

# Computational Psycholinguistics Lecture 3: Inference over infinite tree sets

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# Context-free Grammars

A context-free grammar (CFG) consists of a tuple  $(N, V, S, R)$  such that:

- ▶  $N$  is a finite set of non-terminal symbols;
- ▶  $V$  is a finite set of terminal symbols;
- ▶  $S$  is the start symbol;
- ▶  $R$  is a finite set of rules of the form  $X \rightarrow \alpha$  where  $X \in N$  and  $\alpha$  is a sequence of symbols drawn from  $N \cup V$ .

A CFG *derivation* is the recursive expansion of non-terminal symbols in a string by rules in  $R$ , starting with  $S$ , and a *derivation tree*  $T$  is the history of those rule applications.

# Probabilistic Context-Free Grammars

A *probabilistic* context-free grammar (PCFG) consists of a tuple  $(N, V, S, R, P)$  such that:

- ▶  $N$  is a finite set of non-terminal symbols;
- ▶  $V$  is a finite set of terminal symbols;
- ▶  $S$  is the start symbol;
- ▶  $R$  is a finite set of rules of the form  $X \rightarrow \alpha$  where  $X \in N$  and  $\alpha$  is a sequence of symbols drawn from  $N \cup V$ ;
- ▶  $P$  is a mapping from  $R$  into probabilities, such that for each  $X \in N$ ,

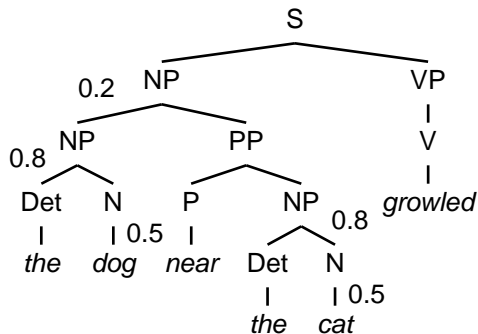
$$\sum_{[X \rightarrow \alpha] \in R} P(X \rightarrow \alpha) = 1$$

PCFG *derivations* and *derivation trees* are just like for CFGs. The probability  $P(T)$  of a derivation tree is simply the product of the probabilities of each rule application.

# Example PCFG

1 S → NP VP  
0.8 NP → Det N  
0.2 NP → NP PP  
1 PP → P NP  
1 VP → V

1 Det → the  
0.5 N → dog  
0.5 N → cat  
1 P → near  
1 V → growled



$$P(T) = 1 \times 0.2 \times 0.8 \times 1 \times 0.5 \times 0.8 \times 1 \times 0.8 \times 1 \times 0.5 \times 1 \times 1 \\ = 0.032$$

## PCFG review (2)

- ▶ We just learned how to calculate the *probability of a tree*
- ▶ The *probability of a string*  $w_{1\dots n}$  is the sum of the probabilities of all trees whose yield **is**  $w_{1\dots n}$
- ▶ The *probability of a string prefix*  $w_{1\dots i}$  is the sum of the probabilities of all trees whose yield **begins with**  $w_{1\dots i}$
- ▶ If we had the probabilities of two string prefixes  $w_{1\dots i-1}$  and  $w_{1\dots i}$ , we could calculate the conditional probability  $P(w_i|w_{1\dots i-1})$  as their ratio:

$$P(w_i|w_{1\dots i-1}) = \frac{P(w_{1\dots i})}{P(w_{1\dots i-1})}$$

# Inference over infinite tree sets

Consider the following noun-phrase grammar:

$\infty$   
 $\omega$   
 $\downarrow$   
2  
1 NP  $\rightarrow$  Det N  
NP  $\rightarrow$  NP PP  
PP  $\rightarrow$  P NP

1 Det  $\rightarrow$  the  
2 N  $\rightarrow$  dog  
3  
1 N  $\rightarrow$  cat  
3  
1 P  $\rightarrow$  near

# Inference over infinite tree sets

Consider the following noun-phrase grammar:

$\frac{2}{3}$	NP $\rightarrow$ Det N	1	Det $\rightarrow$ the
$\frac{1}{3}$	NP $\rightarrow$ NP PP	$\frac{2}{3}$	N $\rightarrow$ dog
1	PP $\rightarrow$ P NP	$\frac{1}{3}$	N $\rightarrow$ cat
		1	P $\rightarrow$ near

Question: given a sentence starting with

*the...*

what is the probability that the next word is *dog*?

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Intuitively, the answers to this question should be

$$P(\text{dog}|\text{the}) = \frac{2}{3}$$

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Question: given a sentence starting with

*the...*

what is the probability that the next word is *dog*?

Intuitively, the answers to this question should be

$$P(\text{dog}|\text{the}) = \frac{2}{3}$$

because the second word HAS to be either *dog* or *cat*.

## Inference over infinite tree sets (2)

$\frac{2}{3}$  NP  $\rightarrow$  Det N  
 $\frac{1}{3}$  NP  $\rightarrow$  NP PP  
1 PP  $\rightarrow$  P NP

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 $\frac{2}{3}$  N  $\rightarrow$  dog  
 $\frac{1}{3}$  N  $\rightarrow$  cat  
1 P  $\rightarrow$  near

- ▶ We “should” just enumerate the trees that cover *the dog ...*,

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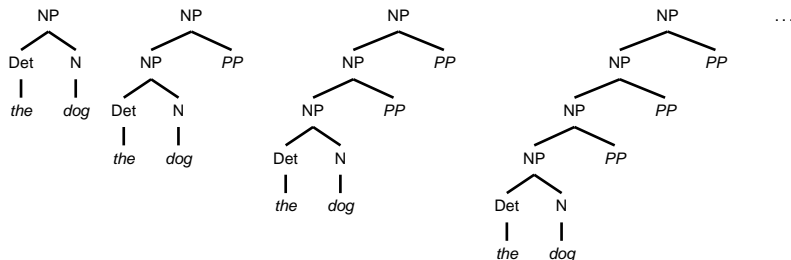
- ▶ We “should” just enumerate the trees that cover *the dog ...*, and divide their total probability by that of *the ...*
- ▶ ...but there are infinitely many trees.

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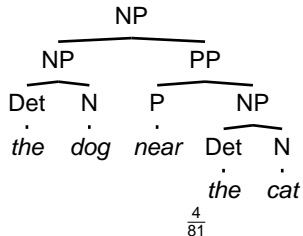
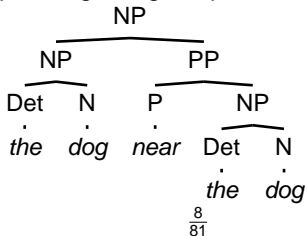
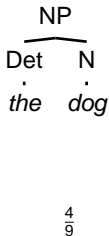


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Shortcut 1: you can think of a *partial* tree as marginalizing over all completions of the partial tree.

It has a corresponding marginal probability in the PCFG.

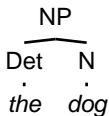


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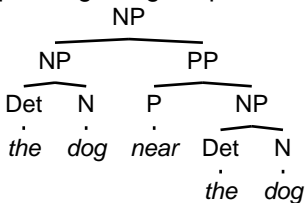
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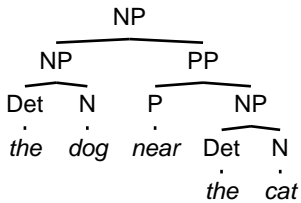
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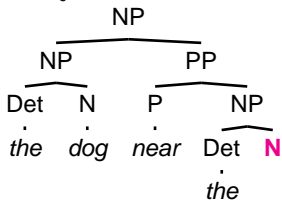
$\frac{4}{9}$



$\frac{8}{81}$



$\frac{4}{81}$



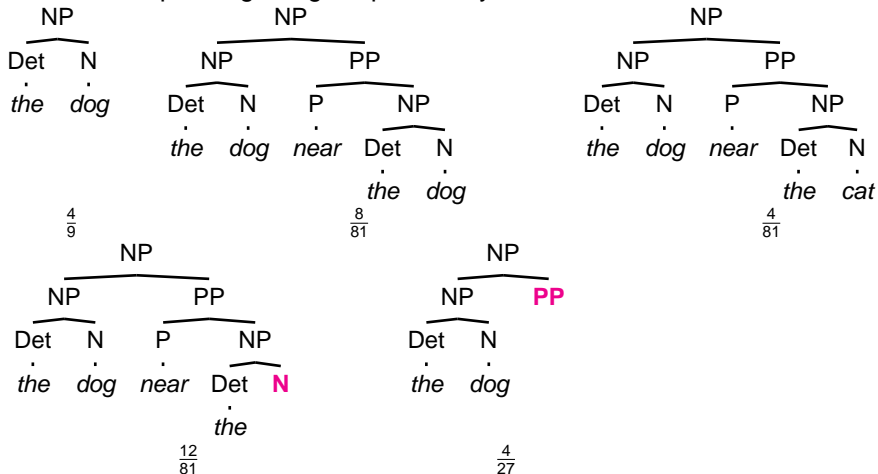
$\frac{12}{81}$

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 1 PP  $\rightarrow$  P NP

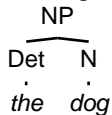
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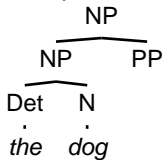
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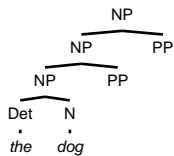
Problem 2: there are still an infinite number of incomplete trees covering a partial input.



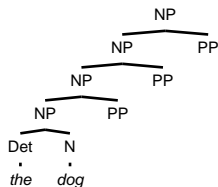
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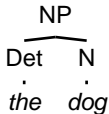


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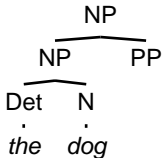


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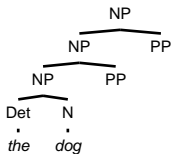
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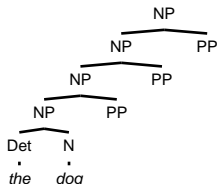
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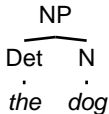


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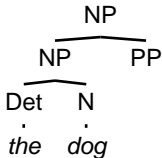
BUT! These tree probabilities form a geometric series:

$$P(\text{the dog} \dots) = \frac{4}{9} + \frac{4}{27} + \frac{4}{81} + \frac{4}{243} + \dots$$

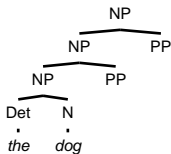
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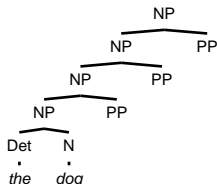
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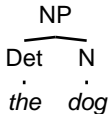


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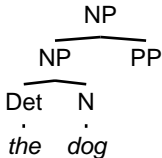
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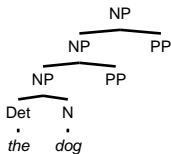
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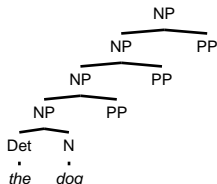
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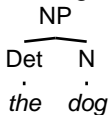


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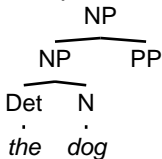
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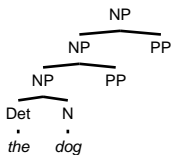
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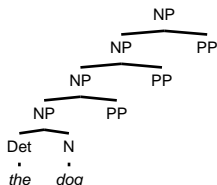
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 \end{aligned}$$

... which matches the original rule probability

$$\frac{2}{3} N \rightarrow \text{dog}$$

# Generalizing the geometric series induced by rule recursion

In general, these infinite tree sets arise due to *left recursion* in a probabilistic grammar

$$A \rightarrow B \alpha$$

$$B \rightarrow A \beta$$

(Stolcke, 1995)

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We can formulate a stochastic *left-corner matrix* of transitions between categories:

$$P_L = \begin{array}{c|cccc} & A & B & \dots & K \\ \hline A & 0.3 & 0.7 & \dots & 0 \\ B & 0.1 & 0.1 & \dots & 0.2 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ K & 0.2 & 0.1 & \dots & 0.2 \end{array}$$

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and solve for its closure  $R_L = (I - P_L)^{-1}$ . (Stolcke, 1995)

# Generalizing the geometric series

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$\frac{2}{3}$	N	→ dog
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- ▶ The closure of our left-corner matrix is

$$R_L = \begin{matrix} & \text{ROOT} & \text{NP} & \text{PP} & \text{Det} & \text{N} & \text{P} \\ \text{ROOT} & \left( \begin{array}{cccccc} 1 & \frac{3}{2} & 0 & 1 & 0 & 0 \\ 0 & \frac{3}{2} & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{array} \right) \end{matrix}$$

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- ▶ Refer to an entry  $(X, Y)$  in this matrix as  $R(X \Rightarrow_L^* Y)$

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- ▶ Refer to an entry  $(X, Y)$  in this matrix as  $R(X \Rightarrow_L^* Y)$
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- ▶ We need to do the same with unary chains, constructing a unary-closure matrix  $R_U$ .

# Efficient incremental parsing: the probabilistic Earley algorithm

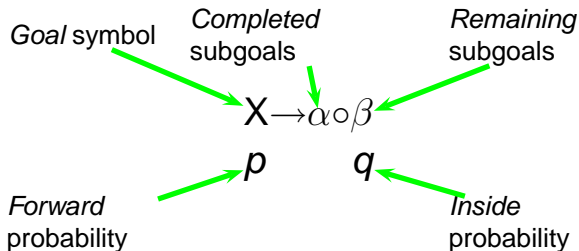
We can use the Earley algorithm (Earley, 1970) in a probabilistic incarnation (Stolcke, 1995) to deal with these infinite tree sets.

The (slightly oversimplified) probabilistic Earley algorithm has two fundamental types of operations:

- ▶ **Prediction:** if  $Y$  is a possible goal, and  $Y$  can lead to  $Z$  through a left corner, choose a rule  $Z \rightarrow \alpha$  and set up  $\alpha$  as a new sequence of possible goals.
- ▶ **Completion:** if  $Y$  is a possible goal,  $Y$  can lead to  $Z$  through unary rewrites, and we encounter a completed  $Z$ , absorb it and move on to the next sub-goal in the sequence.

# Efficient incremental parsing: the probabilistic Earley algorithm

- ▶ Parsing consists of constructing a *chart* of *states* (items)
- ▶ A state has the following structure:



- ▶ The *forward* probability is the total probability of getting **from** the root at the start of the sentence **through to** this state
- ▶ The *inside* probability is the “bottom-up” probability of the state

# Efficient incremental parsing: the probabilistic Earley algorithm

Inference rules for probabilistic Earley:

► **Prediction:**

$$\frac{\begin{array}{cc} X \rightarrow \beta \circ Y \gamma \\ p & q \end{array} \quad a : R(Y \xrightarrow{*}_L Z) \quad b : Z \rightarrow \alpha}{\begin{array}{cc} Z \rightarrow \circ \alpha \\ abp & b \end{array}}$$

# Efficient incremental parsing: the probabilistic Earley algorithm

Inference rules for probabilistic Earley:

► **Prediction:**

$$\frac{\begin{array}{ccc} X \rightarrow \beta \circ Y \gamma & & \\ p & q & \end{array} \quad a : R(Y \xrightarrow{*}_L Z) \quad b : Z \rightarrow \alpha}{\begin{array}{ccc} & & Z \rightarrow \circ \alpha \\ abp & & b \end{array}}$$

► **Completion:**

$$\frac{\begin{array}{ccc} X \rightarrow \beta \circ Y \gamma & & \\ p & q & \end{array} \quad a : R(Y \xrightarrow{*}_U Z) \quad \begin{array}{cc} Z \rightarrow \alpha \circ & \\ b & c \end{array}}{\begin{array}{ccc} X \rightarrow \beta Y \circ \gamma & & \\ acp & & acq \end{array}}$$



# Efficient incremental parsing: probabilistic Earley

ROOT  $\rightarrow$  NP  
1            1



the

dog

near

the

# Efficient incremental parsing: probabilistic Earley

Det  $\rightarrow$  the

1            1

NP  $\rightarrow$  Det N

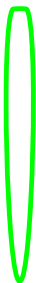
$\frac{2}{3} \times \frac{3}{2}$      $\frac{2}{3}$

NP  $\rightarrow$  NP PP

$\frac{1}{3} \times \frac{3}{2}$      $\frac{1}{3}$

ROOT  $\rightarrow$  NP

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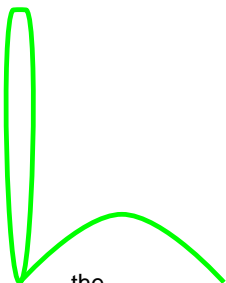
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1             $\frac{2}{3}$

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1            1

NP  $\rightarrow$  Det N

$\frac{2}{3} \times \frac{3}{2}$      $\frac{2}{3}$

NP  $\rightarrow$  NP PP

$\frac{1}{3} \times \frac{3}{2}$      $\frac{1}{3}$

ROOT  $\rightarrow$  NP

1            1

N  $\rightarrow$  cat

$\frac{1}{3}$              $\frac{1}{3}$

N  $\rightarrow$  dog

$\frac{2}{3}$              $\frac{2}{3}$

NP  $\rightarrow$  Det N

1             $\frac{2}{3}$

Det  $\rightarrow$  the

1            1

the

dog

near

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1            1

NP  $\rightarrow$  Det N

$\frac{2}{3} \times \frac{3}{2}$      $\frac{2}{3}$

NP  $\rightarrow$  NP PP

$\frac{1}{3} \times \frac{3}{2}$      $\frac{1}{3}$

ROOT  $\rightarrow$  NP

1            1

N  $\rightarrow$  cat

$\frac{1}{3}$              $\frac{1}{3}$

N  $\rightarrow$  dog

$\frac{2}{3}$              $\frac{2}{3}$

NP  $\rightarrow$  Det N

1             $\frac{2}{3}$

Det  $\rightarrow$  the

1            1

the

dog

near

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Det  $\rightarrow$  the

1 1

NP  $\rightarrow$  Det N

$\frac{2}{3} \times \frac{3}{2}$   $\frac{2}{3}$

NP  $\rightarrow$  NP PP

$\frac{1}{3} \times \frac{3}{2}$   $\frac{1}{3}$

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NP  $\rightarrow$  Det N

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the

dog

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Det  $\rightarrow$  the

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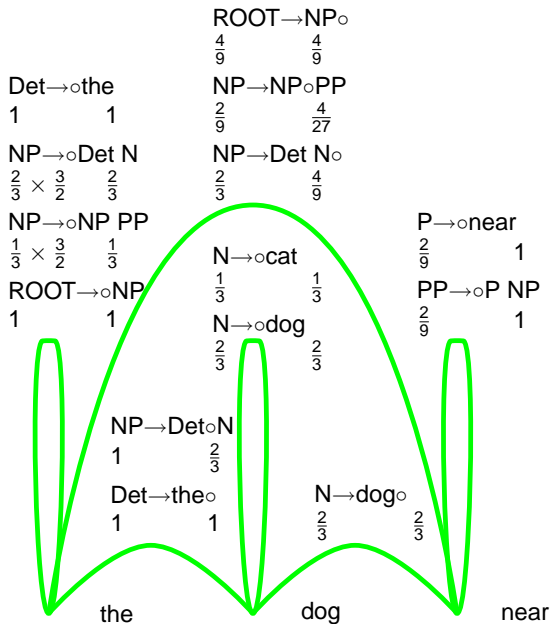
dog

near

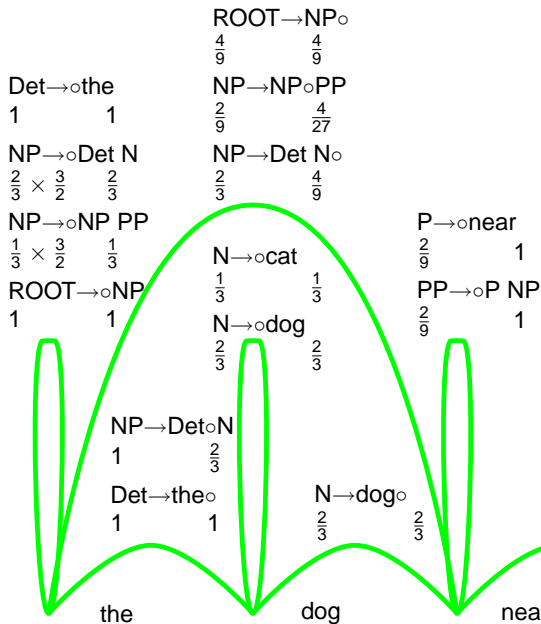




# Efficient incremental parsing: probabilistic Earley



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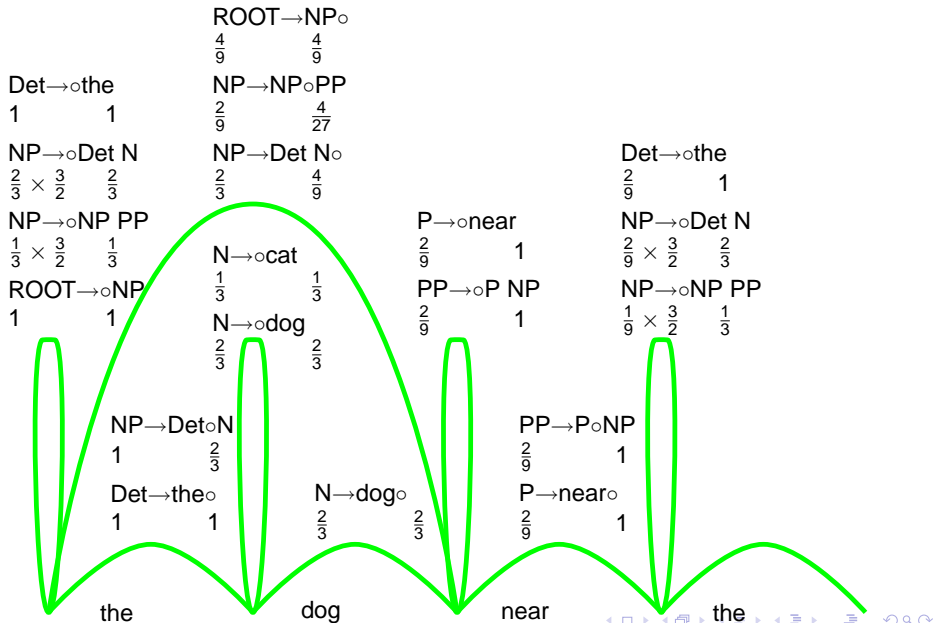




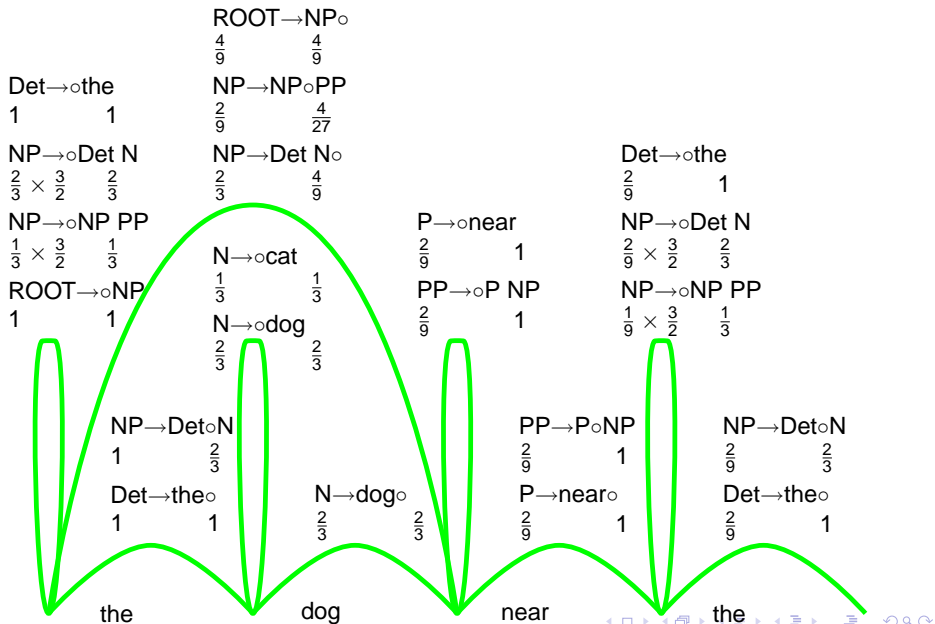




# Efficient incremental parsing: probabilistic Earley



# Efficient incremental parsing: probabilistic Earley



# Prefix probabilities from probabilistic Earley

- ▶ If you have just processed word  $w_i$ , then the prefix probability of  $w_{1\dots i}$  can be obtained by summing all forward probabilities of items that have the form  $X \rightarrow \alpha \circ w_i \beta$

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- ▶ In our example, we see:

$$P(\text{the}) = 1$$

$$P(\text{the dog}) = \frac{2}{3}$$

$$P(\text{the dog near}) = \frac{4}{9}$$

$$P(\text{the dog near the}) = \frac{4}{9}$$

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- ▶ Taking the ratios of these prefix probabilities can give us conditional word probabilities

# Probabilistic Earley as an “eager” algorithm

- ▶ From the *inside probabilities* of the states on the chart, the posterior distribution on (incremental) trees can be directly calculated
- ▶ This posterior distribution is *precisely* the correct result of the application of Bayes’ rule
- ▶ Hence, probabilistic Earley is also performing rational disambiguation
- ▶ Hale (2001) called this the “eager” property of an incremental parsing algorithm.

# Probabilistic Earley algorithm: key ideas

- ▶ We want to use probabilistic grammars for both disambiguation and calculating probability distributions over upcoming events
- ▶ Infinitely many trees can be constructed in polynomial time ( ) and space ( )
- ▶ The *prefix probability* of the string is calculated in the process
- ▶ By taking the log-ratio of two prefix probabilities, the surprisal of a word in its context can be calculated

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# Other introductions

- ▶ You can read about the (non-probabilistic) Earley algorithm in (Jurafsky and Martin, 2000, Chapter 13)
- ▶ Prefix probabilities can also be calculated with an extension of the CKY algorithm due to Jelinek and Lafferty (1991)

Applications of the idea of surprisal to online comprehension

# References I

- Earley, J. (1970). An efficient context-free parsing algorithm. *Communications of the ACM*, 13(2):94–102.
- Hale, J. (2001). A probabilistic Earley parser as a psycholinguistic model. In *Proceedings of the Second Meeting of the North American Chapter of the Association for Computational Linguistics*, pages 159–166.
- Jelinek, F. and Lafferty, J. D. (1991). Computation of the probability of initial substring generation by stochastic context free grammars. *Computational Linguistics*, 17(3):315–323.
- Jurafsky, D. and Martin, J. H. (2000). *Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition*. Prentice-Hall.
- Stolcke, A. (1995). An efficient probabilistic context-free parsing algorithm that computes prefix probabilities. *Computational Linguistics*, 21(2):165–201.