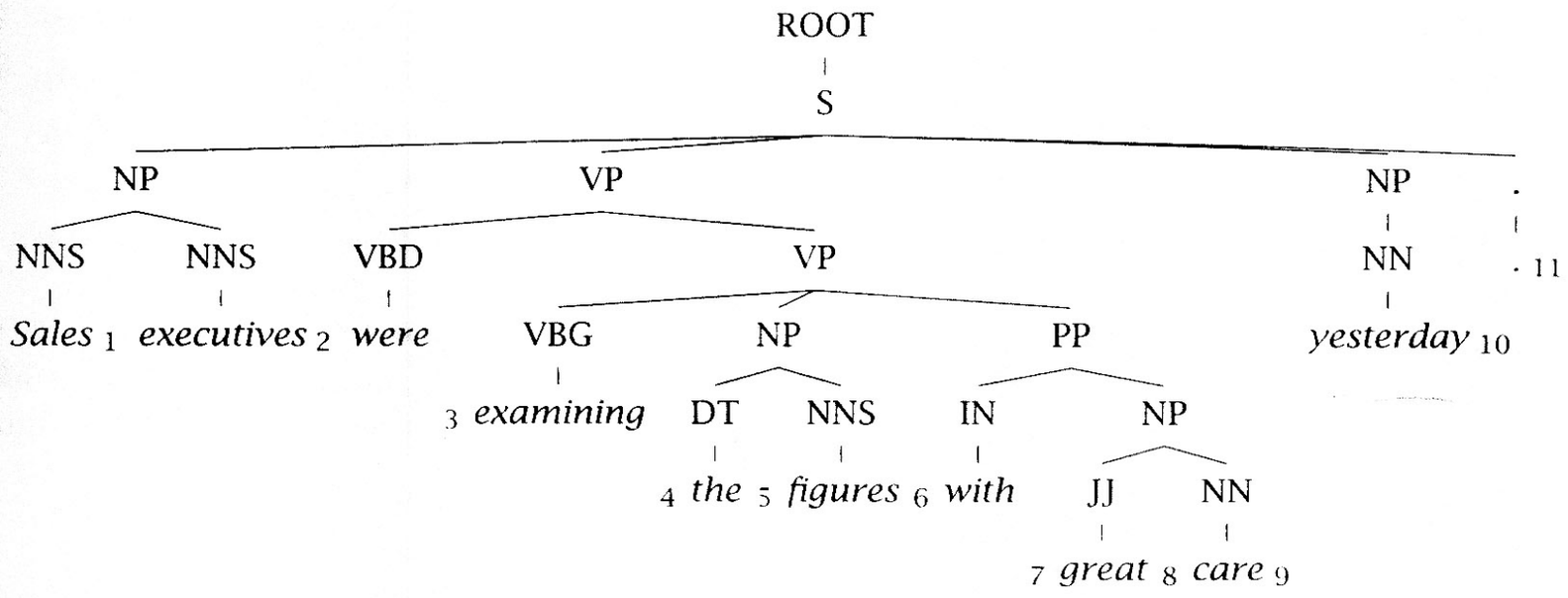
→ High Precision/Recall

The errors in precision and recall are minimal

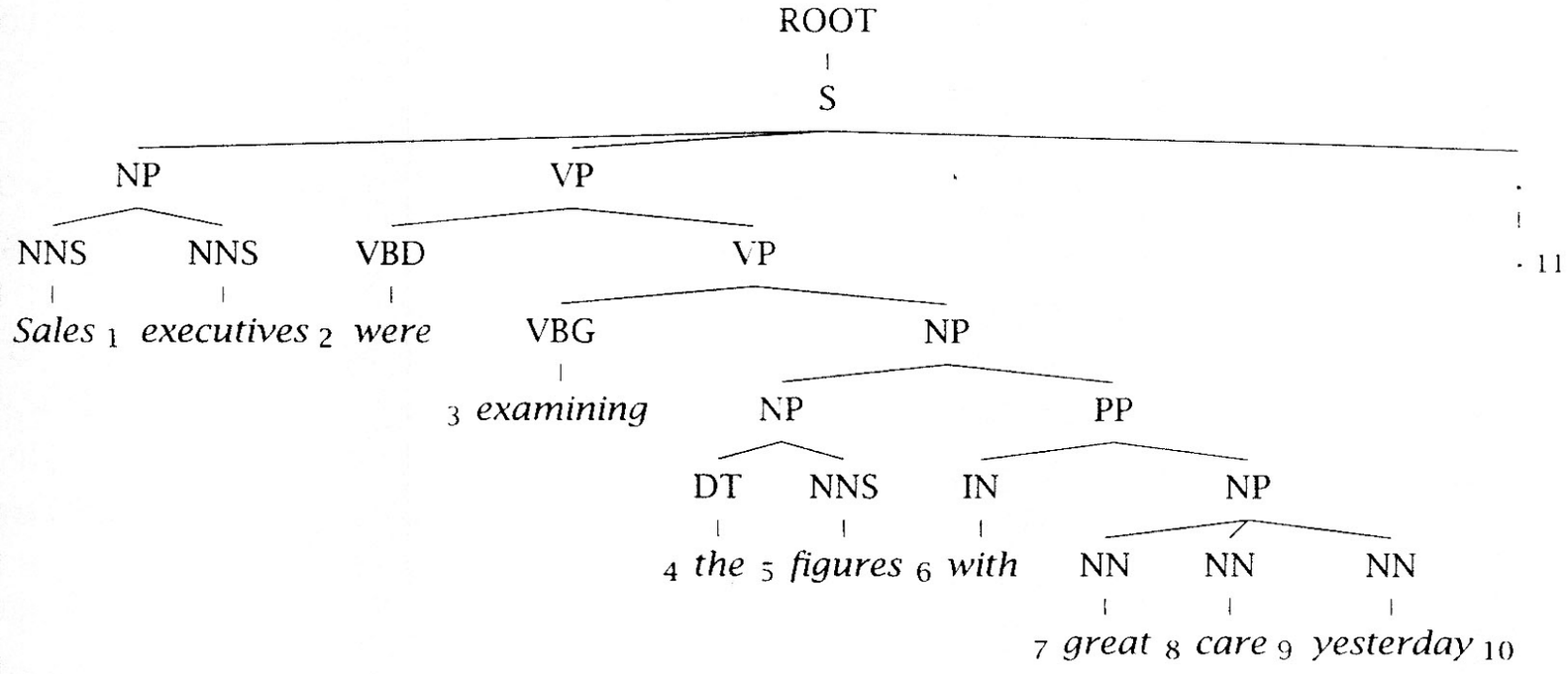
In some cases wrong PP attachment penalizes Precision, Recall and Crossing Bracket Accuracy minimally.

On the other hand, attaching low instead of high, then every node in the right-branching tree will be wrong: serious harm

(a)



(b)



(c) Brackets in gold standard tree (a.):
S-(0:11), **NP-(0:2)**, VP-(2:9), VP-(3:9), **NP-(4:6)**, PP-(6-9), NP-(7,9), *NP-(9:10)

(d) Brackets in candidate parse (b.):
S-(0:11), **NP-(0:2)**, VP-(2:10), VP-(3:10), NP-(4:10), **NP-(4:6)**, PP-(6-10), NP-(7,10)

(e)

Precision:	3/8 = 37.5%	Crossing Brackets:	3
Recall:	3/8 = 37.5%	Crossing Accuracy:	62%
Labeled Precision:	3/8 = 37.5%	Tagging Accuracy:	10/11 = 90.9%
Labeled Recall:	3/8 = 37.5%		

Evaluation

Do PARSEVAL measures succeed in real tasks?

- Many small parsing mistakes might not affect tasks of semantic interpretation
  - (Bonnema 1996,1997)
    - Tree Accuracy of the Parser : 62%
    - Correct Semantic Interpretations : 88%
  - (Hermajakob and Mooney 1997)
    - English to German translation

At the moment, people feel PARSEVAL measures are adequate for the comparing parsers

Lexicalized Parsing

Limitations of PCFGs

- PCFGs assume:
  - Place invariance
  - Context free: P(rule) independent of
    - words outside span
    - *also, words with overlapping derivation*
  - Ancestor free: P(rule) independent of
    - *Non-terminals above.*

- Lack of sensitivity to lexical information
- Lack of sensitivity to structural frequencies

Lack of Lexical Dependency

Means that

P(VP → V NP NP)

is independent of the particular verb involved!

... but much more likely with ditransitive verbs (like ***gave***).

*He **gave** the boy a ball.*

*He **ran** to the store.*

The Need for Lexical Dependency

Probabilities dependent on Lexical words

Problem 1 : Verb subcategorization

VP expansion is independent of the choice of verb

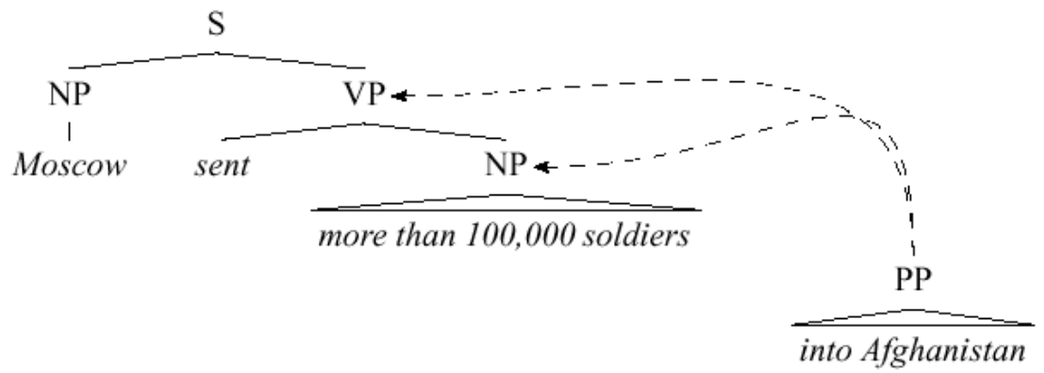
However …

	verb			
	come	take	think	want
VP -> V	9.5%	2.6%	4.6%	5.7%
VP -> V NP	1.1%	32.1%	0.2%	13.9%
VP -> V PP	34.5%	3.1%	7.1%	0.3%
VP -> V SBAR	6.6%	0.3%	73.0%	0.2%
VP -> V S	2.2%	1.3%	4.8%	70.8%

Including actual words information when making decisions about tree structure is necessary

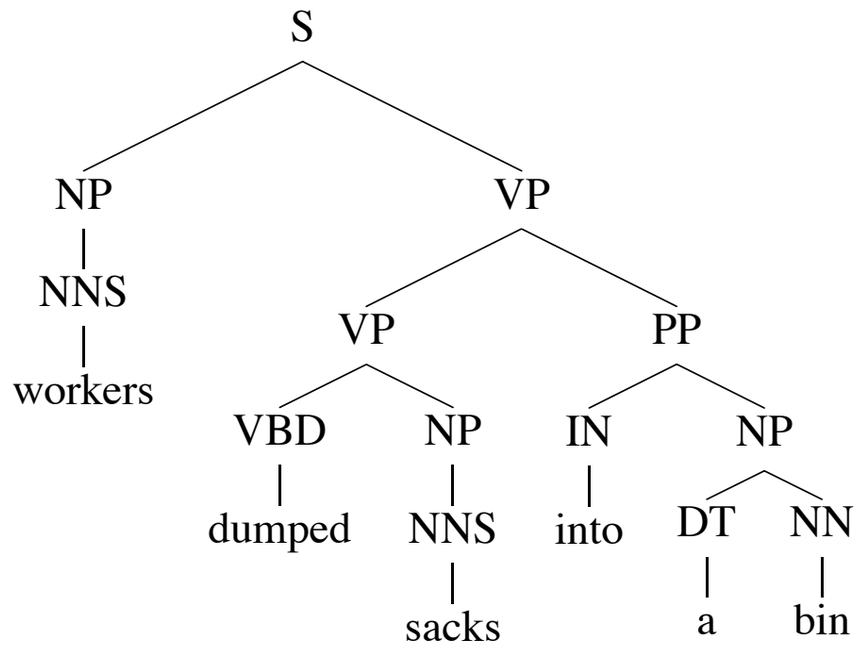
Weakening the independence assumption of PCFG

- Probabilities dependent on Lexical words
  - Problem 2 : Phrasal Attachment
    - Lexical content of phrases provide information for decision
    - Syntactic category of the phrases provide very little information
    - Standard PCFG is worse than n-gram models



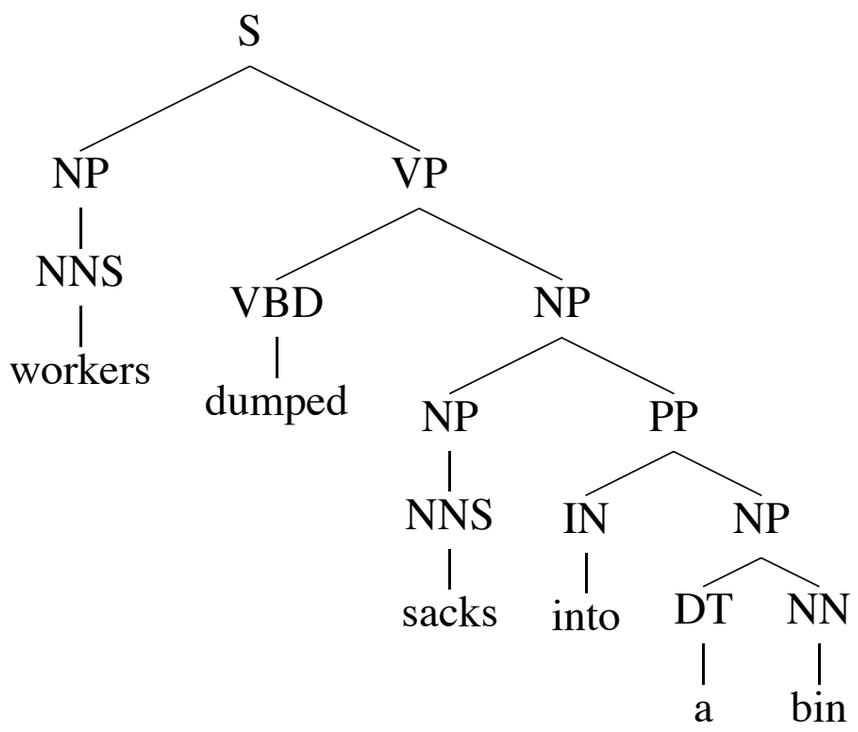
Another case of PP attachment ambiguity

(a)



Another case of PP attachment ambiguity

(b)



Another case of PP attachment ambiguity

(a)

Rules
S → NP VP
NP → NNS
VP → VP PP
VP → VBD NP
NP → NNS
PP → IN NP
NP → DT NN
NNS → workers
VBD → dumped
NNS → sacks
IN → into
DT → a
NN → bin

(b)

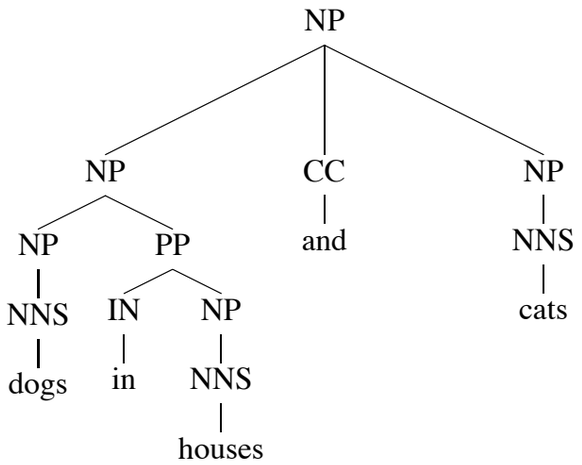
Rules
S → NP VP
NP → NNS
NP → NP PP
VP → VBD NP
NP → NNS
PP → IN NP
NP → DT NN
NNS → workers
VBD → dumped
NNS → sacks
IN → into
DT → a
NN → bin

If $P(\text{NP} \rightarrow \text{NP PP} \mid \text{NP}) > P(\text{VP} \rightarrow \text{VP PP} \mid \text{VP})$ then (b) is more probable, else (a) is more probable.

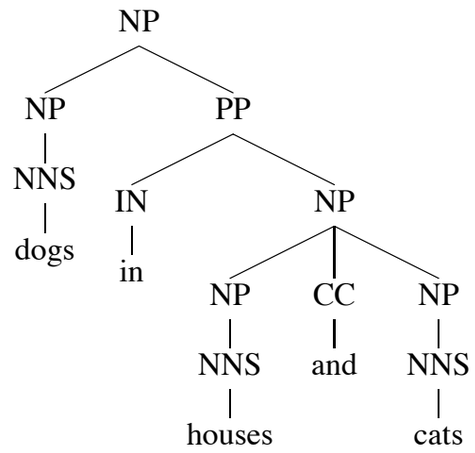
Attachment decision is completely independent of the words

A case of coordination ambiguity

(a)



(b)



(a)

Rules
NP → NP CC NP
NP → NP PP
NP → NNS
PP → IN NP
NP → NNS
NP → NNS
NNS → dogs
IN → in
NNS → houses
CC → and
NNS → cats

(b)

Rules
NP → NP CC NP
NP → NP PP
NP → NNS
PP → IN NP
NP → NNS
NP → NNS
NNS → dogs
IN → in
NNS → houses
CC → and
NNS → cats

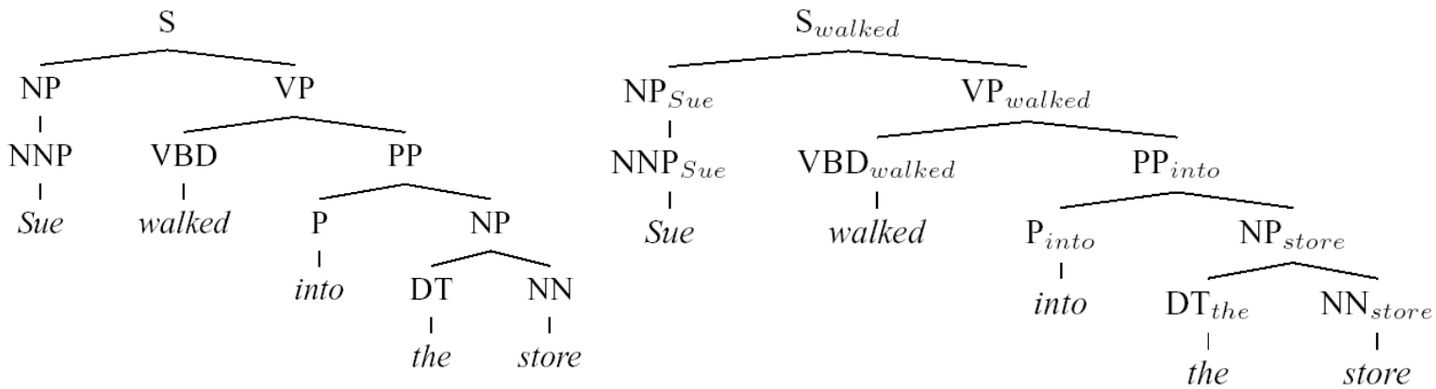
Here the two parses have identical rules, and therefore have identical probability under any assignment of PCFG rule probabilities

Weakening the independence assumption of PCFG

Probabilities dependent on Lexical words

Solution

Lexicalize CFG : Each phrasal node with its head word



Background idea

Strong lexical dependencies between heads and their dependents

Heads in Context-Free Rules

Add annotations specifying the "head" of each rule:

S	⇒	NP	VP
VP	⇒	Vi	
VP	⇒	Vt	NP
VP	⇒	VP	PP
NP	⇒	DT	NN
NP	⇒	NP	PP
PP	⇒	IN	NP

Vi	⇒	sleeps
Vt	⇒	saw
NN	⇒	man
NN	⇒	woman
NN	⇒	telescope
DT	⇒	the
IN	⇒	with
IN	⇒	in

Note: S=sentence, VP=verb phrase, NP=noun phrase, PP=prepositional phrase, DT=determiner, Vi=intransitive verb, Vt=transitive verb, NN=noun, IN=preposition

More about heads

- Each context-free rule has one "special" child that is the head of the rule. e.g.,

S	$\Rightarrow$	NP	VP		(VP is the head)
VP	$\Rightarrow$	Vt	NP		(Vt is the head)
NP	$\Rightarrow$	DT	NN	NN	(NN is the head)

- A core idea in linguistics
  (X-bar Theory, Head-Driven Phrase Structure Grammar)

- Some intuitions:
  - The central sub-constituent of each rule.
  - The semantic predicate in each rule.

Rules which recover heads: Example rules for NPs

If the rule contains NN, NNS, or NNP:
Choose the rightmost NN, NNS, or NNP

Else If the rule contains an NP: Choose the leftmost NP

Else If the rule contains a JJ: Choose the rightmost JJ

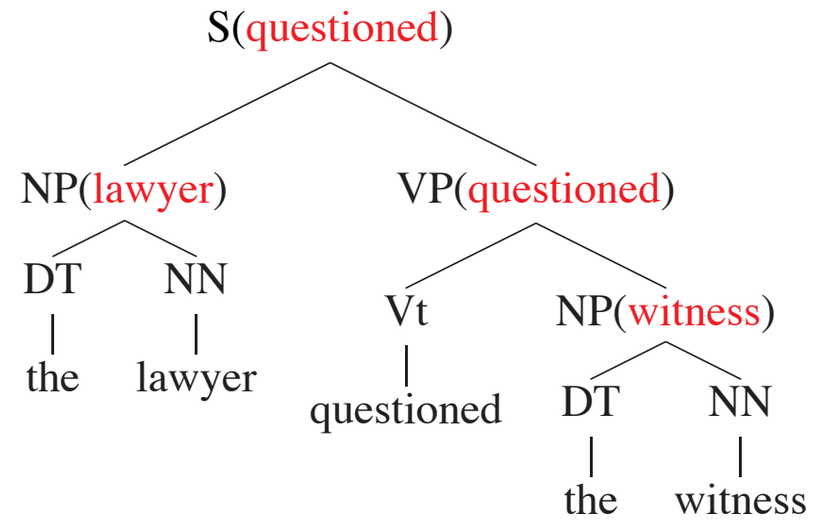
Else If the rule contains a CD: Choose the rightmost CD

Else Choose the rightmost child

e.g.,

NP	⇒	DT	NNP	NN
NP	⇒	DT	NN	NNP
NP	⇒	NP	PP	
NP	⇒	DT	JJ	
NP	⇒	DT		

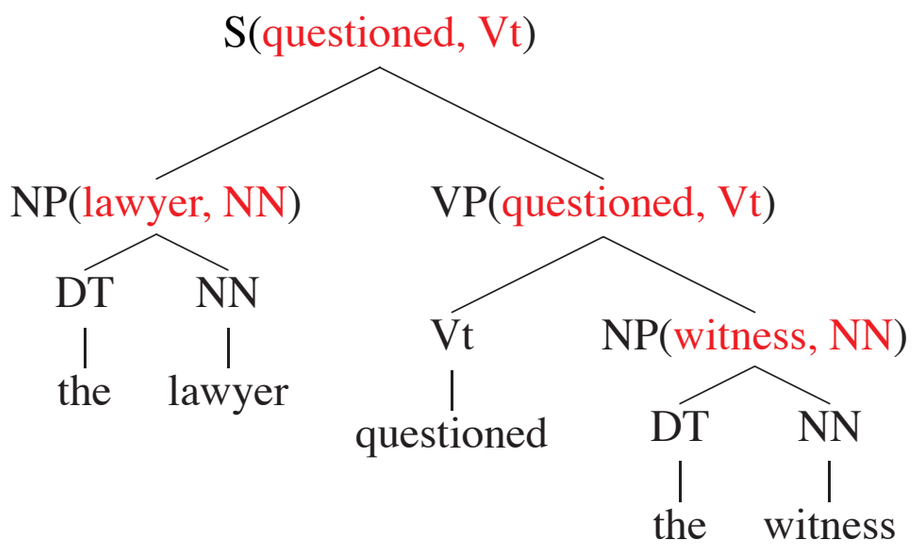
Adding Headwords to Trees



- A constituent receives its headword from its **head child**.

S	$\Rightarrow$	NP	VP		(S receives headword from VP)
VP	$\Rightarrow$	Vt	NP		(VP receives headword from Vt)
NP	$\Rightarrow$	DT		NN	(NP receives headword from NN)

Adding Headtags to Trees



- Also propogate **part-of-speech tags** up the trees

Explosion of number of rules

New rules might look like:

VP[gave] → V[gave] NP[man] NP[book]

But this would be a massive explosion in number of rules (and parameters)

Sparseness and the Penn Treebank

- The Penn Treebank – 1 million words of parsed English *WSJ* – has been a key resource (because of the widespread reliance on supervised learning)
- But 1 million words is like nothing:
  - 965,000 constituents, but only 66 WHADJP, of which only 6 aren't *how much* or *how many*, but there is an infinite space of these (*how clever/original/incompetent* (*at risk assessment and evaluation*))
- Most of the probabilities that you would like to compute, you can't compute

Sparseness and the Penn Treebank

- Most intelligent processing depends on bilexical statistics: likelihoods of relationships between pairs of words.
- Extremely sparse, even on topics central to the *WSJ*:
  - stocks plummeted 2 occurrences
  - stocks stabilized 1 occurrence
  - stocks skyrocketed 0 occurrences
  - #stocks discussed 0 occurrences
- So far there has been very modest success augmenting the Penn Treebank with extra unannotated materials or using semantic classes or clusters (cf. Charniak 1997, Charniak 2000) – as soon as there are more than tiny amounts of annotated training data.

Lexicalized, Markov out from head

Collins 1997: Markov model out from head

- Charniak (1997) expands each phrase structure tree in a single step.
- This is good for capturing dependencies between child nodes
- But it is bad because of data sparseness
- A pure dependency, one child at a time, model is worse
- But one can do better by in between models, such as generating the children as a Markov process on both sides of the head (Collins 1997; Charniak 2000)

Modeling Rule Productions as Markov Processes

- Step 1: generate category of head child

S(told,V[6])

S(told,V[6])

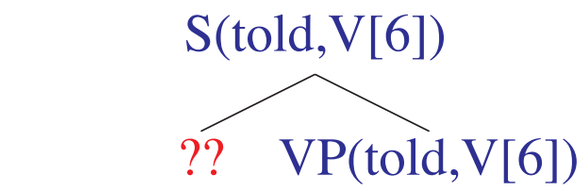
|

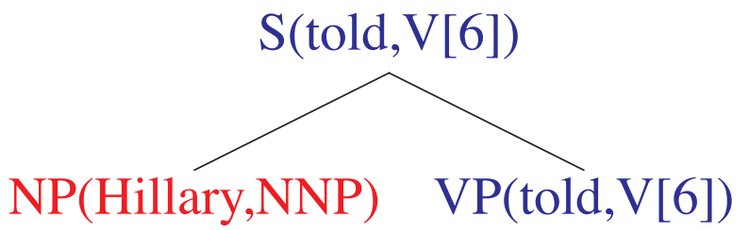
VP(told,V[6])

P_h(VP | S, told, V[6])

Modeling Rule Productions as Markov Processes

- Step 2: generate left modifiers in a Markov chain

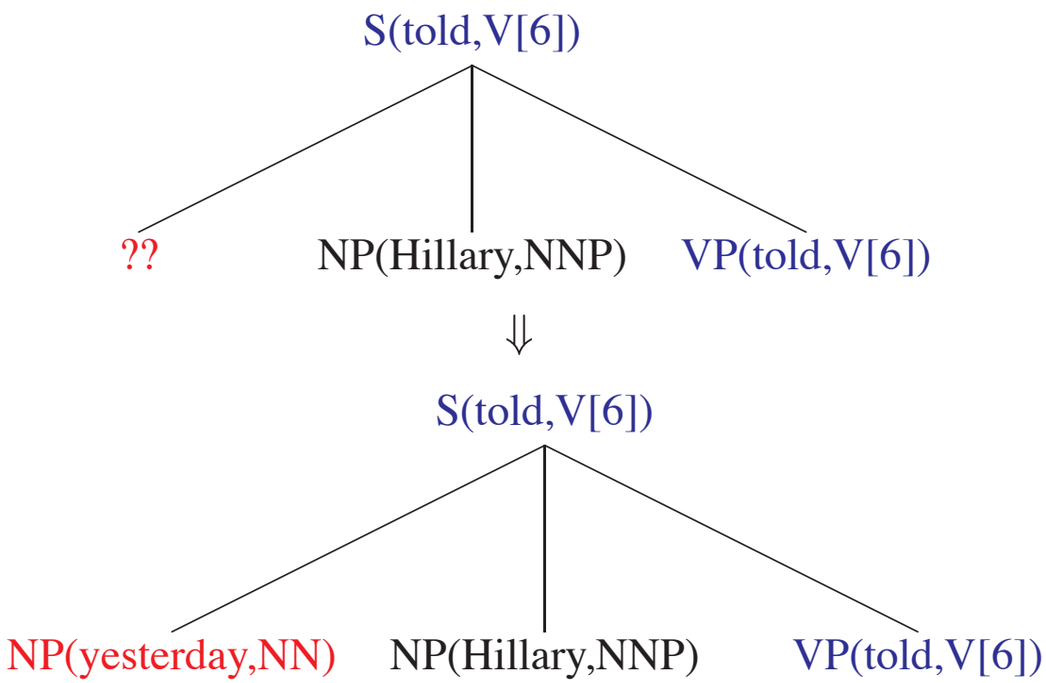




$$P_h(\text{VP} \mid \text{S, told, V[6]}) \times P_d(\text{NP(Hillary,NNP)} \mid \text{S,VP,told,V[6],LEFT})$$

Modeling Rule Productions as Markov Processes

- Step 2: generate left modifiers in a Markov chain



$P_h(\text{VP} \mid \text{S, told, V[6]}) \times P_d(\text{NP(Hillary,NNP)} \mid \text{S,VP,told,V[6],LEFT}) \times$
$P_d(\text{NP(yesterday,NN)} \mid \text{S,VP,told,V[6],LEFT})$

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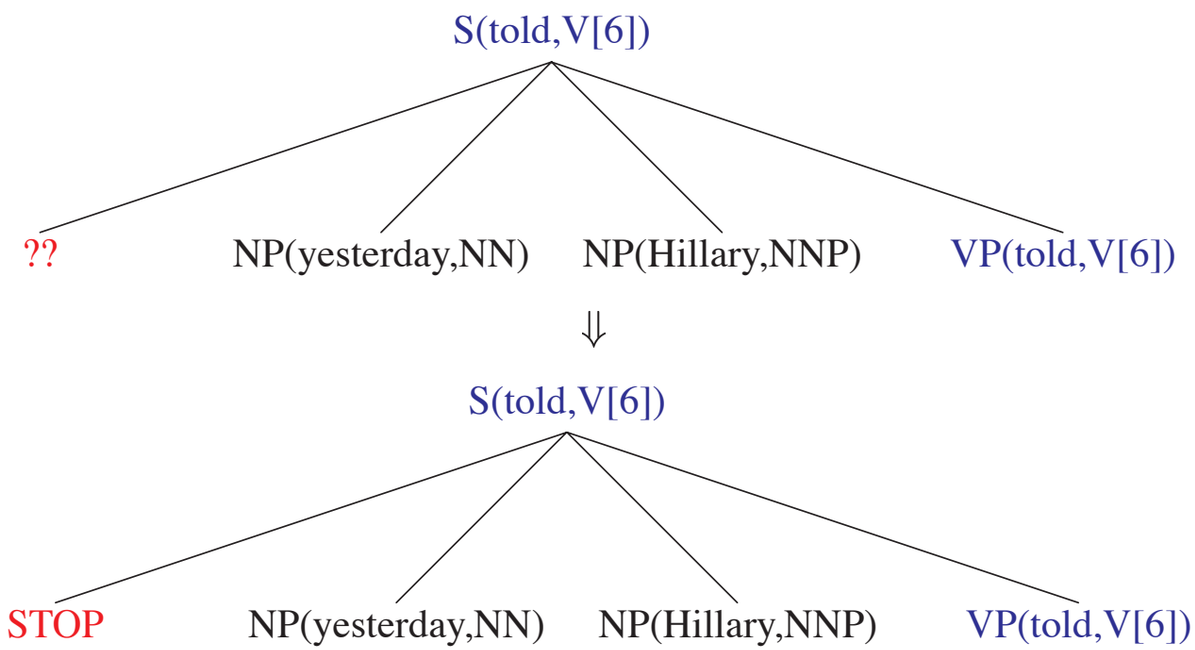
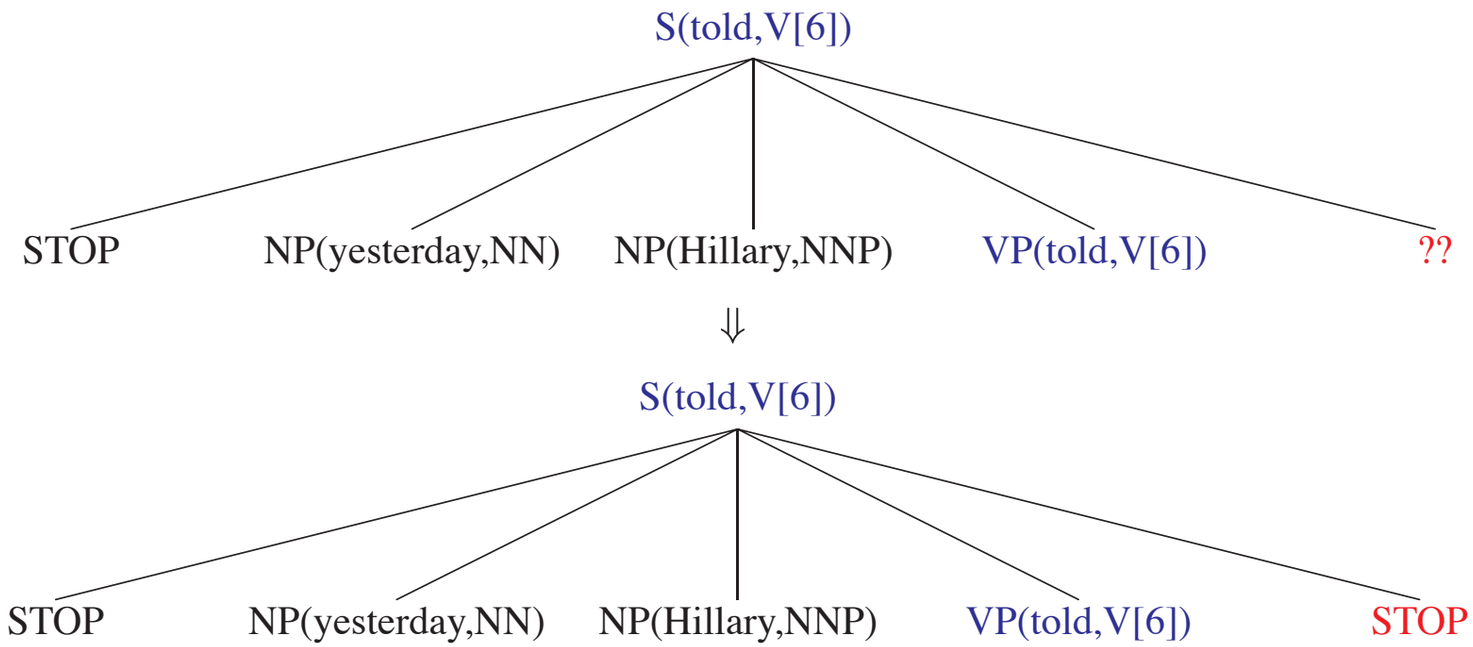


P_h(VP | S, told, V[6]) $\times$ P_d(NP(Hillary,NNP) | S,VP,told,V[6],LEFT)$\times$
P_d(NP(yesterday,NN) | S,VP,told,V[6],LEFT) $\times$ P_d(STOP | S,VP,told,V[6],LEFT)

Modeling Rule Productions as Markov Processes

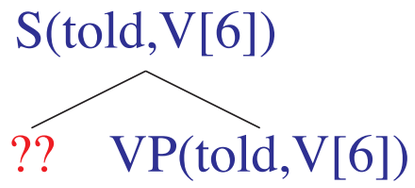
- Step 3: generate right modifiers in a Markov chain

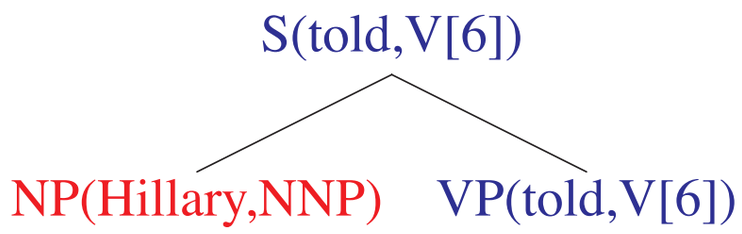


$P_h(\text{VP} \mid \text{S, told, V[6]}) \times P_d(\text{NP(Hillary,NNP)} \mid \text{S,VP,told,V[6],LEFT}) \times$
$P_d(\text{NP(yesterday,NN)} \mid \text{S,VP,told,V[6],LEFT}) \times P_d(\text{STOP} \mid \text{S,VP,told,V[6],LEFT}) \times$
$P_d(\text{STOP} \mid \text{S,VP,told,V[6],RIGHT})$

A Refinement: Adding a Distance Variable

- $\Delta = 1$ if position is adjacent to the head.





$P_h(\text{VP} \mid \text{S, told, V[6]}) \times$
$P_d(\text{NP(Hillary,NNP)} \mid \text{S,VP,told,V[6],LEFT},\Delta = 1)$

Adding dependency on structure

Weakening the independence assumption of PCFG

Probabilities dependent on structural context

PCFGs are also deficient on purely structural grounds too

Really context independent?

Expansion	% as Subj	% as Obj
NP → PRP	13.7%	2.1%
NP → NNP	3.5%	0.9%
NP → DT NN	5.6%	4.6%
NP → NN	1.4%	2.8%
NP → NP SBAR	0.5%	2.6%
NP → NP PP	5.6%	14.1%

Weakening the independence assumption of PCFG