Syntax And Parsing

Jonathan May
CSCI 662
October 14/16, 2014

Credits/Further Reading

- Michael Collins' notes:
  - http://www.cs.columbia.edu/~mcollins/courses/nlp2011/notes/pcfgs.pdf
  - http://www.cs.columbia.edu/~mcollins/courses/nlp2011/notes/lexpcfgs.pdf
- Luke Zettlemoyer's/Dan Klein's notes:
  - http://homes.cs.washington.edu/~lsz/lectures/parsing.pdf
- Yoav Goldberg's notes:
  - http://u.cs.biu.ac.il/~89-680/parsing-and-cky.pdf
- Jason Eisner's notes:
  - http://u.cs.biu.ac.il/~89-680/eisner-parse.pdf
- Chris Manning's lectures:
  - http://nlp.stanford.edu/courses/lsa354/
- Klein and Manning on parsing:
  - http://www.cs.berkeley.edu/~klein/papers/unlexicalized-parsing.pdf

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- A system of arrangement of words and phrases of (human) language
- There’s a lot of ways to communicate but we can still identify verbs, nouns, phrases acting like verbs and nouns, modifiers, etc.
- The structure helps us create sentences and inherently knowing the structure helps us interpret the unfamiliar.

Syntax

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- “Hexy planars garumphed by the snox three zamfirs ago.”

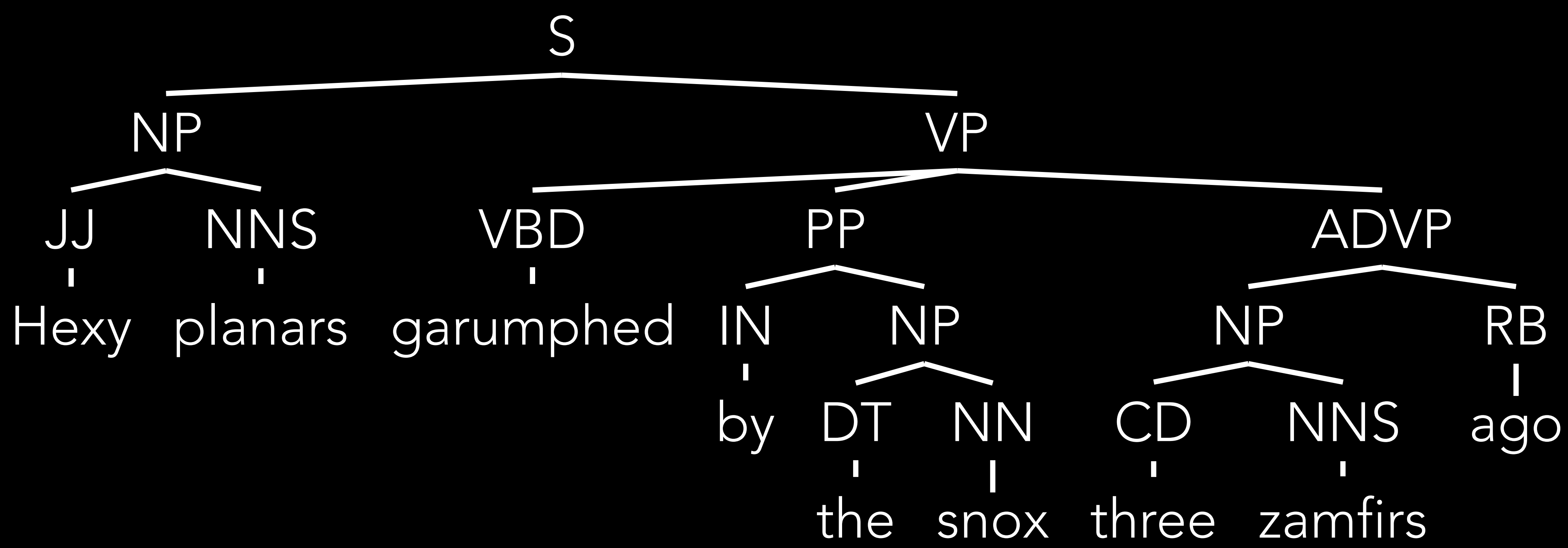
Syntax

- “Hexy planars garumphed by the snox three zamfirs ago.”
- What kind of planars are being discussed?

Syntax

- “Hexy planars garumphed by the snox three zamfirs ago.”
- What kind of planars are being discussed?
- Why do you know that?

Syntax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JJ
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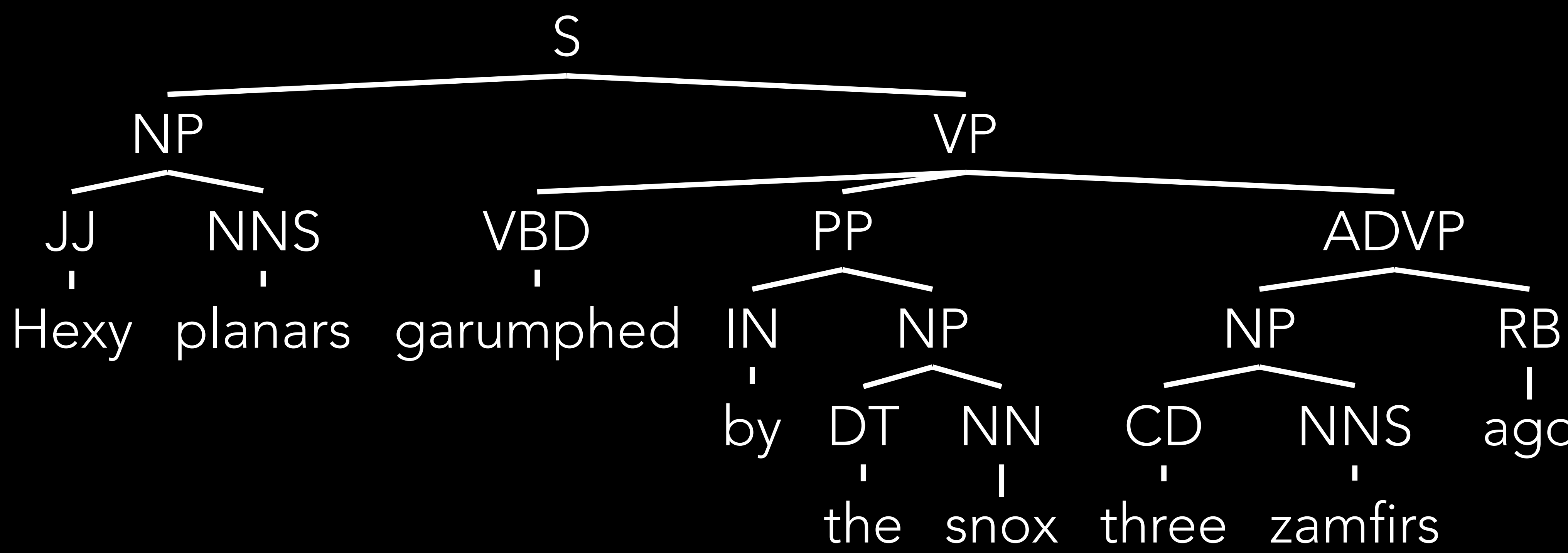

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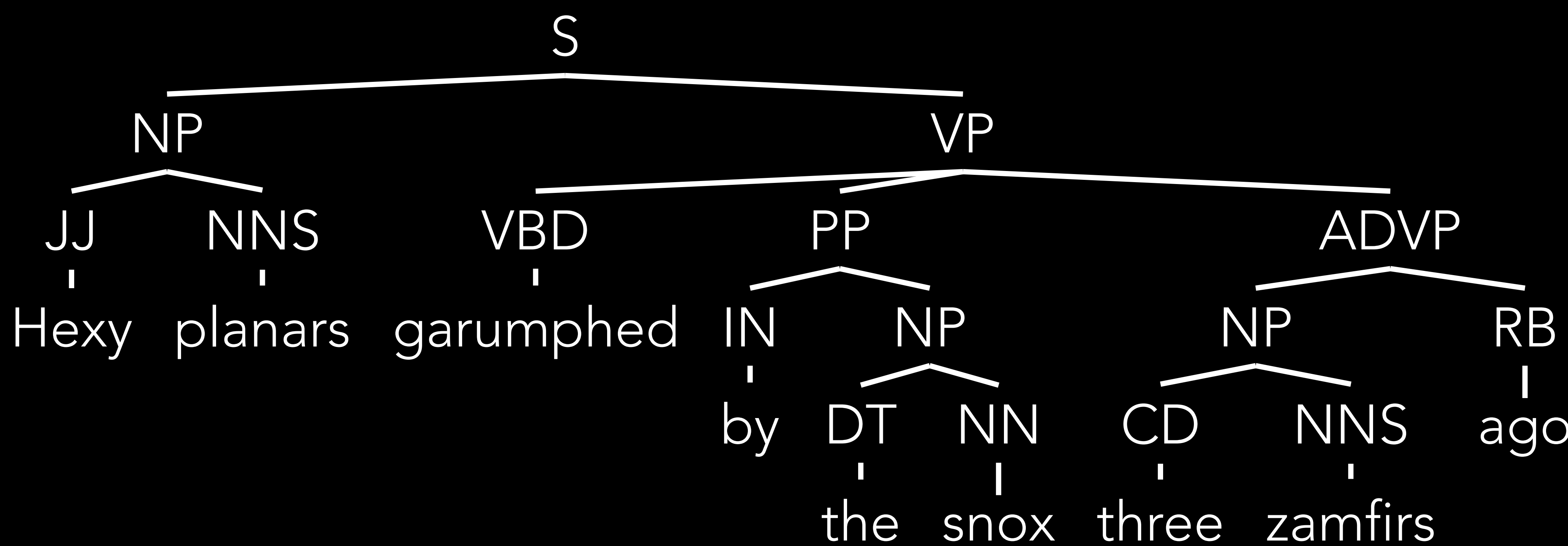

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- Goal of *parsing* is to write a computer program to generate this automatically.

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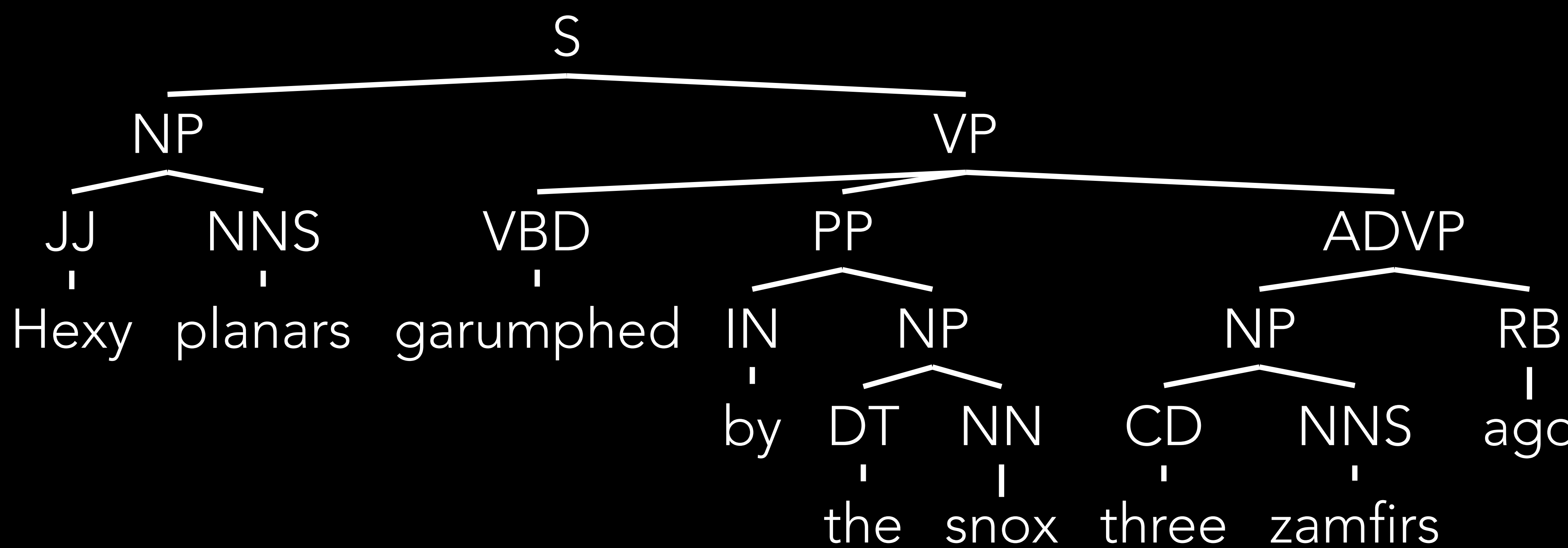

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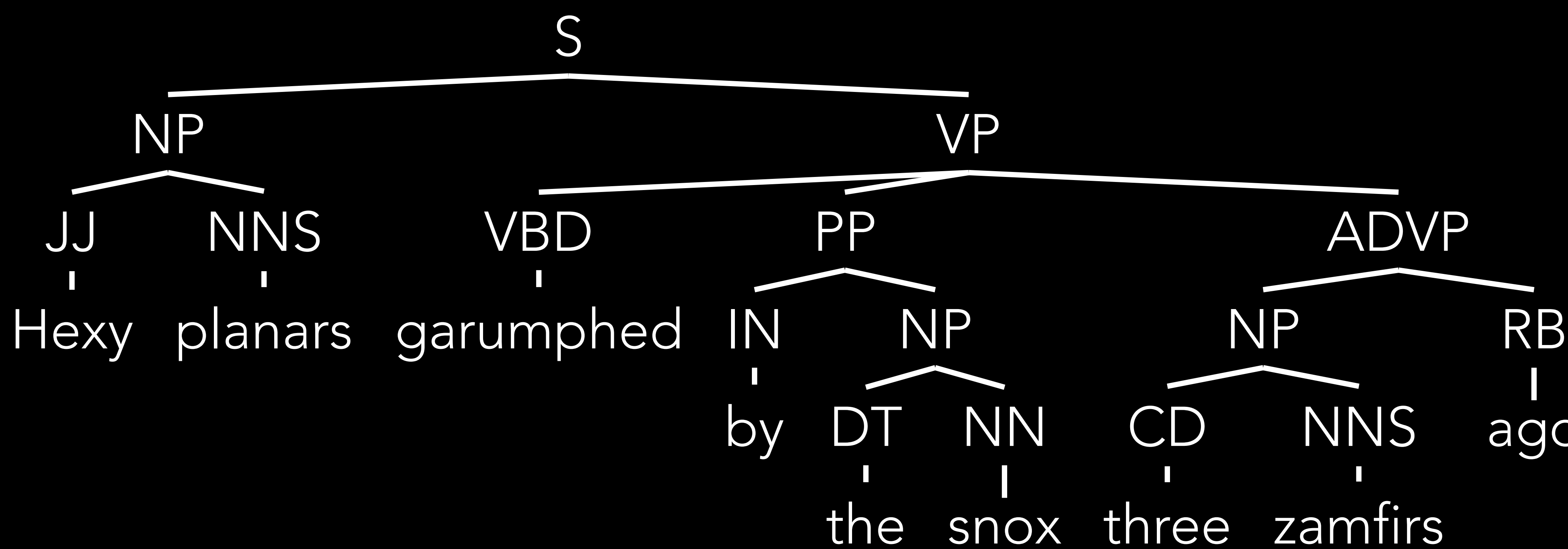

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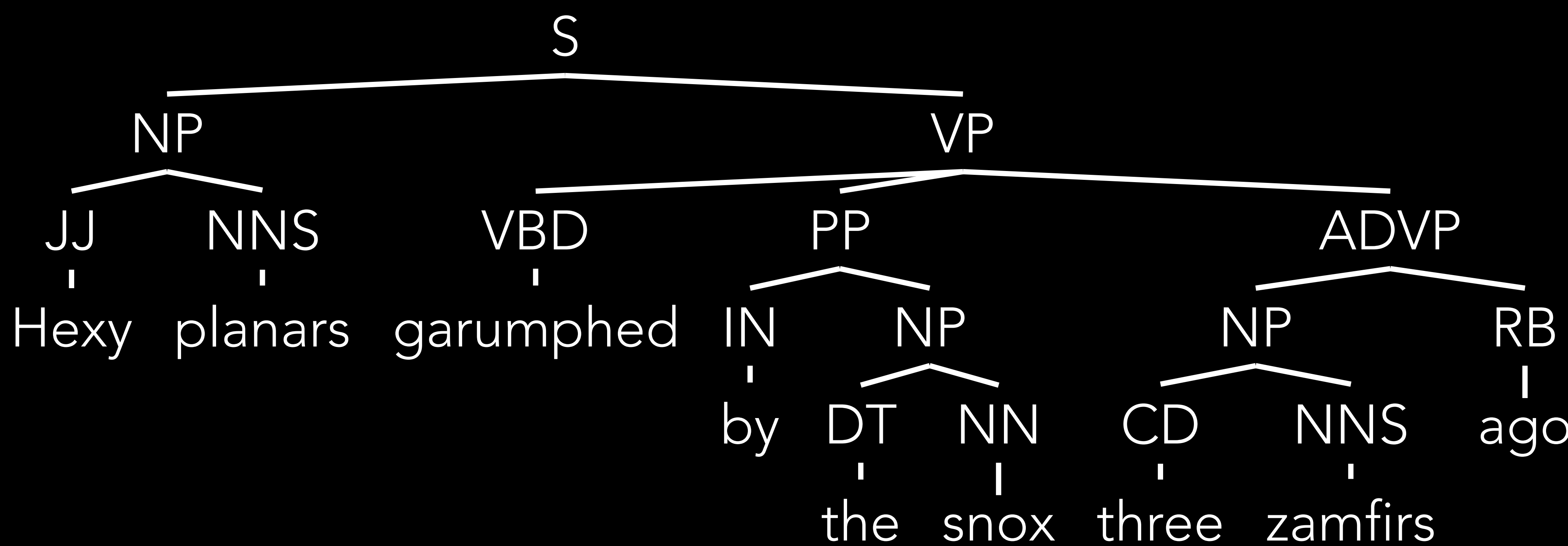

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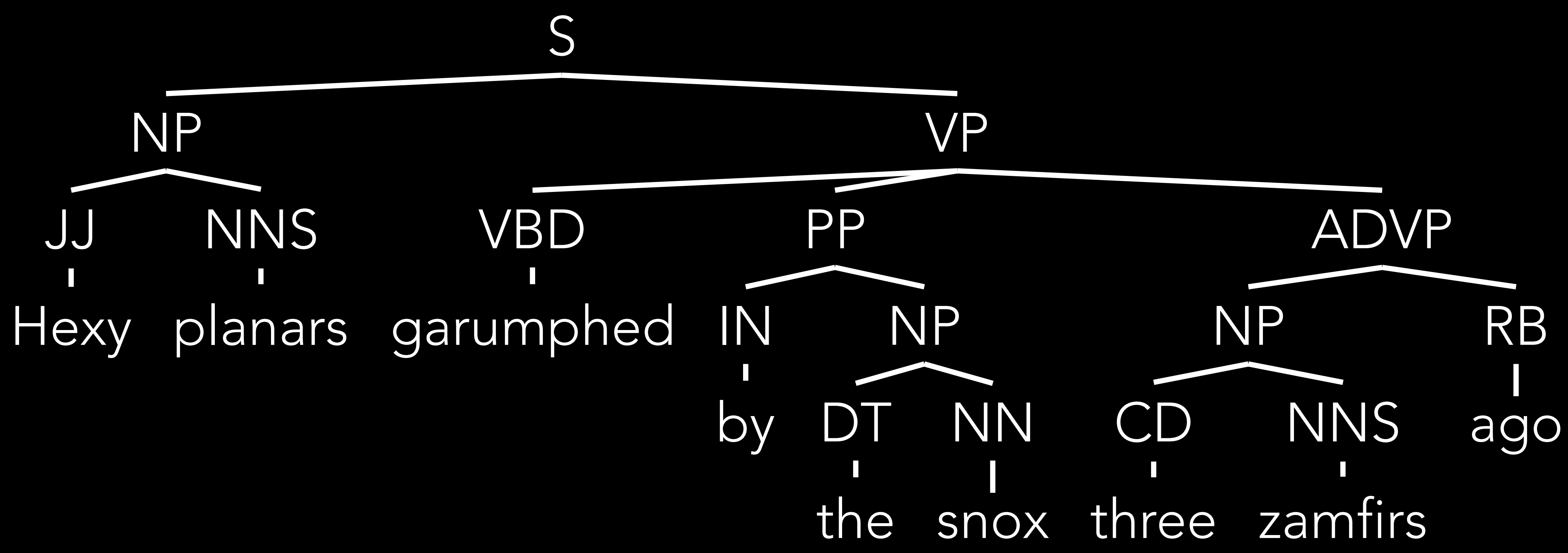

- Question answering (When did hexy planars garumph?)
- Sentence compression (Hexy planars garumphed.)
- Machine translation (Planares hexos …)

Penn Treebank
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- 1 million words of English Wall Street Journal text in 40,000 sentences, annotated with syntactic structure
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- Since then, treebanks have been created for many other languages

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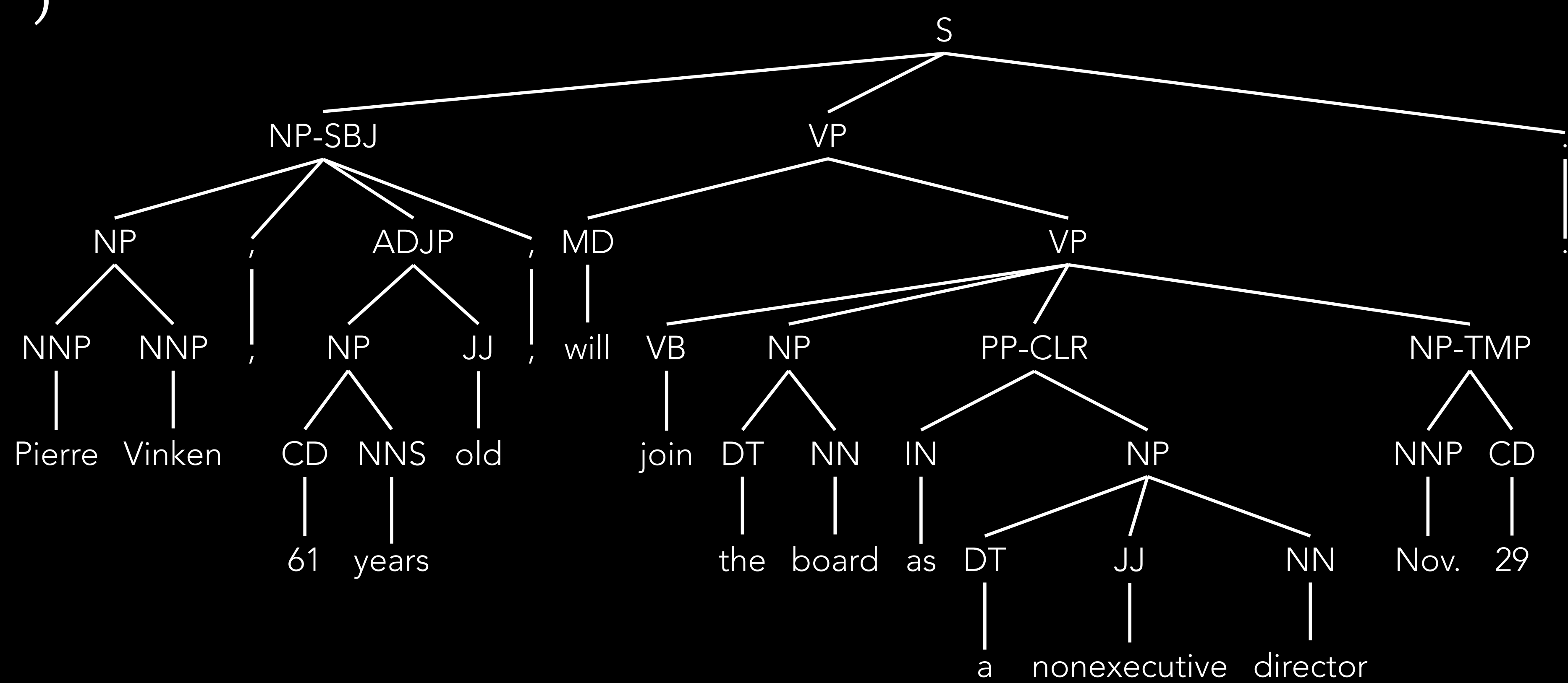

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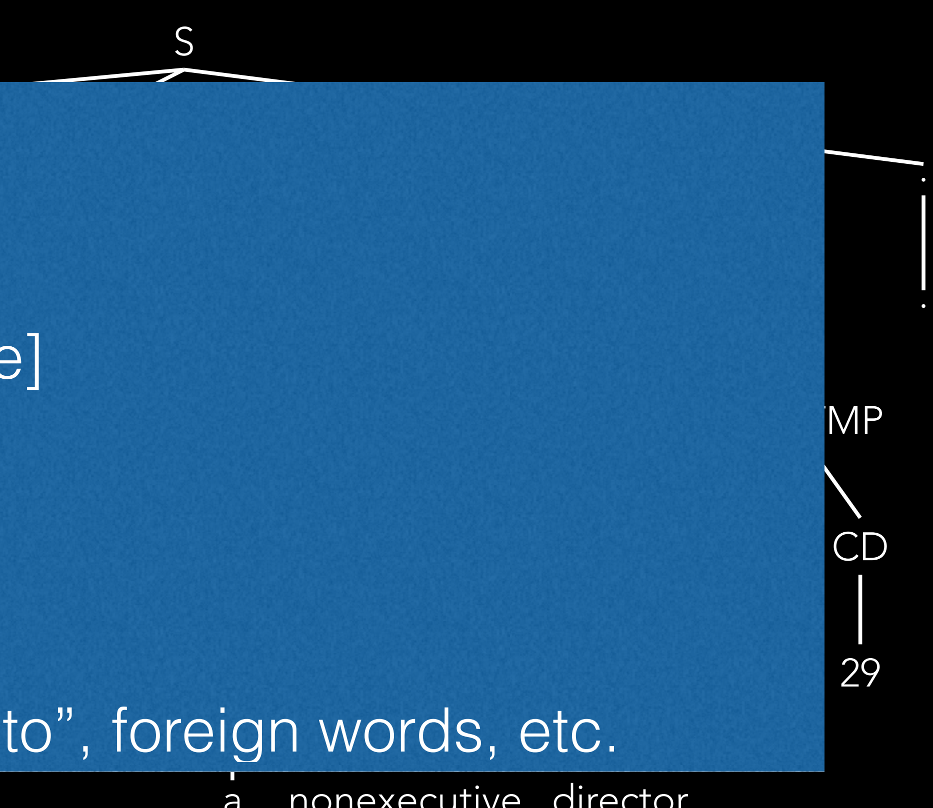

36 POS (part of speech) tags:

NN[P][S] = noun [proper] [plural]
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VB[D|G|N|P|Z] = verbs [various kinds]
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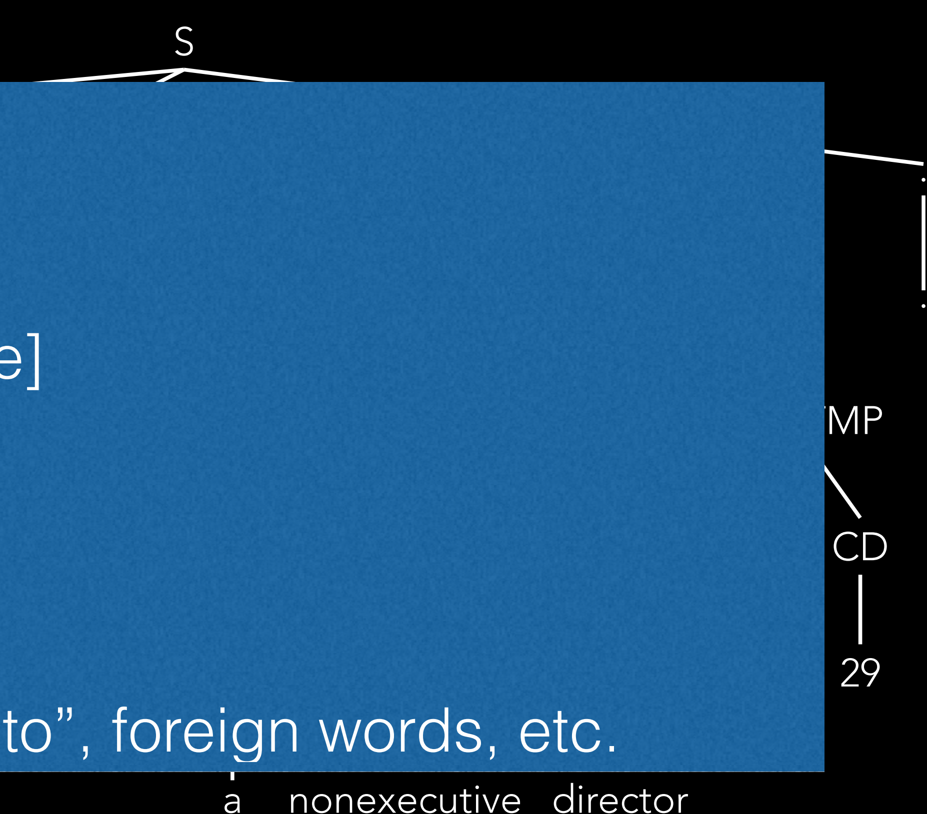

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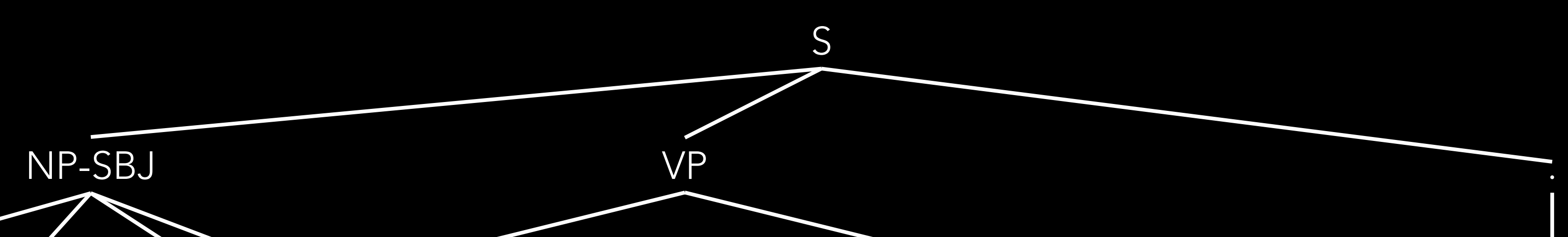

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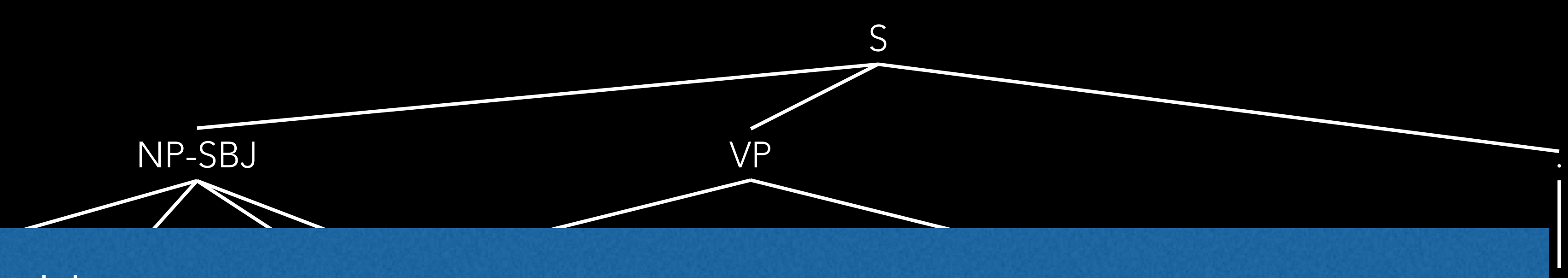

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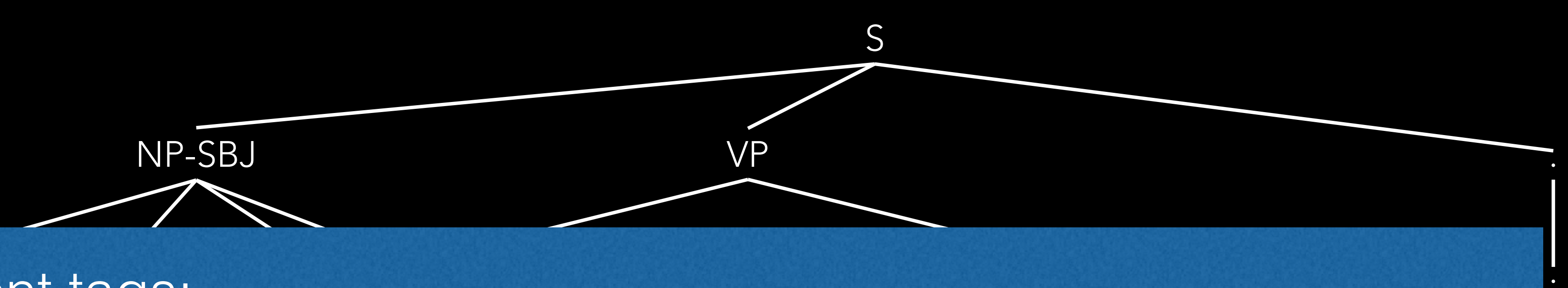

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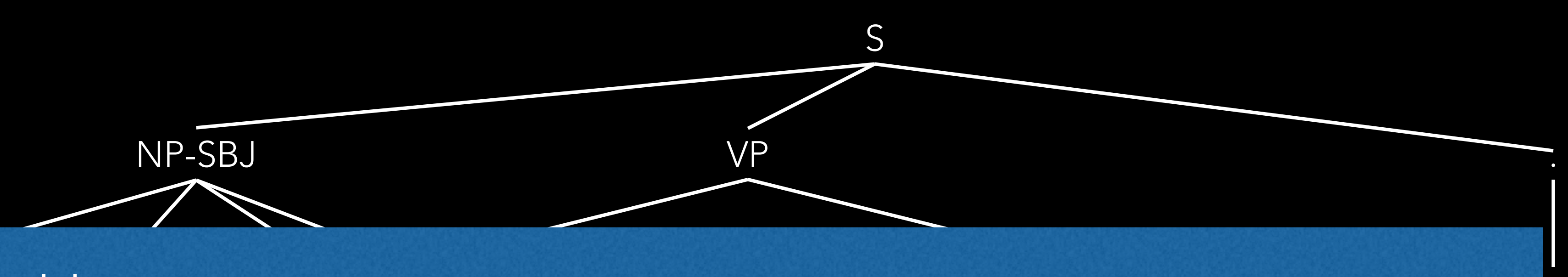

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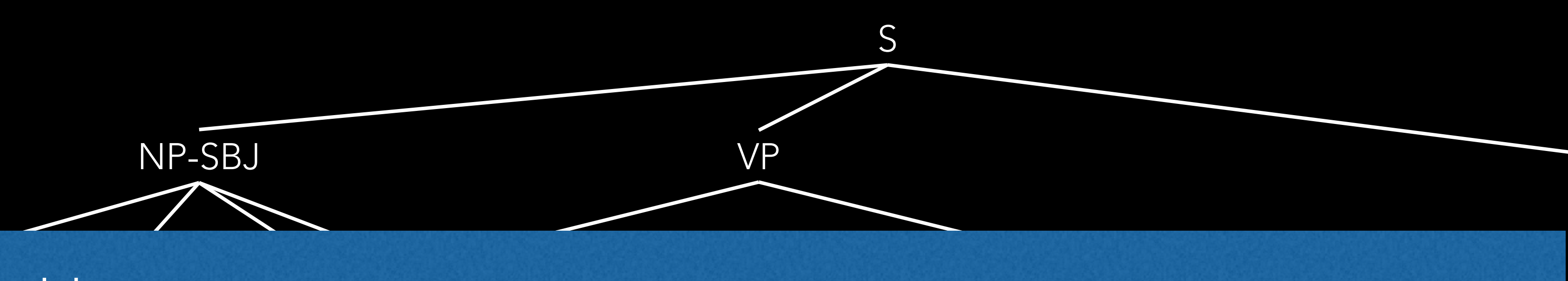

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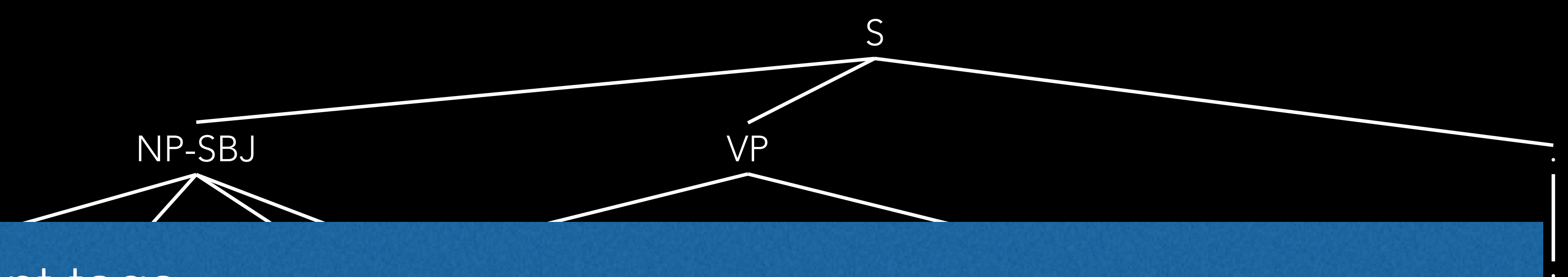

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20 function tags:

-SBJ = subject of sentence
-CLR = closely related (in this case, to the verb)
-TMP = temporal
…

These are usually not considered in parsing. I've never paid any attention to them.

Why make the Treebank?

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- The Treebank provides a documentation of how (a very specific subset of) people actually structure English.
- Constructed with this goal: given a new sentence, can we automatically put the tree on top? (i.e. syntactic parsing)

How to Use The Treebank

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- Evaluation:
  - I’ll give you some of the sentences from the treebank (without trees).
  - You give me the trees your computer parser produced.
  - I’ll tell you how close you were to the human trees.

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- Training:
  - Use the treebank trees as input to some data-driven parsing algorithm (just don’t use the same trees to evaluate)
  - Standard split: sections 2-21 for training, section 23 for test

Parser Evaluation

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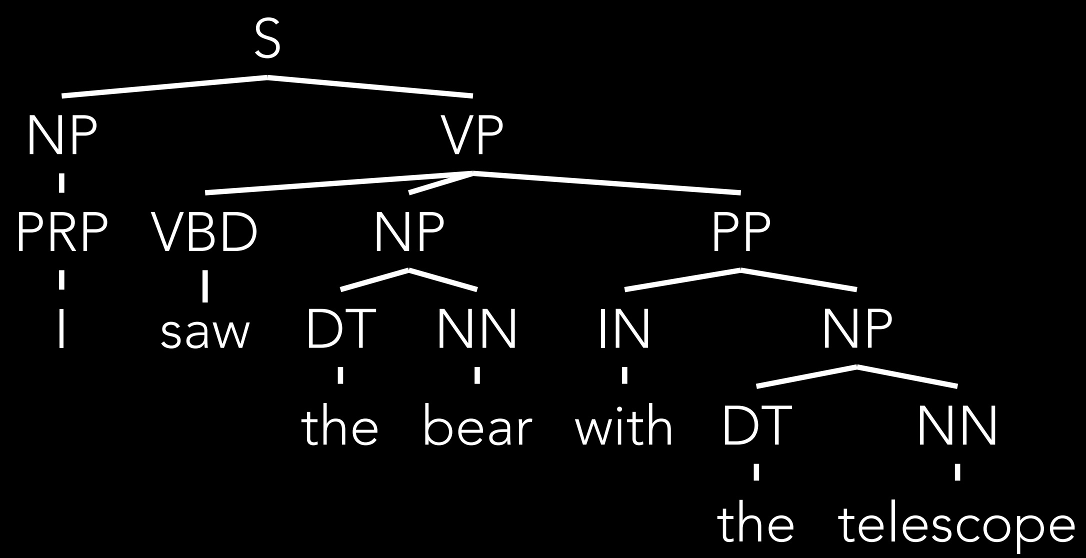

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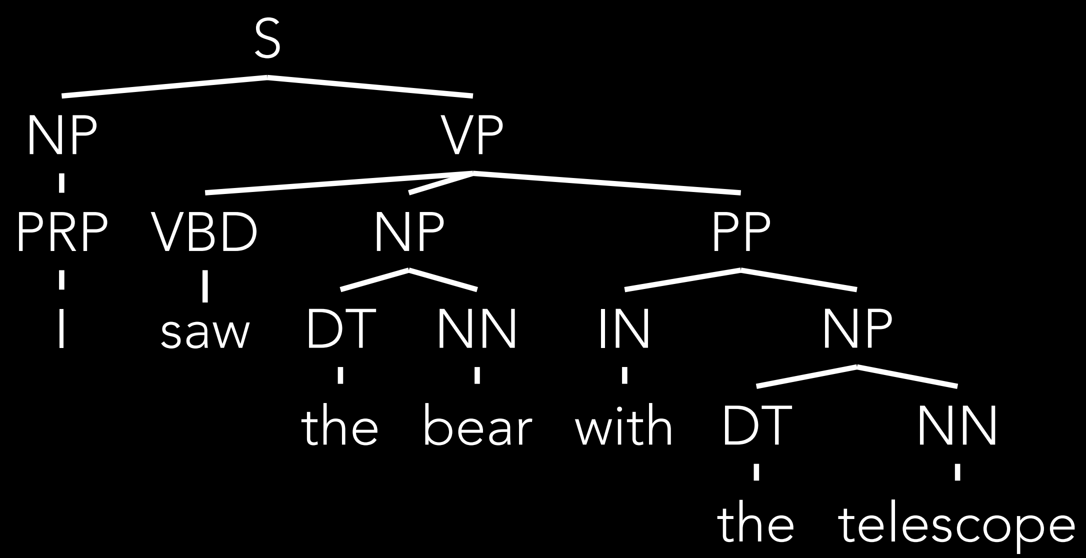

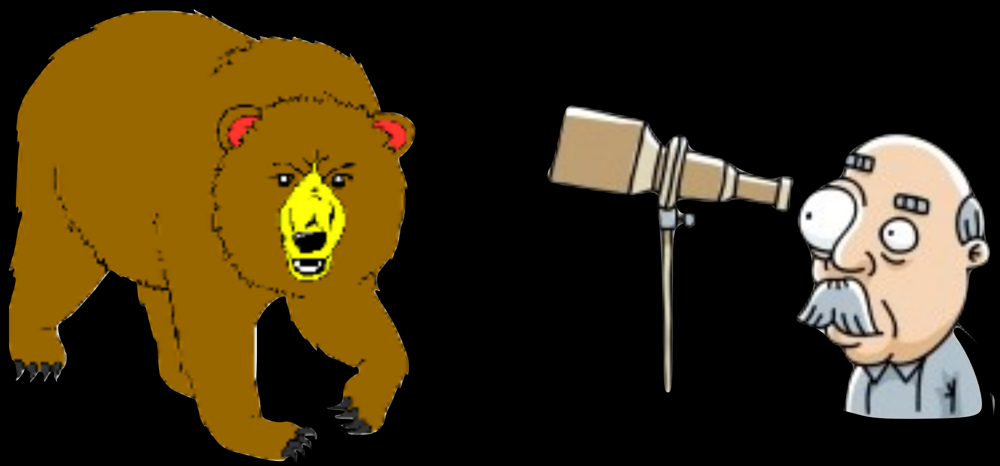

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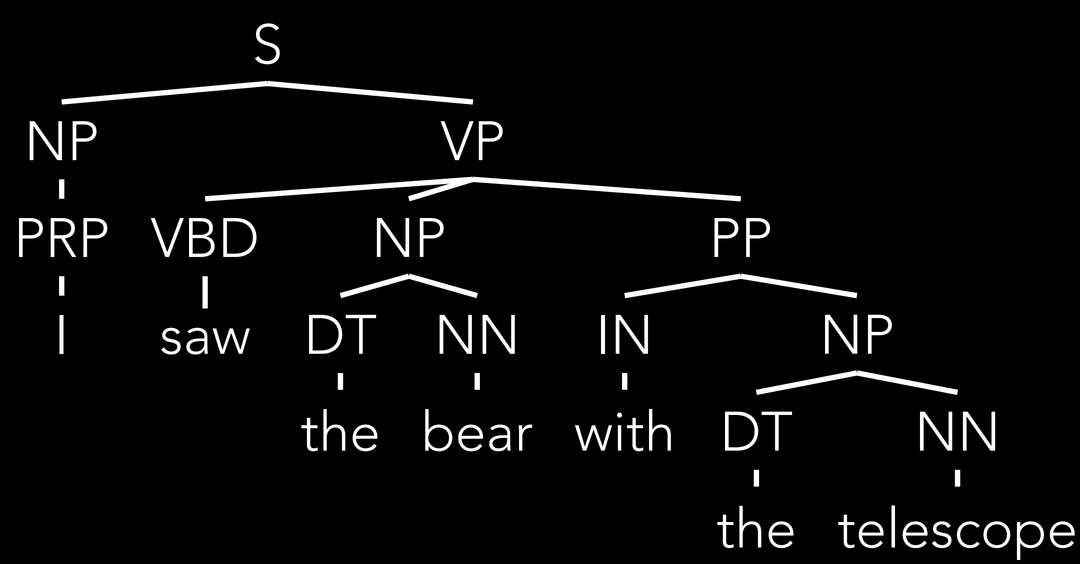
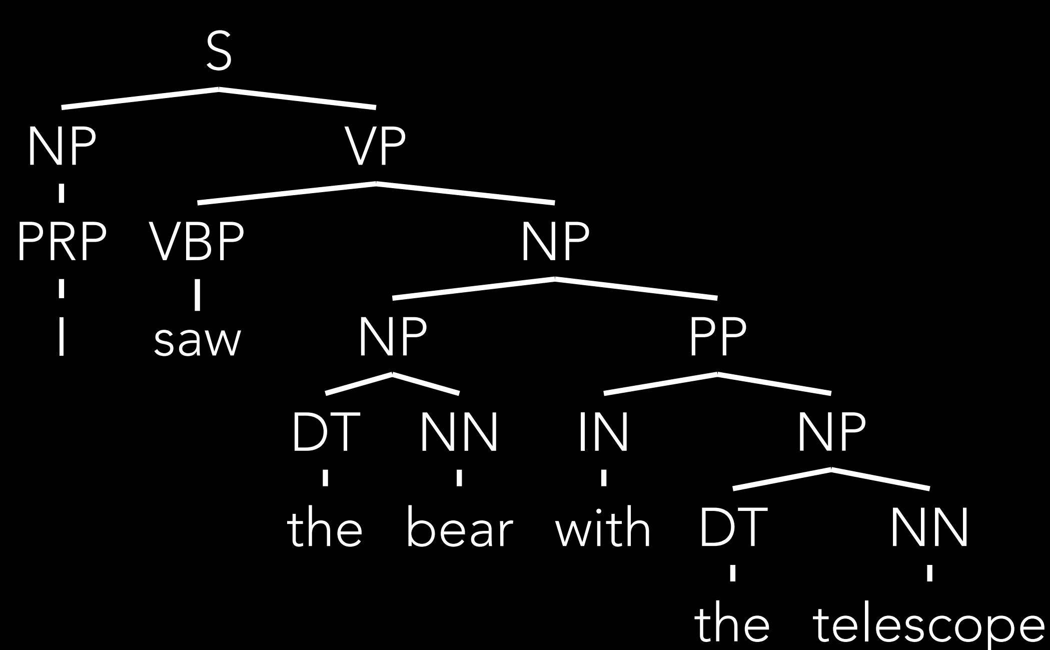
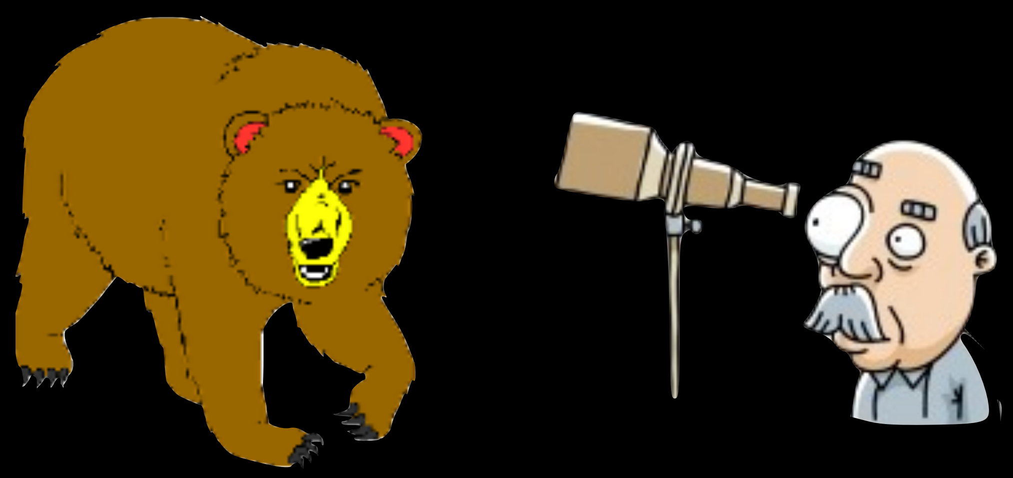
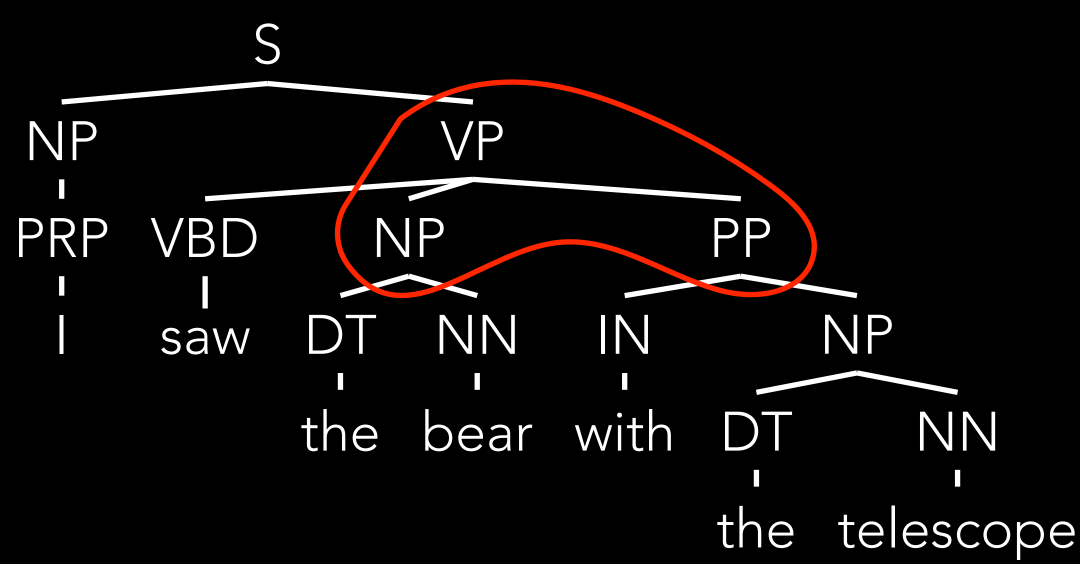
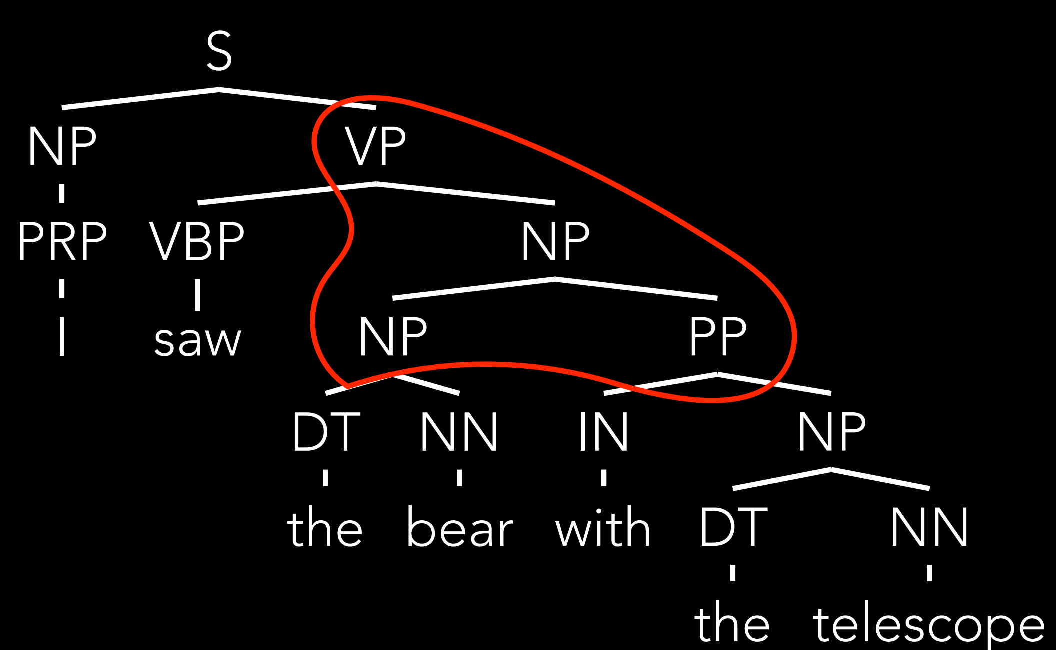




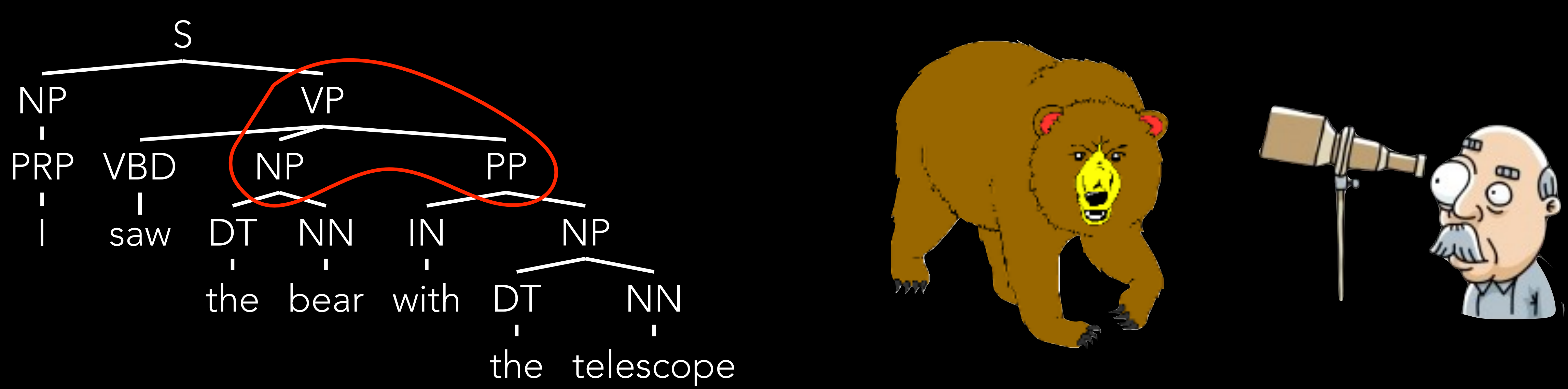


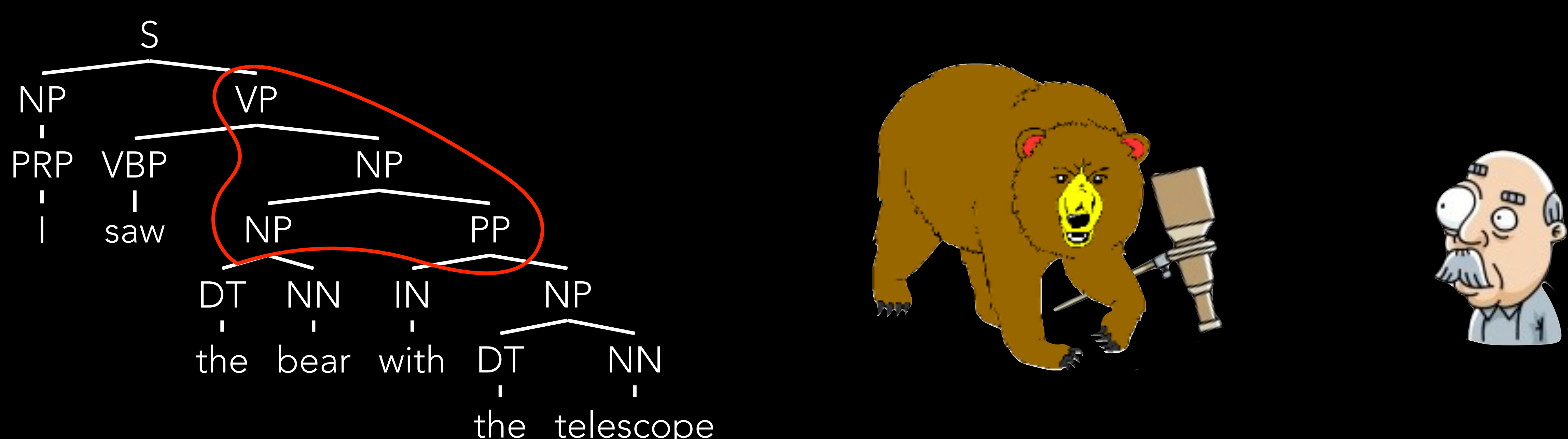
Parser Evaluation





Parser Evaluation





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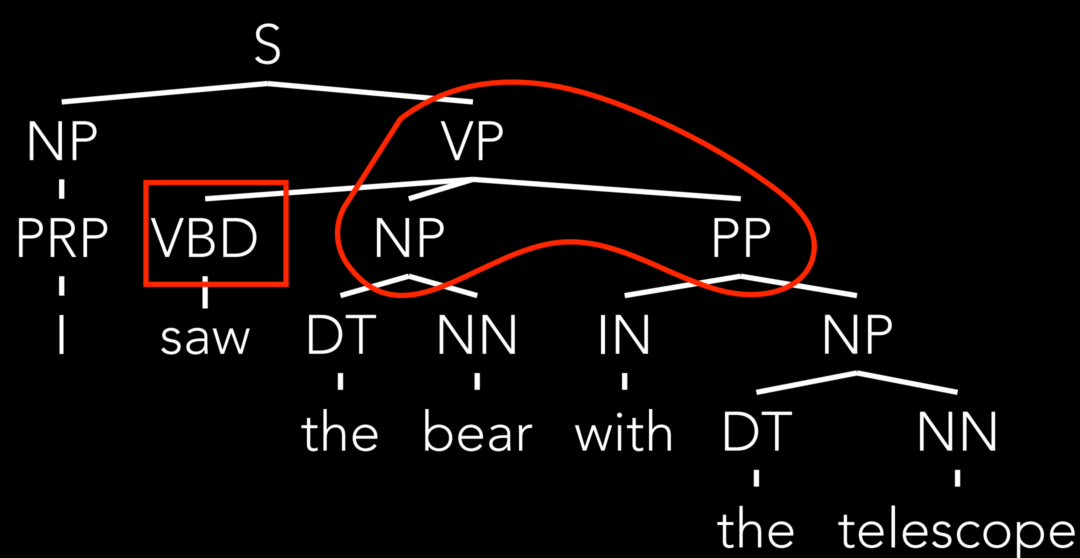

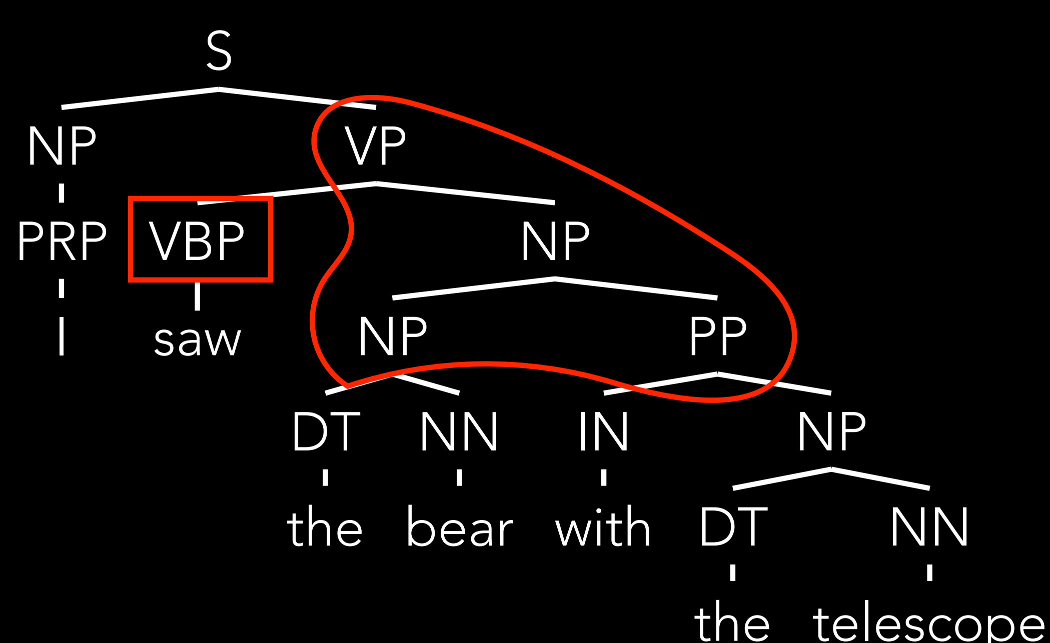

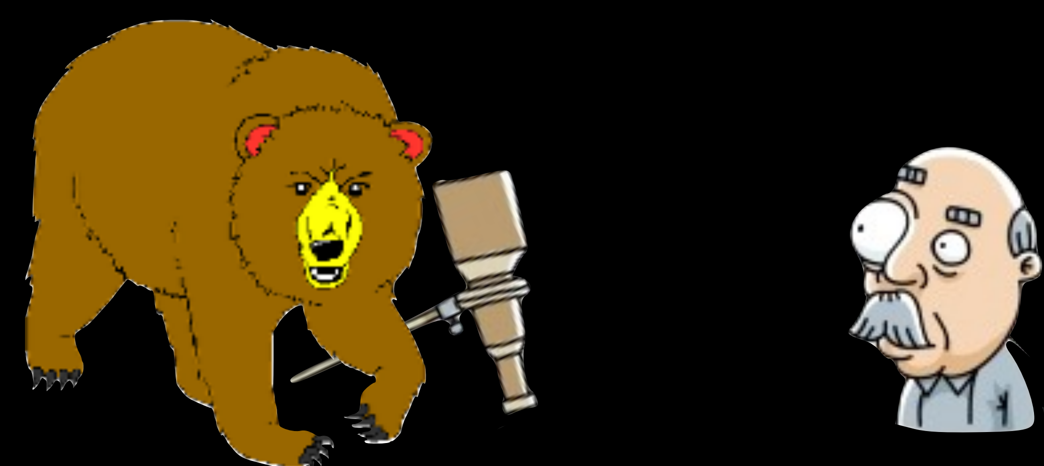

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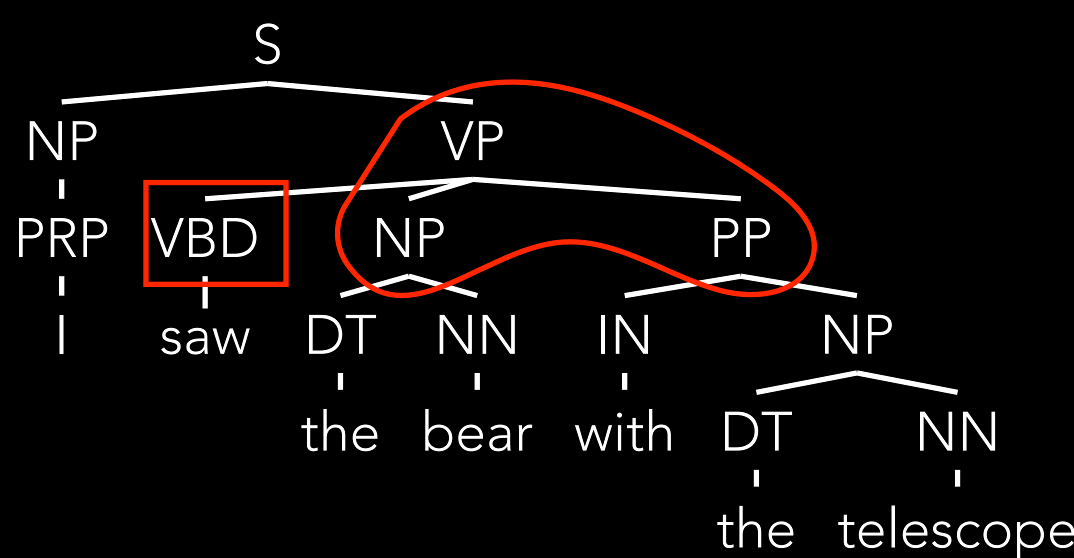

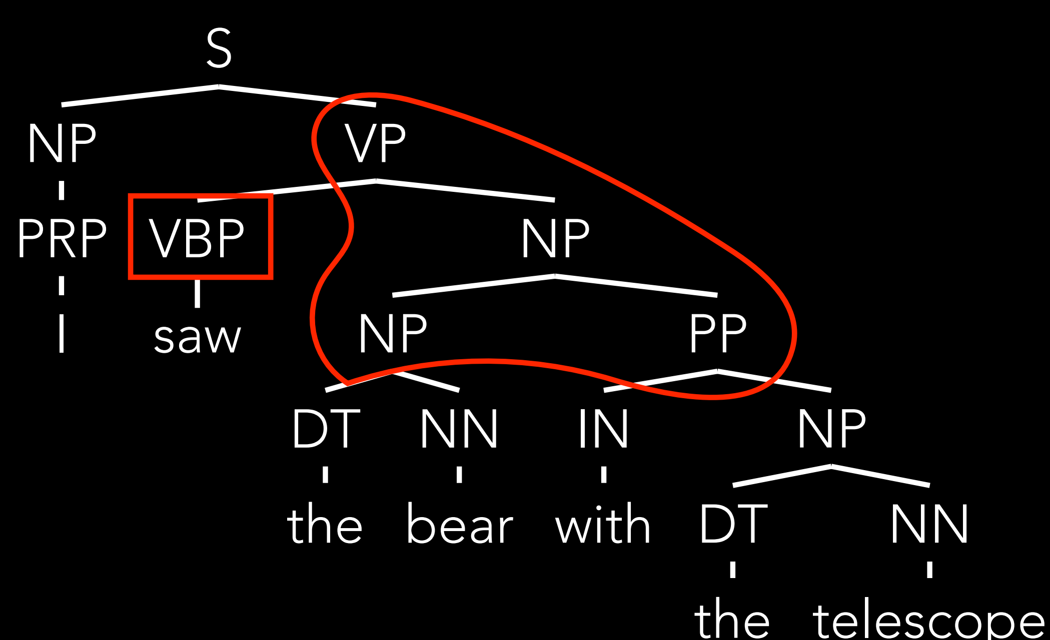

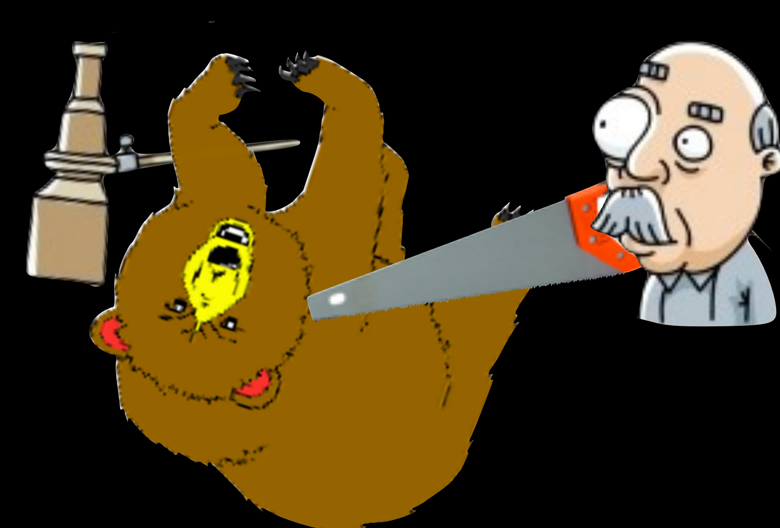

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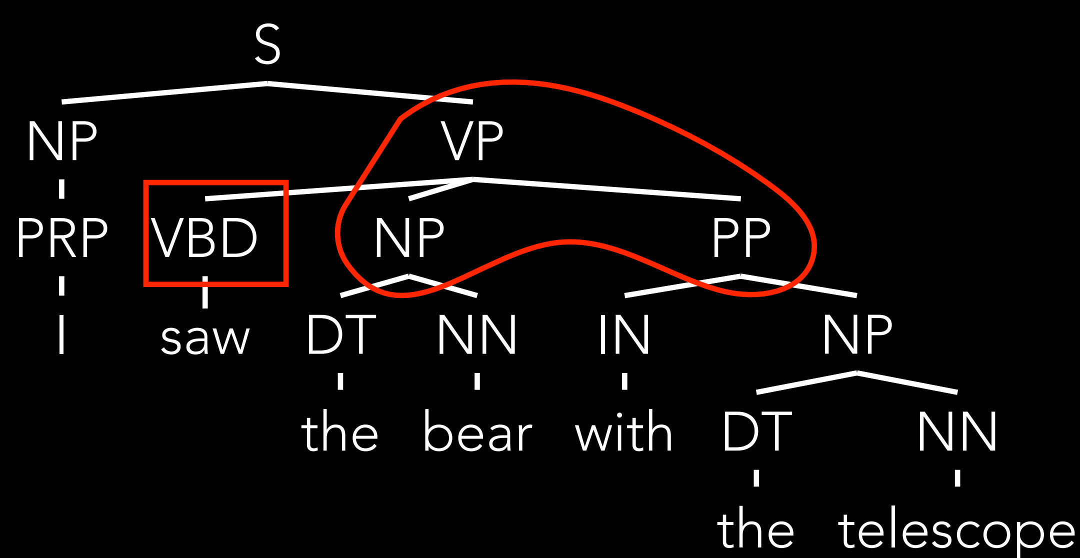

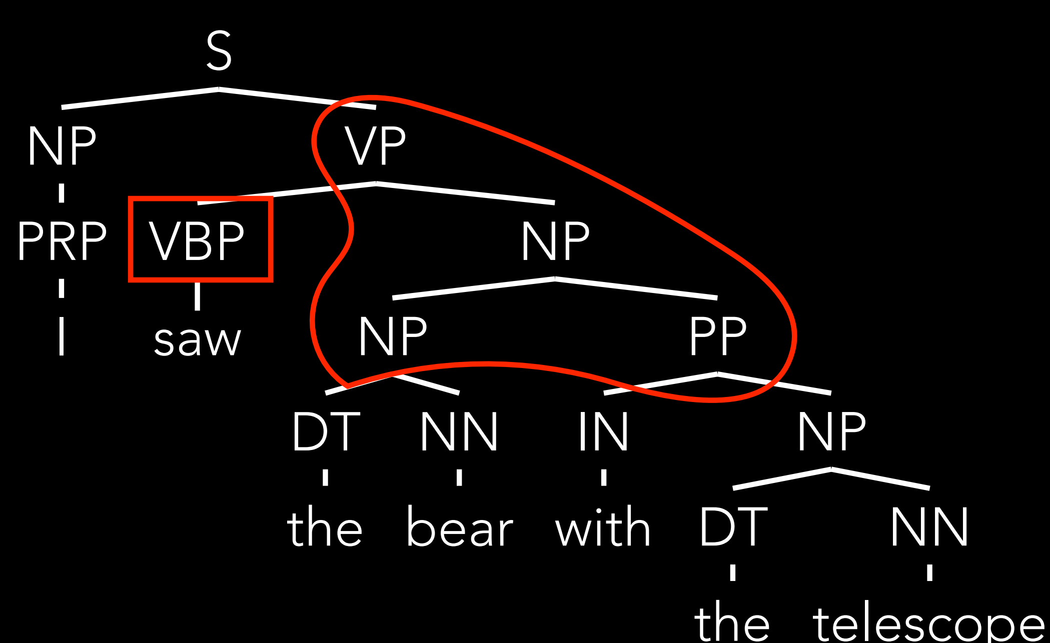

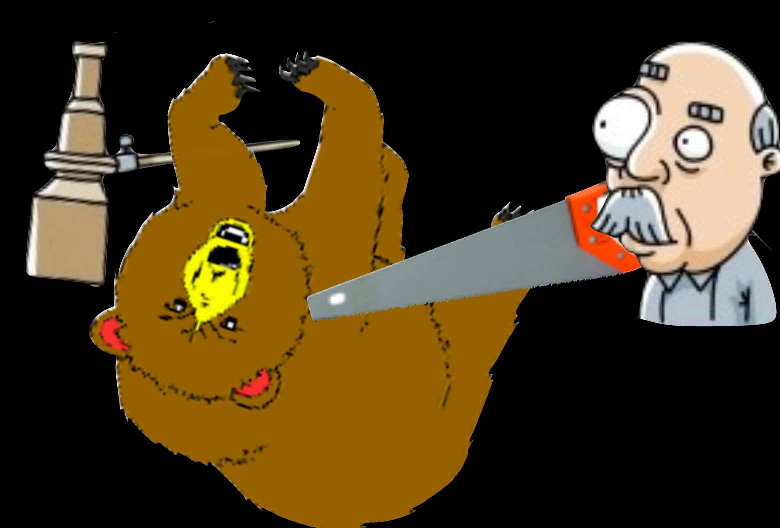

How do we quantify parse errors?

Parser Evaluation

Parseval (Black et al. ’91)

Parser Evaluation

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1. Decompose tree into labeled *constituent* spans (note: POS tags not considered!)

Parser Evaluation

Parseval (Black et al. ’91)

1. Decompose tree into labeled *constituent* spans
   (note: POS tags not considered!)
2. Calculate balanced precision and recall (f-measure)

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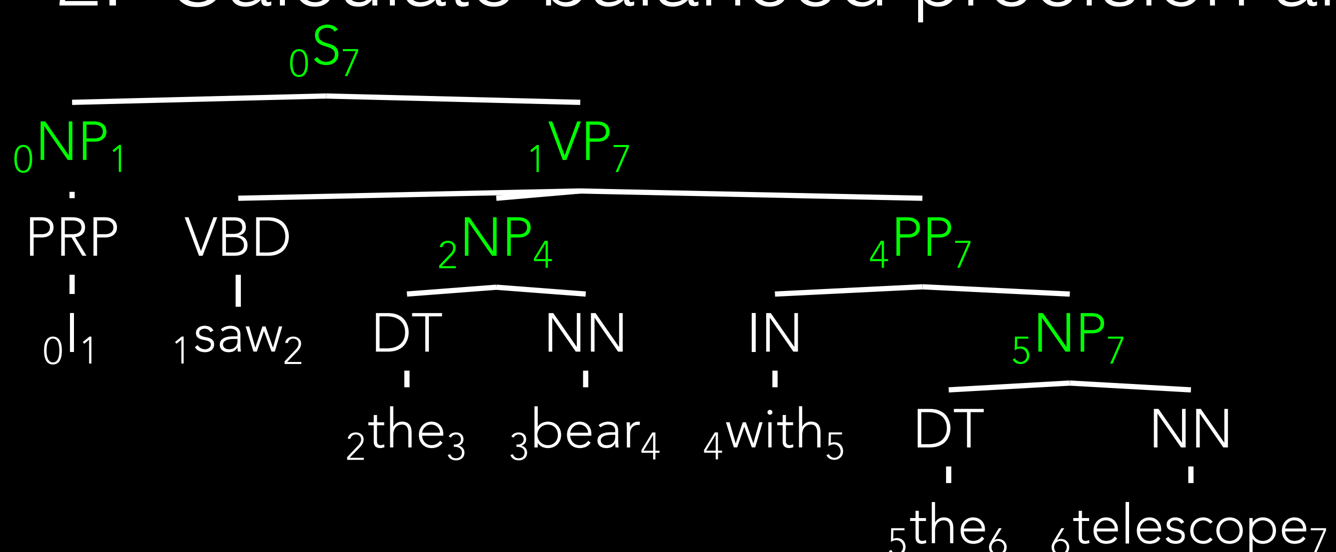

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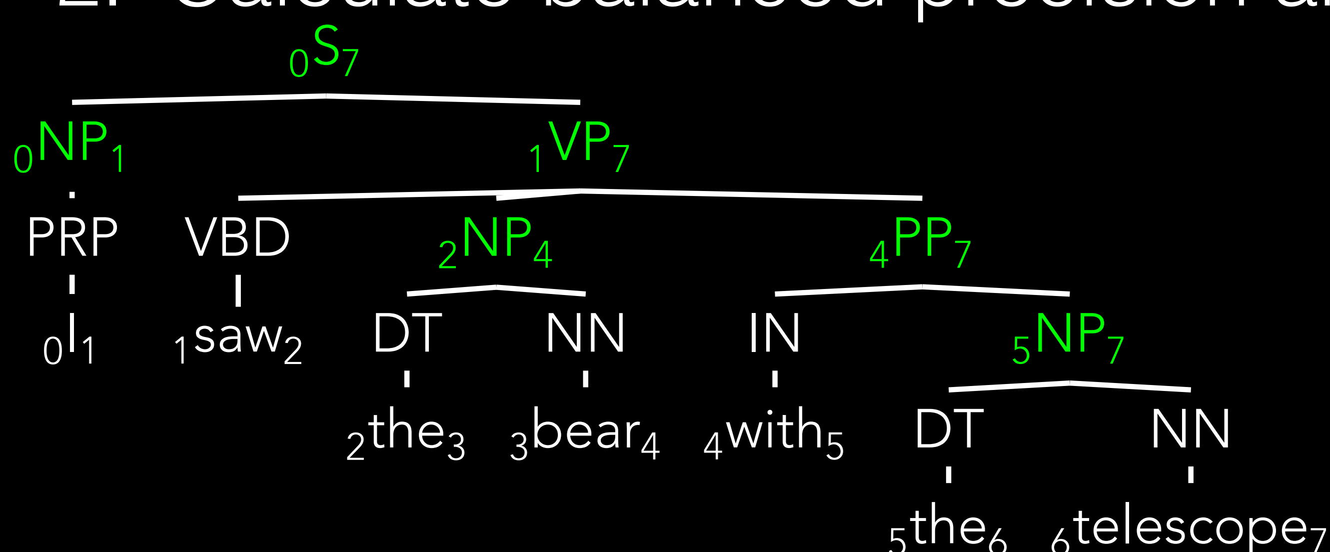

(S 0 7)
(NP 0 1)
(VP 1 7)
(NP 2 4)
(PP 4 7)
(NP 5 7)

Parser Evaluation

Parseval (Black et al. ’91)

1. Decompose tree into labeled *constituent* spans (note: POS tags not considered!)
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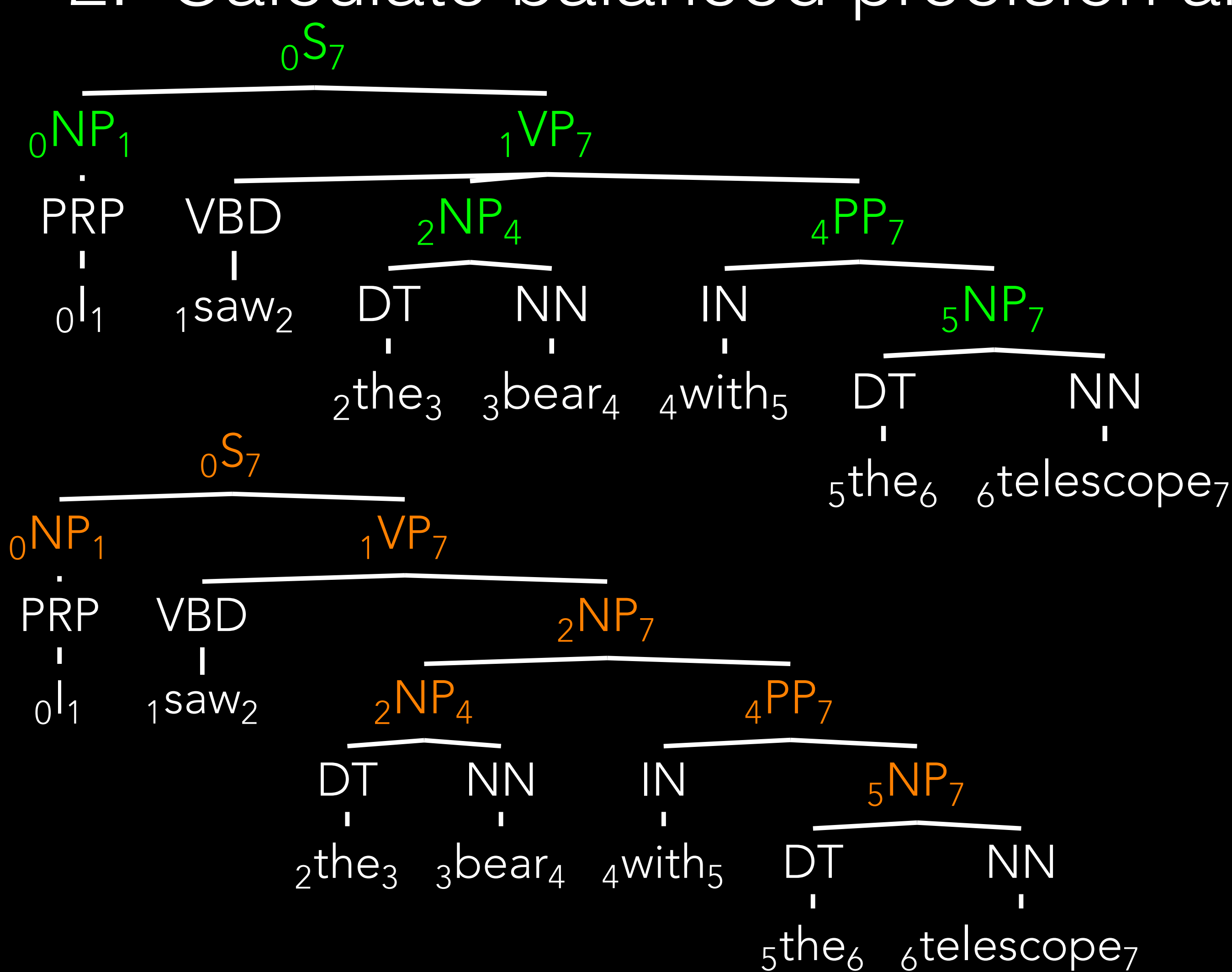

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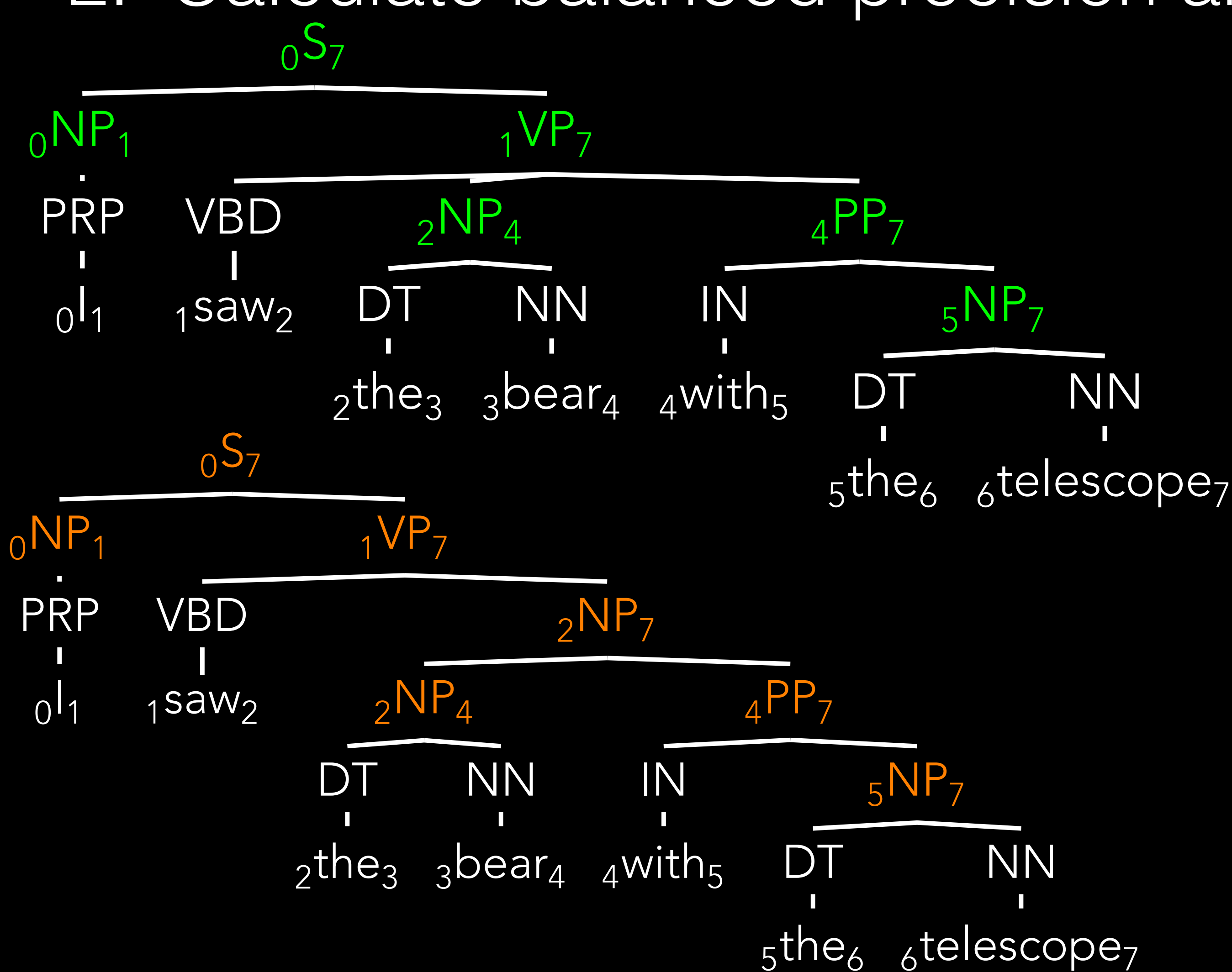

(S 0 7)
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(NP 2 4)
(PP 4 7)
(NP 5 7)

(S 0 7)
(NP 0 1)
(VP 1 7)
(NP 2 7)
(NP 2 4)
(PP 4 7)
(NP 5 7)

Parser Evaluation

(S 0 7)
(NP 0 1)
(VP 1 7)
(NP 2 7)
(NP 2 4)
(PP 4 7)
(NP 5 7)

A = answers

C = correct

(S 0 7)
(NP 0 1)
(VP 1 7)
(NP 2 4)
(PP 4 7)
(NP 5 7)

Parser Evaluation

(S 0 7)
(NP 0 1)
(VP 1 7)
(NP 2 7)
(NP 2 4)
(PP 4 7)
(NP 5 7)

A = answers   C = correct

(S 0 7)
(NP 0 1)
(VP 1 7)
(NP 2 4)
(PP 4 7)
(NP 5 7)

Precision: Of the answers I gave, what percent were correct?

Parser Evaluation

(S 0 7)
(NP 0 1)
(VP 1 7)
(NP 2 7)
(NP 2 4)
(PP 4 7)
(NP 5 7)

A = answers

C = correct

(S 0 7)
(NP 0 1)
(VP 1 7)
(NP 2 4)
(PP 4 7)
(NP 5 7)

Precision: Of the answers I gave, what percent were correct?

$$\frac{|A \cap C|}{|A|}$$

Parser Evaluation

(S 0 7)
(NP 0 1)
(VP 1 7)
(NP 2 7)
(NP 2 4)
(PP 4 7)
(NP 5 7)

A = answers

C = correct

(S 0 7)
(NP 0 1)
(VP 1 7)
(NP 2 4)
(PP 4 7)
(NP 5 7)

Precision: Of the answers I gave, what percent were correct?

$$\frac{|A \cap C|}{|A|}$$

Recall: What percent of the correct answers did I give?

Parser Evaluation

(S 0 7)
(NP 0 1)
(VP 1 7)
(NP 2 7)
(NP 2 4)
(PP 4 7)
(NP 5 7)

A = answers   C = correct

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(NP 0 1)
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$$\frac{|A \cap C|}{|A|}$$

Recall: What percent of the correct answers did I give?

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Parser Evaluation

(S 0 7)
(NP 0 1)
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(NP 2 7)
(NP 2 4)
(PP 4 7)
(NP 5 7)

A = answers   C = correct

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(NP 0 1)
(VP 1 7)
(NP 2 4)
(PP 4 7)
(NP 5 7)

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$$\frac{|A \cap C|}{|C|}$$

F1: Harmonic mean of Precision and Recall (reciprocal of mean of reciprocals)

Parser Evaluation

(S 0 7)
(NP 0 1)
(VP 1 7)
(NP 2 7)
(NP 2 4)
(PP 4 7)
(NP 5 7)

A = answers   C = correct

(S 0 7)
(NP 0 1)
(VP 1 7)
(NP 2 4)
(PP 4 7)
(NP 5 7)

Precision: Of the answers I gave, what percent were correct?

$$\frac{|A \cap C|}{|A|}$$

Recall: What percent of the correct answers did I give?

$$\frac{|A \cap C|}{|C|}$$

F1: Harmonic mean of Precision and Recall (reciprocal of mean of reciprocals)

$$\frac{2|A \cap C|}{|C| + |A|}$$

Parser Evaluation

A = answers

(S 0 7)
(NP 0 1)
(VP 1 7)
(NP 2 7)
(NP 2 4)
(PP 4 7)
(NP 5 7)

$|A| = 7$

C = correct

(S 0 7)
(NP 0 1)
(VP 1 7)
(NP 2 4)
(PP 4 7)
(NP 5 7)

$|C| = 6$

Parser Evaluation

A = answers

(S 0 7)
(NP 0 1)
(VP 1 7)
(NP 2 7)
(NP 2 4)
(PP 4 7)
(NP 5 7)

$|A| = 7$

$|A \cap C| = 6$

C = correct

(S 0 7)
(NP 0 1)
(VP 1 7)
(NP 2 4)
(PP 4 7)
(NP 5 7)

$|C| = 6$

Parser Evaluation

A = answers

(S 0 7)
(NP 0 1)
(VP 1 7)
extra! $\boxed{\text{(NP 2 7)}}$
(NP 2 4)
(PP 4 7)
(NP 5 7)

$|A| = 7$

$|A \cap C| = 6$

C = correct

(S 0 7)
(NP 0 1)
(VP 1 7)
(NP 2 4)
(PP 4 7)
(NP 5 7)

$|C| = 6$

Parser Evaluation

A = answers

(S 0 7)
(NP 0 1)
(VP 1 7)
(NP 2 7)
(NP 2 4)
(PP 4 7)
(NP 5 7)

C = correct

(S 0 7)
(NP 0 1)
(VP 1 7)
(NP 2 4)
(PP 4 7)
(NP 5 7)

$|A \cap C| = 6$

$|A| = 7$

$|C| = 6$

$$R = \frac{|A \cap C|}{|C|} = 1.0$$

Parser Evaluation

A = answers

(S 0 7)
(NP 0 1)
(VP 1 7)
(NP 2 7)
(NP 2 4)
(PP 4 7)
(NP 5 7)

C = correct

(S 0 7)
(NP 0 1)
(VP 1 7)
(NP 2 4)
(PP 4 7)
(NP 5 7)

$|A \cap C| = 6$

$|A| = 7$

$|C| = 6$

$$R = \frac{|A \cap C|}{|C|} = 1.0$$

$$P = \frac{|A \cap C|}{|A|} = .857$$

Parser Evaluation

A = answers

(S 0 7)
(NP 0 1)
(VP 1 7)
(NP 2 7)
(NP 2 4)
(PP 4 7)
(NP 5 7)

C = correct

(S 0 7)
(NP 0 1)
(VP 1 7)
(NP 2 4)
(PP 4 7)
(NP 5 7)

$|A \cap C| = 6$

$|A| = 7$

$|C| = 6$

$$R = \frac{|A \cap C|}{|C|} = 1.0 \qquad P = \frac{|A \cap C|}{|A|} = .857$$

$$F1 = \frac{2|A \cap C|}{|C| + |A|} = .923$$

How to parse a sentence?

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- Input: word-separated sentence

How to parse a sentence?

- Input: word-separated sentence
- Output: syntactic tree with POS tag/word labels

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- How you get there is up to you!
- So far in this class we've used wFSAs and wFSTs. Can we keep using them?

How to parse a sentence?

- Input: word-separated sentence
- Output: syntactic tree with POS tag/word labels
- How you get there is up to you!
- So far in this class we've used wFSAs and wFSTs. Can we keep using them?
- NO! (Why?)

Context-Free Grammars

Context-Free Grammars

S
NP
VP
NNS
PP
VB
...

Nonterminals
(start)

Context-Free Grammars

S NP
VP NNS
PP
VB
…

Nonterminals
(start)

cats I
mice the
telescope
… eat

Terminals

Context-Free Grammars

Nonterminals (start)	Terminals	Rules
S, NP, VP, NNS, PP, VB, …	cats, I, mice, the, telescope, eat, …	S → NP VP VP → VB NP NP → NNS NNS → cats NNS → mice VB → eat

Context-Free Grammars

S NP VP NNS PP VB …

Nonterminals (start)

cats I mice the telescope eat …

Terminals

S → NP VP
VP → VB NP
NP → NNS
NNS → cats
NNS → mice
VB → eat

Rules

S

Extend leftmost nonterminal by RHS of matching rule until done

Context-Free Grammars

S NP VP NNS PP VB …

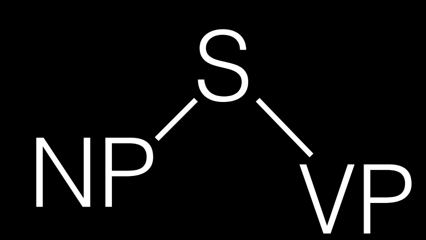
Nonterminals (start)

cats I mice the telescope eat …

Terminals

S → NP VP
VP → VB NP
NP → NNS
NNS → cats
NNS → mice
VB → eat

Rules



Extend leftmost nonterminal by RHS of matching rule until done

Context-Free Grammars

S NP
VP NNS
PP
VB
…

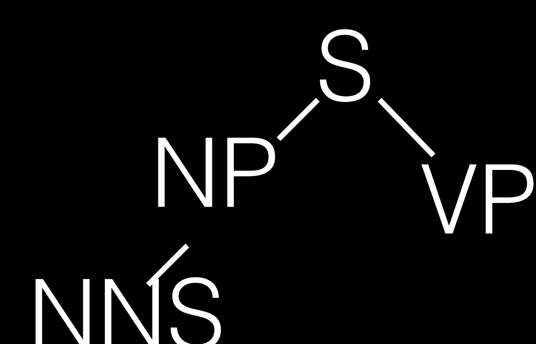
Nonterminals
(start)

cats I
mice the
telescope
… eat

Terminals

S → NP VP
VP → VB NP
NP → NNS
NNS → cats
NNS → mice
VB → eat

Rules



Extend leftmost nonterminal by RHS of matching rule until done

Context-Free Grammars

S NP
VP NNS
PP
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…

Nonterminals
(start)

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Terminals

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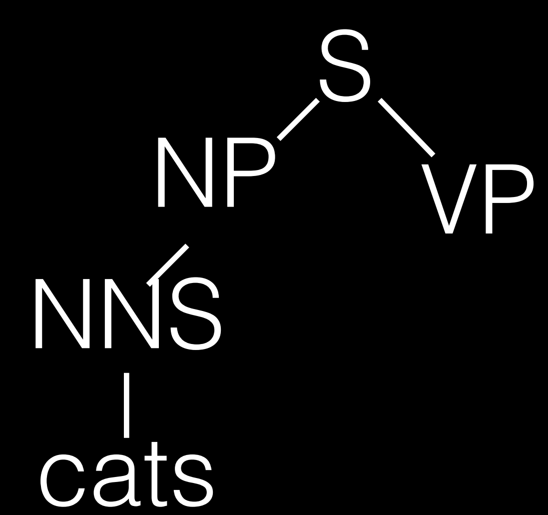
Rules



Extend leftmost nonterminal by RHS of matching rule until done

Context-Free Grammars

Nonterminals (start)

S

NP

VP

NNS

PP

VB

…

Terminals

cats

I

mice

the

telescope

eat

…

Rules

S → NP VP

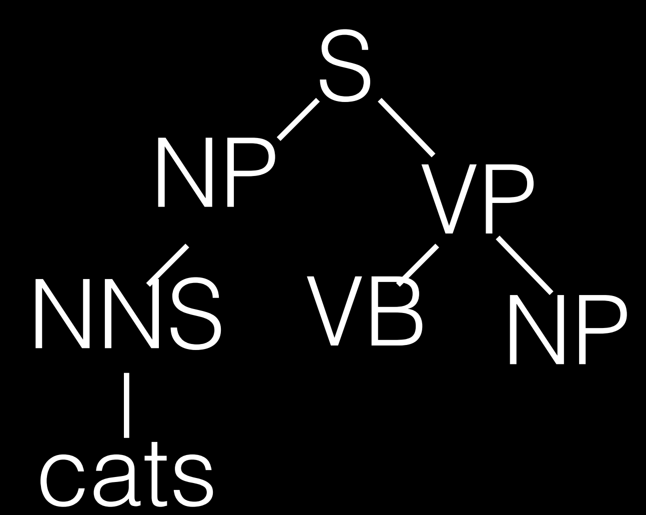
VP → VB NP

NP → NNS

NNS → cats

NNS → mice

VB → eat



Extend leftmost nonterminal by RHS of matching rule until done

Context-Free Grammars

S NP
VP NNS
PP
VB
…

Nonterminals
(start)

cats I
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… eat

Terminals

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VP → VB NP
NP → NNS
NNS → cats
NNS → mice
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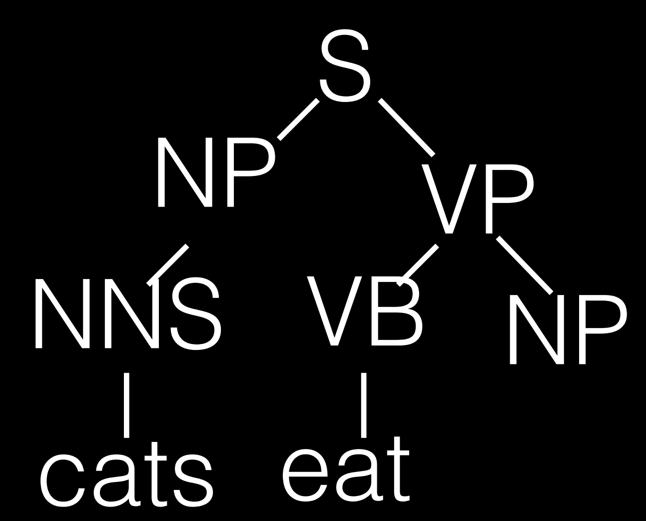
Rules



Extend leftmost
nonterminal
by RHS of matching
rule until done

Context-Free Grammars

S
NP
VP
NNS
PP
VB
…

Nonterminals
(start)

cats
I
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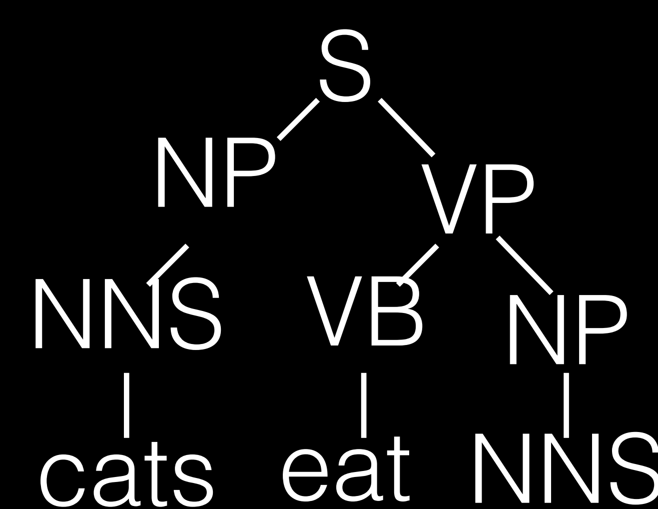

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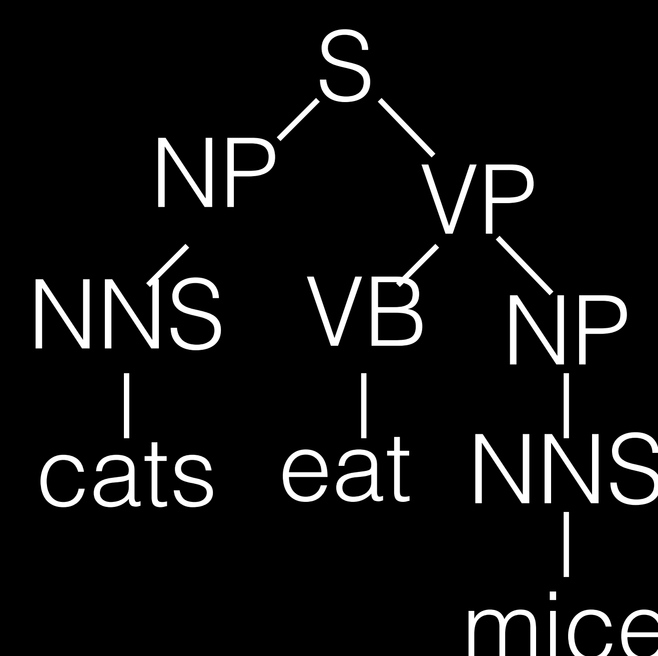
Rules



Extend leftmost nonterminal by RHS of matching rule until done

Baseline Parser

Left-branching chain of NPs

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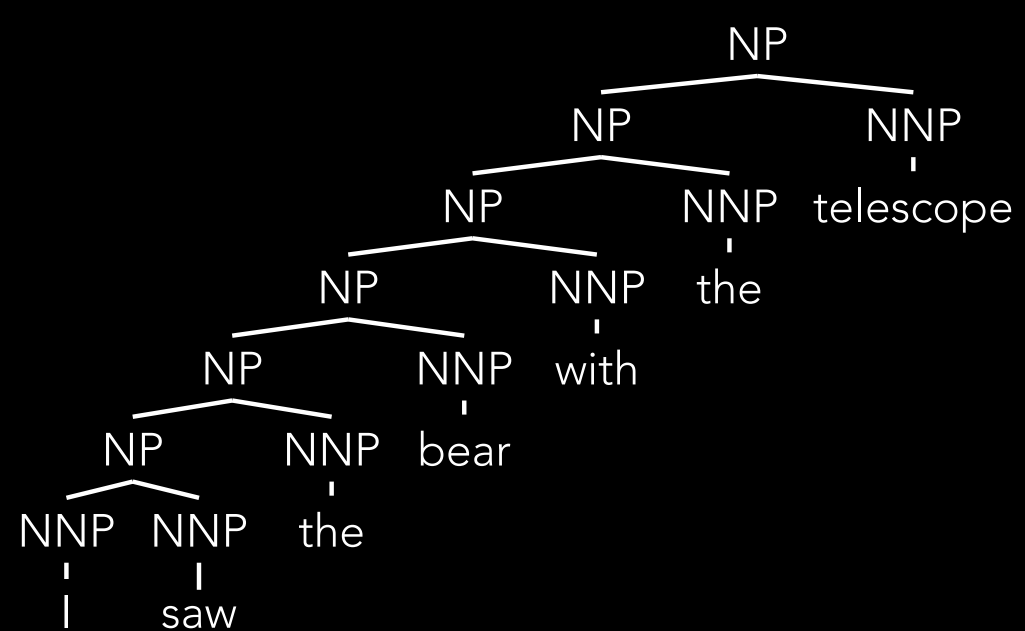
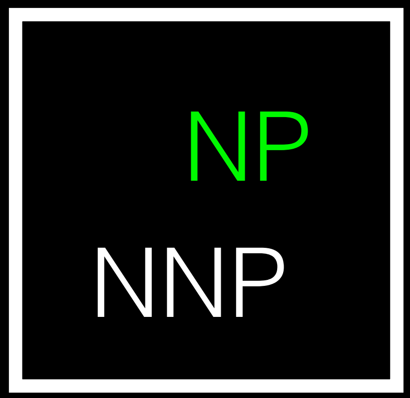
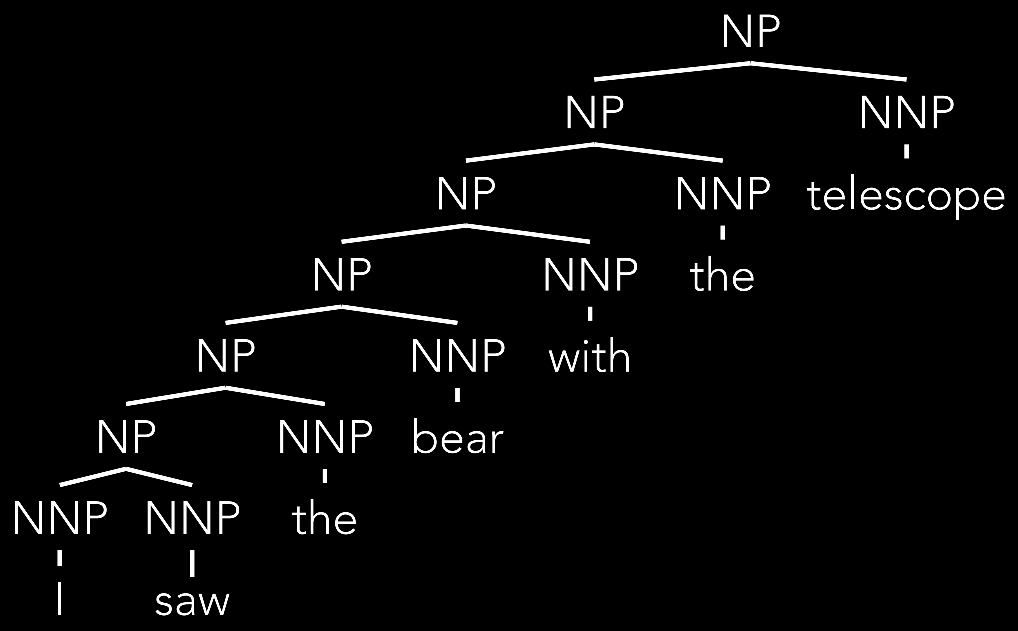
Left-branching chain of NPs



Baseline Parser

Left-branching chain of NPs



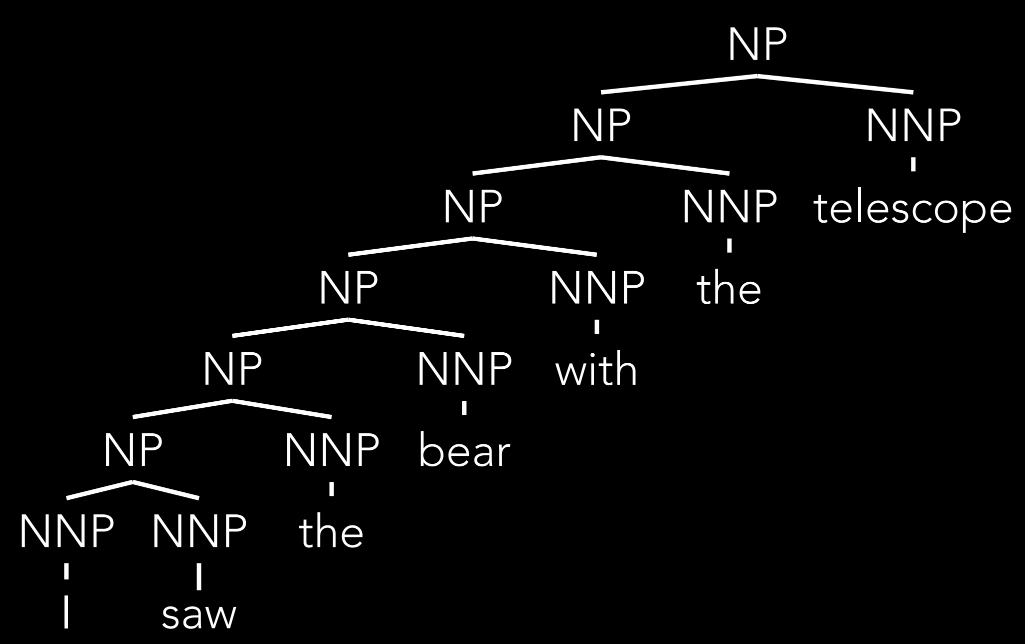


Baseline Parser

Left-branching chain of NPs

NP
NNP

$$\begin{aligned} NP &\rightarrow NP\ NNP \\ NP &\rightarrow NNP\ NNP \\ NNP &\rightarrow \text{I/saw/the/…} \end{aligned}$$



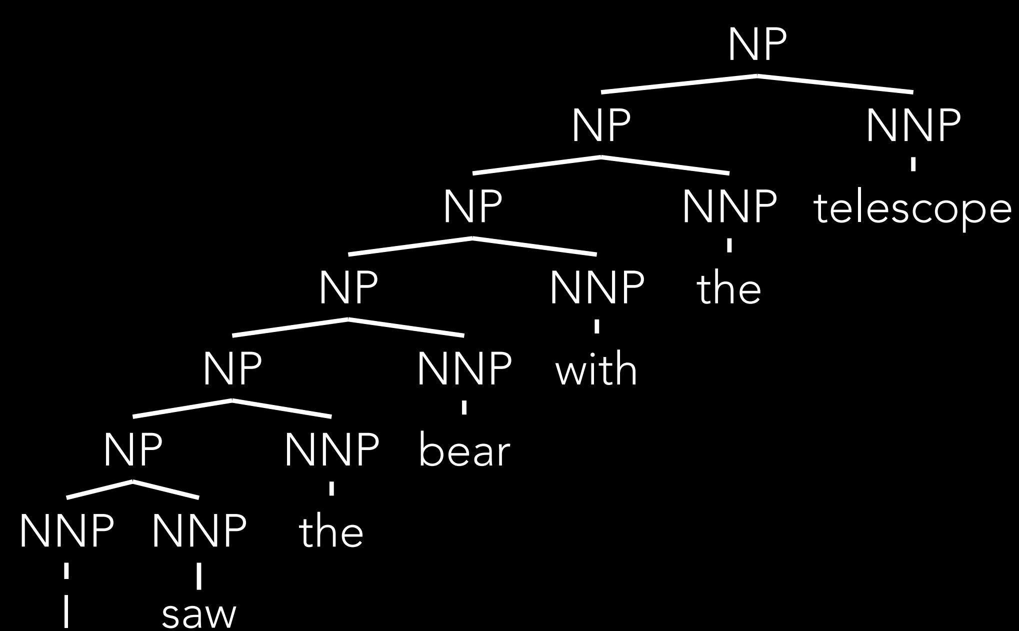
Baseline Parser

Left-branching chain of NPs

NP

NNP

NP → NP NNP
NP → NNP NNP
NNP → I/saw/the/…



- Data-driven! (Most popular tag/constituent in PTB)

Baseline Parser

Left-branching chain of NPs

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NNP

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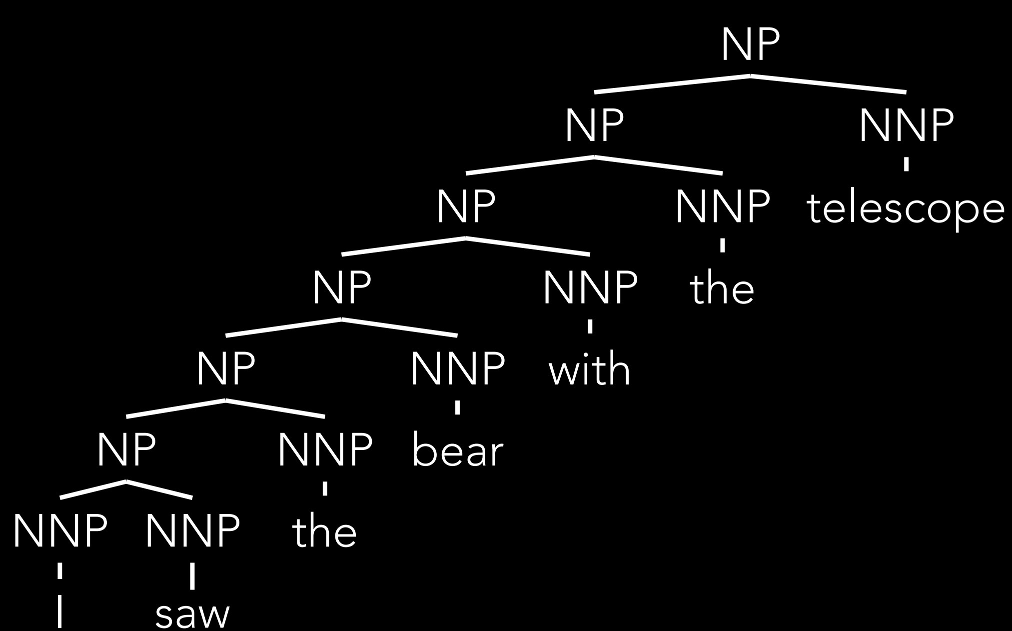
NP → NNP NNP
NNP → I/saw/the/…



- Data-driven! (Most popular tag/constituent in PTB)
- Easy!

Baseline Parser

Left-branching chain of NPs

NP
NNP

NP → NP NNP
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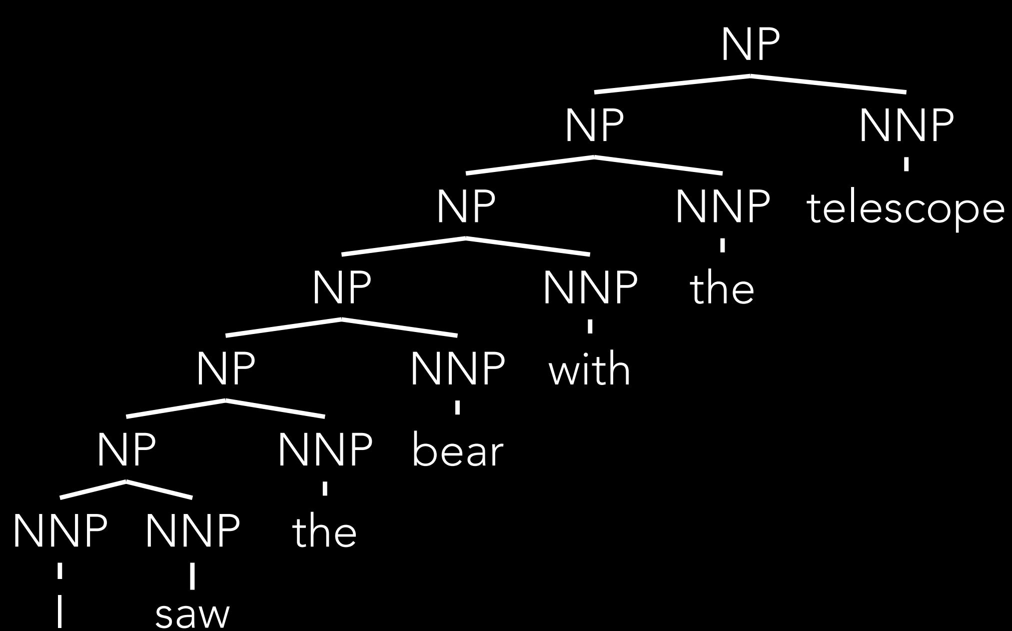
NNP → I/saw/the/…



- Data-driven! (Most popular tag/constituent in PTB)
- Easy!
- F1 of around 0.03

But how do you actually *parse*?

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- CFG operations showed how to *generate* a tree, not put a tree on a given string.

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- We’re intersecting two languages, so we can use the *Bar-Hillel* construction: annotate the CFG rules with indices corresponding to the words in the string.

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$$\begin{aligned} NP &\rightarrow NP\ NNP \\ NP &\rightarrow NNP\ NNP \\ NNP &\rightarrow \text{I} \mid \text{saw} \mid \text{the} \mid \text{bear} \end{aligned}$$

But how do you actually *parse*?

- CFG operations showed how to *generate* a tree, not put a tree on a given string.
- We're intersecting two languages, so we can use the *Bar-Hillel* construction: annotate the CFG rules with indices corresponding to the words in the string.

$$\boxed{\begin{array}{l} \mathrm{NP} \rightarrow \mathrm{NP}\ \mathrm{NNP} \\ \mathrm{NP} \rightarrow \mathrm{NNP}\ \mathrm{NNP} \\ \mathrm{NNP} \rightarrow \mathrm{I} \mid \mathrm{saw} \mid \mathrm{the} \mid \mathrm{bear} \end{array}}$$

I saw the bear

But how do you actually *parse*?

- CFG operations showed how to *generate* a tree, not put a tree on a given string.

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$$\mathrm{NP} \rightarrow \mathrm{NP\ NNP}$$
$$\mathrm{NP} \rightarrow \mathrm{NNP\ NNP}$$
$$\mathrm{NNP} \rightarrow \mathrm{I} \mid \mathrm{saw} \mid \mathrm{the} \mid \mathrm{bear}$$

I saw the bear
0 1 2 3

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I saw the bear
0 1 2 3

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$$NP \rightarrow NNP\ NNP$$
$$NNP \rightarrow I \mid saw \mid the \mid bear$$

I saw the bear
0 1 2 3

$NNP_0 \rightarrow$ I $\quad NNP_2 \rightarrow$ the

$NNP_1 \rightarrow$ saw $\quad NNP_3 \rightarrow$ bear

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$NP \rightarrow NP\ NNP$
$NP \rightarrow NNP\ NNP$
$NNP \rightarrow$ I | saw | the | bear

I saw the bear
0 1 2 3

$NP_{i\_j} \rightarrow NP_{i\_j-1}\ NNP_j$

$NNP_0 \rightarrow$ I
$NNP_1 \rightarrow$ saw
$NNP_2 \rightarrow$ the
$NNP_3 \rightarrow$ bear

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$\mathrm{NP} \rightarrow \mathrm{NP}\ \mathrm{NNP}$
$\mathrm{NP} \rightarrow \mathrm{NNP}\ \mathrm{NNP}$
$\mathrm{NNP} \rightarrow$ I | saw | the | bear

I saw the bear
0 1 2 3

$\mathrm{NP}_{i\_j} \rightarrow \mathrm{NP}_{i\_j-1}\ \mathrm{NNP}_j$

$\mathrm{NP}_{i\_i+1} \rightarrow \mathrm{NNP}_i\ \mathrm{NNP}_{i+1}$

$\mathrm{NNP}_0 \rightarrow$ I $\quad \mathrm{NNP}_2 \rightarrow$ the
$\mathrm{NNP}_1 \rightarrow$ saw $\quad \mathrm{NNP}_3 \rightarrow$ bear

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$$0 \le i < j \le 3$$

$$\boxed{\begin{array}{l} NP \rightarrow NP\ NNP \\ NP \rightarrow NNP\ NNP \\ NNP \rightarrow \text{I} \mid \text{saw} \mid \text{the} \mid \text{bear} \end{array}}$$

I saw the bear
0 1 2 3

$$NP_{i\_j} \rightarrow NP_{i\_j-1}\ NNP_j$$

$$NP_{i\_i+1} \rightarrow NNP_i\ NNP_{i+1}$$

$NNP_0 \rightarrow \text{I}$ $\quad$ $NNP_2 \rightarrow \text{the}$

$NNP_1 \rightarrow \text{saw}$ $\quad$ $NNP_3 \rightarrow \text{bear}$

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$NP \rightarrow NP\ NNP$

$NP \rightarrow NNP\ NNP$

$NNP \rightarrow I \mid saw \mid the \mid bear$

I saw the bear
0 1 2 3

NP_{0_3} $\quad 0 \leq i < j \leq 3$

$NP_{i\_j} \rightarrow NP_{i\_j-1}\ NNP_j$

$NP_{i\_i+1} \rightarrow NNP_i\ NNP_{i+1}$

$NNP_0 \rightarrow I$ $\quad NNP_2 \rightarrow the$

$NNP_1 \rightarrow saw$ $\quad NNP_3 \rightarrow bear$

CKY Parsing

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- Reasonably efficient — $O(n^3)$ for n words

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$$X \rightarrow Y\ Z$$

nonterminal rule

CKY Parsing

- Reasonably efficient — $O(n^3)$ for n words
- Easy to code
- Easily extendable to weighted case
- Requires *Chomsky Normal Form*

$X \rightarrow Y\ Z$	$X \rightarrow x$
nonterminal rule	terminal rule

CKY Parsing

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- Input: sentence of length n+1 = <w0, w1…wn>, CFG

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- Input: sentence of length n+1 = <w0, w1…wn>, CFG
- Build states of the form [X, i, j] = “I can cover from words i through j with at least one tree rooted in X”

CKY Parsing

- Input: sentence of length n+1 = <w0, w1…wn>, CFG
- Build states of the form [X, i, j] = "I can cover from words i through j with at least one tree rooted in X"
- States contain backpointers of the form {R, k} = "To satisfy my state I will use R (X -> YZ) and states [Y, i, k] and [Z, k, j]"

CKY Parsing

CKY Parsing

- Initialize: build [X, i, i+1] for every lexical rule R = X -> wi; add backpointer {R, ()}

CKY Parsing

- Initialize: build [X, i, i+1] for every lexical rule R = X -> wi; add backpointer {R, ()}

- Recursively: build [X, i, j] for every nonlexical rule R = X -> Y Z and pair of states ([Y, i, k], [Z, k, j]) where i < k < j; add backpointer {R, k}

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- Recursively: build [X, i, j] for every nonlexical rule R = X -> Y Z and pair of states ([Y, i, k], [Z, k, j]) where i < k < j; add backpointer {R, k}
- If state is already built, just add backpointer

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- If state is already built, just add backpointer

- Goal: build [X, 0, n+1] for start symbol X

time	flies	like	an	arrow
[0,1]	[0,2]	[0,3]	[0,4]	[0,5]
	[1,2]	[1,3]	[1,4]	[1,5]
		[2,3]	[2,4]	[2,5]
			[3,4]	[3,5]
				[4,5]

S → NP VP
NP → DT NN
NP → time | fruit
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

time	flies	like	an	arrow
[0,1]	[0,2]	[0,3]	[0,4]	[0,5]
	[1,2]	[1,3]	[1,4]	[1,5]
		[2,3]	[2,4]	[2,5]
			[3,4]	[3,5]
				[4,5]

Length 1

S → NP VP
NP → DT NN
NP → time | fruit
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
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time	flies	like	an	arrow
[0,1]	[0,2]	[0,3]	[0,4]	[0,5]
	[1,2]	[1,3]	[1,4]	[1,5]
		[2,3]	[2,4]	[2,5]
			[3,4]	[3,5]
				[4,5]

Length 2

S → NP VP

NP → DT NN

NP → time | fruit

NP → NN NNS

VP → VBP NP

VP → flies

VP → VP PP

PP → IN NP

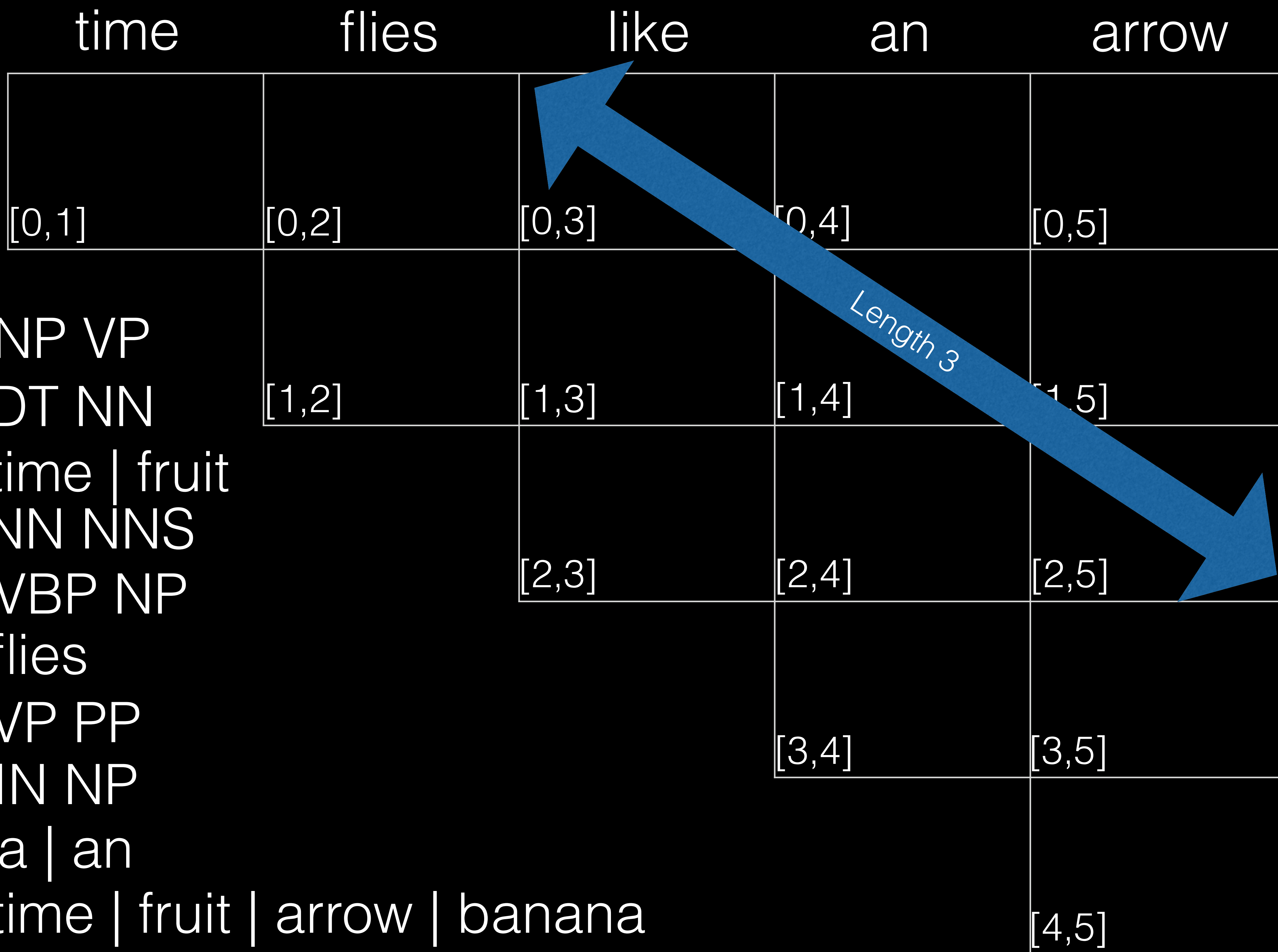
DT → a | an

NN → time | fruit | arrow | banana

NNS → flies

VBP → like

IN → like



S → NP VP
NP → DT NN
NP → time | fruit
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
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NN → time | fruit | arrow | banana
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IN → like

time	flies	like	an	arrow
[0,1]	[0,2]	[0,3]	[0,4]	[0,5]
	[1,2]	[1,3]	[1,4]	[1,5]
		[2,3]	[2,4]	[2,5]
			[3,4]	[3,5]
				[4,5]

Length 4

S → NP VP
NP → DT NN
NP → time | fruit
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

time	flies	like	an	arrow
[0,1]	[0,2]	[0,3]	[0,4]	[0,5]
	[1,2]	[1,3]	[1,4]	[1,5]
		[2,3]	[2,4]	[2,5]
			[3,4]	[3,5]
				[4,5]

Length 5

S → NP VP
NP → DT NN
NP → time | fruit
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

time	flies	like	an	arrow
NP NN [0,1]	[0,2]	[0,3]	[0,4]	[0,5]
	[1,2]	[1,3]	[1,4]	[1,5]
		[2,3]	[2,4]	[2,5]
			[3,4]	[3,5]
				[4,5]

S → NP VP
NP → DT NN
NP → time | fruit
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

Seed length-1 cells
with lexical coverage

time	flies	like	an	arrow
NP NN [0,1]	[0,2]	[0,3]	[0,4]	[0,5]
	VP NNS [1,2]	[1,3]	[1,4]	[1,5]
		[2,3]	[2,4]	[2,5]
			[3,4]	[3,5]
				[4,5]

S → NP VP

NP → DT NN

NP → time | fruit

NP → NN NNS

VP → VBP NP

VP → flies

VP → VP PP

PP → IN NP

DT → a | an

NN → time | fruit | arrow | banana

NNS → flies

VBP → like

IN → like

Seed length-1 cells
with lexical coverage

time	flies	like	an	arrow
NP NN [0,1]	[0,2]	[0,3]	[0,4]	[0,5]
	VP NNS [1,2]	[1,3]	[1,4]	[1,5]
		IN VBP [2,3]	[2,4]	[2,5]
			[3,4]	[3,5]
				[4,5]

S → NP VP
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NP → time | fruit
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

Seed length-1 cells
with lexical coverage

time	flies	like	an	arrow
NP NN [0,1]	[0,2]	[0,3]	[0,4]	[0,5]
	VP NNS [1,2]	[1,3]	[1,4]	[1,5]
		IN VBP [2,3]	[2,4]	[2,5]
			DT [3,4]	[3,5]
				[4,5]

S → NP VP
NP → DT NN
NP → time | fruit
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

Seed length-1 cells
with lexical coverage

time	flies	like	an	arrow
NP NN [0,1]	[0,2]	[0,3]	[0,4]	[0,5]
	VP NNS [1,2]	[1,3]	[1,4]	[1,5]
		IN VBP [2,3]	[2,4]	[2,5]
			DT [3,4]	[3,5]
				NN [4,5]

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NP → NN NNS
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VP → flies
VP → VP PP
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DT → a | an
NN → time | fruit | $\boxed{\text{arrow}}$ | banana
NNS → flies
VBP → like
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Seed length-1 cells
with lexical coverage

time	flies	like	an	arrow
NP NN [0,1]	[0,2]	[0,3]	[0,4]	[0,5]
	VP NNS [1,2]	[1,3]	[1,4]	[1,5]
		IN VBP [2,3]	[2,4]	[2,5]
			DT [3,4]	[3,5]
				NN [4,5]

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VP → VP PP
PP → IN NP
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IN → like

Now check length-2 spans.
Match rules to subspans

time	flies	like	an	arrow
NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	[0,5]
	VP NNS [1,2]	[1,3]	[1,4]	[1,5]
		IN VBP [2,3]	[2,4]	[2,5]
			DT [3,4]	[3,5]
				NN [4,5]

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NP → time | fruit
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
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IN → like

Two new states!

	time	flies	like	an	arrow
	NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	[0,5]
		VP NNS [1,2]	[1,3]	[1,4]	[1,5]
			IN VBP [2,3]	[2,4]	[2,5]
				DT [3,4]	[3,5]
					NN [4,5]

S → NP VP
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NP → time | fruit
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

Annotate with backpointer
for future reconstruction (not part of state)

time	flies	like	an	arrow
NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	[0,5]
	VP NNS [1,2]	[1,3]	[1,4]	[1,5]
		IN VBP [2,3]	[2,4]	[2,5]
			DT [3,4]	[3,5]
				NN [4,5]

S → NP VP
NP → DT NN
NP → time | fruit
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
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IN → like

No matching rule

time	flies	like	an	arrow
NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	[0,5]
	VP NNS [1,2]	[1,3]	[1,4]	[1,5]
		IN VBP [2,3]	[2,4]	[2,5]
			DT [3,4]	[3,5]
				NN [4,5]

S → NP VP
NP → DT NN
NP → time | fruit
NP → NN NNS
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VP → flies
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No matching rule

time	flies	like	an	arrow
NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	[0,5]
	VP NNS [1,2]	[1,3]	[1,4]	[1,5]
		IN VBP [2,3]	[2,4]	[2,5]
			DT [3,4]	NP [3,5]
				NN [4,5]

S → NP VP

NP → DT NN

NP → time | fruit

NP → NN NNS

VP → VBP NP

VP → flies

VP → VP PP

PP → IN NP

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IN → like

New state!

time	flies	like	an	arrow
NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	[0,5]
	VP NNS [1,2]	[1,3]	[1,4]	[1,5]
		IN VBP [2,3]	[2,4]	[2,5]
			DT [3,4]	NP [3,5]
				NN [4,5]

S → NP VP
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NP → time | fruit
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DT → a | an
NN → time | fruit | arrow | banana
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Check every split point for rule

	time	flies	like	an	arrow
	NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	[0,5]
		VP NNS [1,2]	[1,3]	[1,4]	[1,5]
			IN VBP [2,3]	[2,4]	[2,5]
				DT [3,4]	NP [3,5]
					NN [4,5]

$S \rightarrow NP\ VP$

$NP \rightarrow DT\ NN$

$NP \rightarrow$ time | fruit

$NP \rightarrow NN\ NNS$

$VP \rightarrow VBP\ NP$

$VP \rightarrow$ flies

$VP \rightarrow VP\ PP$

$PP \rightarrow IN\ NP$

$DT \rightarrow$ a | an

$NN \rightarrow$ time | fruit | arrow | banana

$NNS \rightarrow$ flies

$VBP \rightarrow$ like

$IN \rightarrow$ like

Empty cell

time	flies	like	an	arrow
NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	[0,5]
	VP NNS [1,2]	[1,3]	[1,4]	[1,5]
		IN VBP [2,3]	[2,4]	[2,5]
			DT [3,4]	NP [3,5]
				NN [4,5]

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NP → time | fruit
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
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NN → time | fruit | arrow | banana
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IN → like

No matching rule

time	flies	like	an	arrow
NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	[0,5]
	VP NNS [1,2]	[1,3]	[1,4]	[1,5]
		IN VBP [2,3]	[2,4]	[2,5]
			DT [3,4]	NP [3,5]
				NN [4,5]

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VP → flies
VP → VP PP
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VBP → like
IN → like

(Skipping)

	time	flies	like	an	arrow
	NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	[0,5]
		VP NNS [1,2]	[1,3]	[1,4]	[1,5]
			IN VBP [2,3]	[2,4]	PP VP [2,5]
				DT [3,4]	NP [3,5]
					NN [4,5]

S → NP VP
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NP → time | fruit
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
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IN → like

Two new states!

time	flies	like	an	arrow
NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	[0,5]
	VP NNS [1,2]	[1,3]	[1,4]	[1,5]
		IN VBP [2,3]	[2,4]	PP VP [2,5]
			DT [3,4]	NP [3,5]
				NN [4,5]

S → NP VP
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NP → time | fruit
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

Empty cell

time	flies	like	an	arrow
NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	[0,5]
	VP NNS [1,2]	[1,3]	[1,4]	[1,5]
		IN VBP [2,3]	[2,4]	PP VP [2,5]
			DT [3,4]	NP [3,5]
				NN [4,5]

S → NP VP
NP → DT NN
NP → time | fruit
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(Skipping)

time	flies	like	an	arrow
NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	[0,5]
	VP NNS [1,2]	[1,3]	[1,4]	VP [1,5]
		IN VBP [2,3]	[2,4]	PP VP [2,5]
			DT [3,4]	NP [3,5]
				NN [4,5]

S → NP VP
NP → DT NN
NP → time | fruit
NP → NN NNS
VP → VBP NP
VP → flies
$\boxed{\text{VP → VP PP}}$
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

New state!

time	flies	like	an	arrow
NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	[0,5]
	VP NNS [1,2]	[1,3]	[1,4]	VP [1,5]
		IN VBP [2,3]	[2,4]	PP VP [2,5]
			DT [3,4]	NP [3,5]
				NN [4,5]

S → NP VP
NP → DT NN
NP → time | fruit
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

Empty Cell

	time	flies	like	an	arrow
	NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	[0,5]
		VP NNS [1,2]	[1,3]	[1,4]	VP [1,5]
			IN VBP [2,3]	[2,4]	PP VP [2,5]
				DT [3,4]	NP [3,5]
					NN [4,5]

S $\rightarrow$ NP VP
NP $\rightarrow$ DT NN
NP $\rightarrow$ time | fruit
NP $\rightarrow$ NN NNS
VP $\rightarrow$ VBP NP
VP $\rightarrow$ flies
VP $\rightarrow$ VP PP
PP $\rightarrow$ IN NP
DT $\rightarrow$ a | an
NN $\rightarrow$ time | fruit | arrow | banana
NNS $\rightarrow$ flies
VBP $\rightarrow$ like
IN $\rightarrow$ like

Empty Cell

time	flies	like	an	arrow
NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	S [0,5]
	VP NNS [1,2]	[1,3]	[1,4]	VP [1,5]
		IN VBP [2,3]	[2,4]	PP VP [2,5]
			DT [3,4]	NP [3,5]
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NN → time | fruit | arrow | banana

NNS → flies

VBP → like

IN → like

New state!

time	flies	like	an	arrow
NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	S [0,5]
	VP NNS [1,2]	[1,3]	[1,4]	VP [1,5]
		IN VBP [2,3]	[2,4]	PP VP [2,5]
			DT [3,4]	NP [3,5]
				NN [4,5]

S → NP VP

NP → DT NN

NP → time | fruit

NP → NN NNS

VP → VBP NP

VP → flies

VP → VP PP

PP → IN NP

DT → a | an

NN → time | fruit | arrow | banana

NNS → flies

VBP → like

IN → like

Alternate (no new state)

time	flies	like	an	arrow
NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	S [0,5]
	VP NNS [1,2]	[1,3]	[1,4]	VP [1,5]
		IN VBP [2,3]	[2,4]	PP VP [2,5]
			DT [3,4]	NP [3,5]
				NN [4,5]

S → NP VP
NP → DT NN
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Empty Cell

	time	flies	like	an	arrow
	NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	S [0,5]
		VP NNS [1,2]	[1,3]	[1,4]	VP [1,5]
			IN VBP [2,3]	[2,4]	PP VP [2,5]
				DT [3,4]	NP [3,5]
					NN [4,5]

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NP → DT NN
NP → time | fruit
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Empty Cell

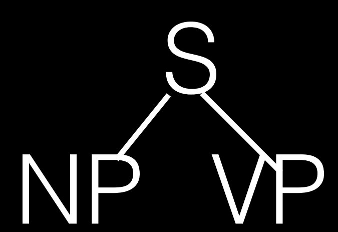
time	flies	like	an	arrow
NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	S [0,5]
	VP NNS [1,2]	[1,3]	[1,4]	VP [1,5]
		IN VBP [2,3]	[2,4]	PP VP [2,5]
			DT [3,4]	NP [3,5]
				NN [4,5]

Start at top of the chart
Follow backpointers
to build tree

time	flies	like	an	arrow
NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	S [0,5]
	VP NNS [1,2]	[1,3]	[1,4]	VP [1,5]
		IN VBP [2,3]	[2,4]	PP VP [2,5]
			DT [3,4]	NP [3,5]
				NN [4,5]

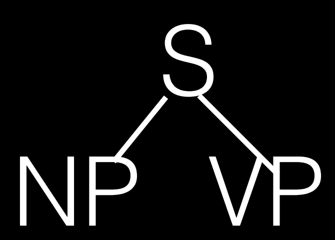
S

time	flies	like	an	arrow
NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	S [0,5]
	VP NNS [1,2]	[1,3]	[1,4]	VP [1,5]
		IN VBP [2,3]	[2,4]	PP VP [2,5]
			DT [3,4]	NP [3,5]
				NN [4,5]



Backpointer: $S \rightarrow NP\ VP$,1

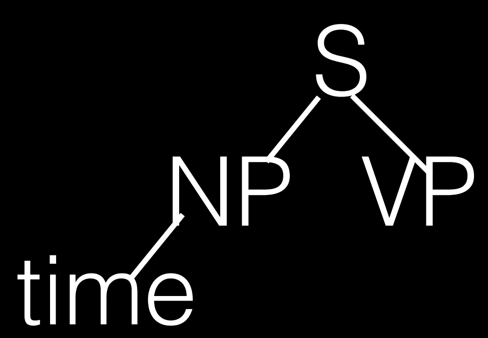
time	flies	like	an	arrow
NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	S [0,5]
	VP NNS [1,2]	[1,3]	[1,4]	VP [1,5]
		IN VBP [2,3]	[2,4]	PP VP [2,5]
			DT [3,4]	NP [3,5]
				NN [4,5]



(could have used $S \rightarrow NP\ VP$,2
to generate the other tree)

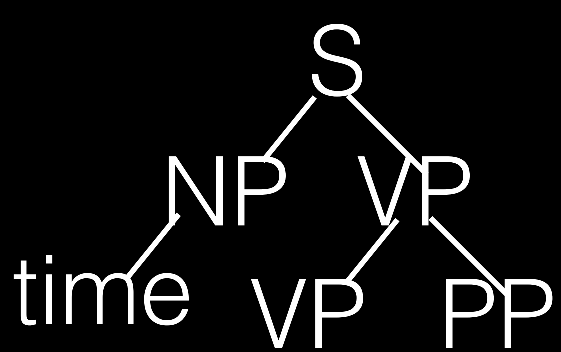
Backpointer: $S \rightarrow NP\ VP$,1

time	flies	like	an	arrow
NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	S [0,5]
	VP NNS [1,2]	[1,3]	[1,4]	VP [1,5]
		IN VBP [2,3]	[2,4]	PP VP [2,5]
			DT [3,4]	NP [3,5]
				NN [4,5]



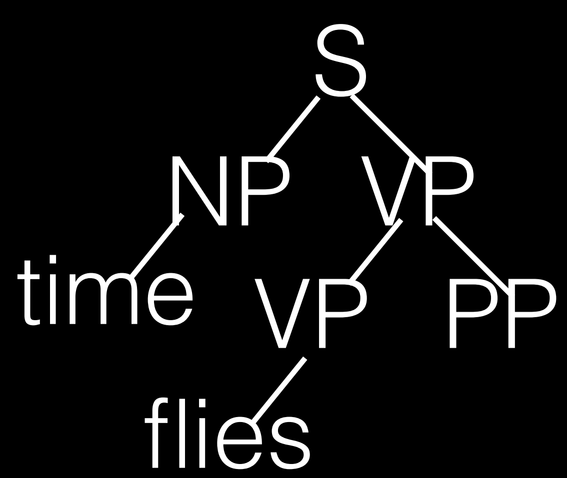
Backpointer: NP → time

	time	flies	like	an	arrow
	NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	S [0,5]
		VP NNS [1,2]	[1,3]	[1,4]	VP [1,5]
			IN VBP [2,3]	[2,4]	PP VP [2,5]
				DT [3,4]	NP [3,5]
					NN [4,5]



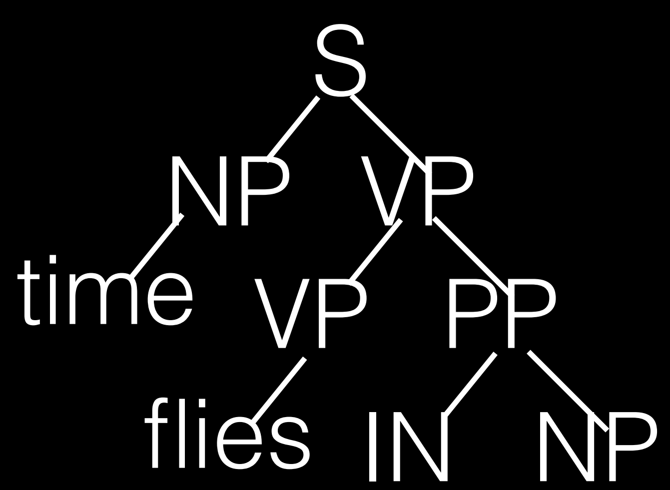
Backpointer: VP → VP PP ,2

time	flies	like	an	arrow
NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	S [0,5]
	VP NNS [1,2]	[1,3]	[1,4]	VP [1,5]
		IN VBP [2,3]	[2,4]	PP VP [2,5]
			DT [3,4]	NP [3,5]
				NN [4,5]



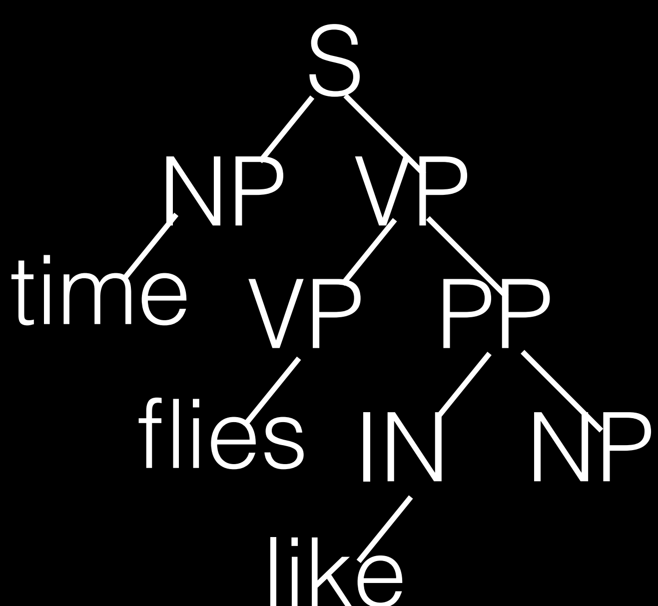
Backpointer: VP → flies

time	flies	like	an	arrow
NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	S [0,5]
	VP NNS [1,2]	[1,3]	[1,4]	VP [1,5]
		IN VBP [2,3]	[2,4]	PP VP [2,5]
			DT [3,4]	NP [3,5]
				NN [4,5]



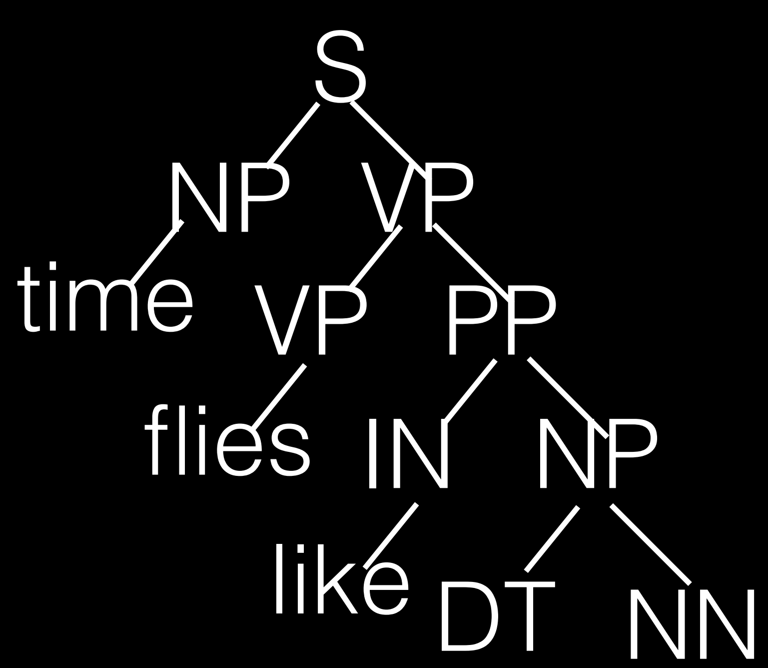
Backpointer: PP → IN NP ,3

time	flies	like	an	arrow
NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	S [0,5]
	VP NNS [1,2]	[1,3]	[1,4]	VP [1,5]
		IN VBP [2,3]	[2,4]	PP VP [2,5]
			DT [3,4]	NP [3,5]
				NN [4,5]



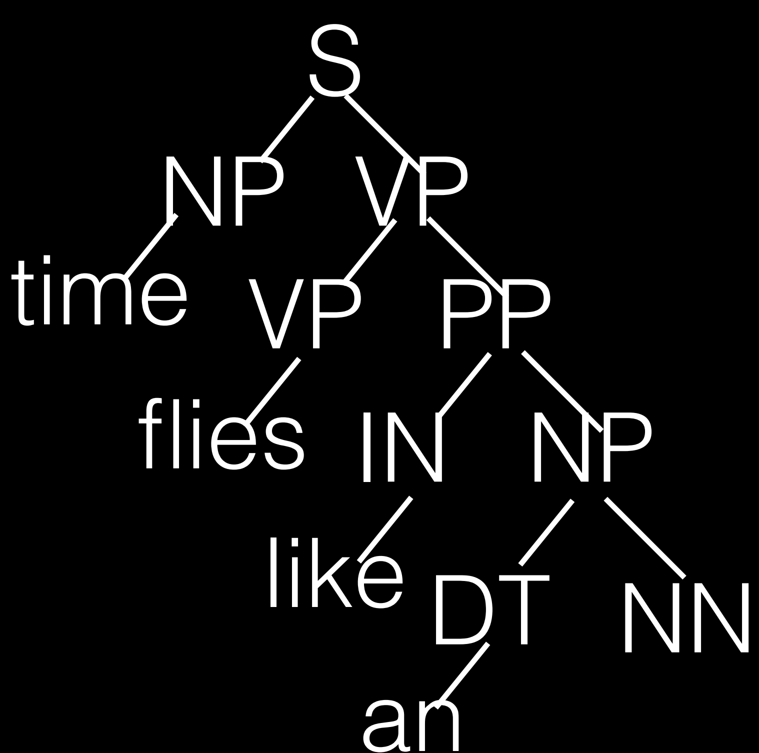
Backpointer: IN → like

time	flies	like	an	arrow
NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	S [0,5]
	VP NNS [1,2]	[1,3]	[1,4]	VP [1,5]
		IN VBP [2,3]	[2,4]	PP VP [2,5]
			DT [3,4]	$\boxed{\text{NP}}$ [3,5]
				NN [4,5]



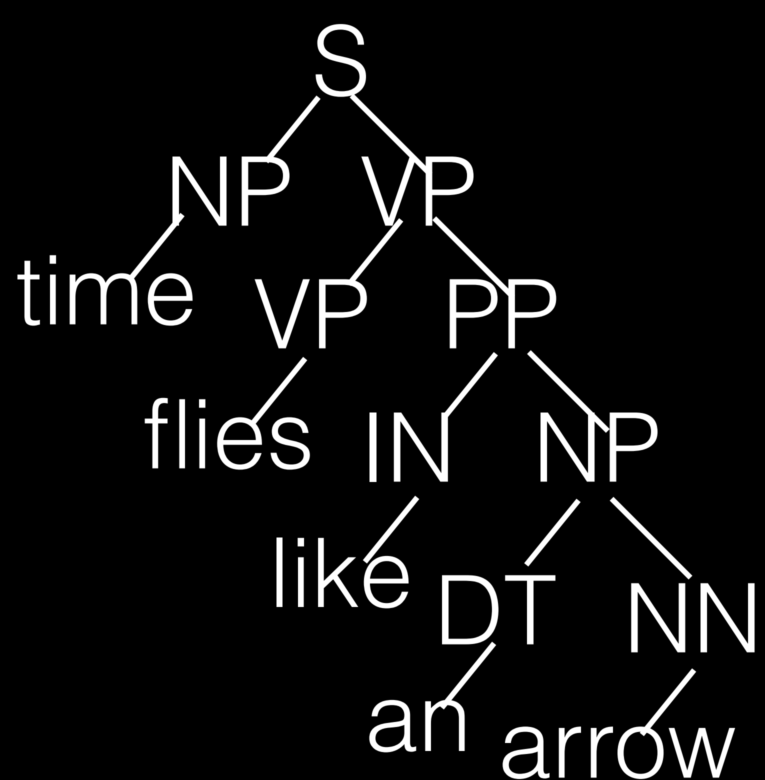
Backpointer: NP → DT NN ,4

time	flies	like	an	arrow
NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	S [0,5]
	VP NNS [1,2]	[1,3]	[1,4]	VP [1,5]
		IN VBP [2,3]	[2,4]	PP VP [2,5]
			DT [3,4]	NP [3,5]
				NN [4,5]



Backpointer: DT → an

time	flies	like	an	arrow
NP NN [0,1]	S NP [0,2]	[0,3]	[0,4]	S [0,5]
	VP NNS [1,2]	[1,3]	[1,4]	VP [1,5]
		IN VBP [2,3]	[2,4]	PP VP [2,5]
			DT [3,4]	NP [3,5]
				NN [4,5]



Backpointer: NN$\rightarrow$ arrow

Other things to do with CKY

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- Generate entire forest of trees: Keep all backpointers instead of just one

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- Generate entire forest of trees: Keep all backpointers instead of just one
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- Count trees:

$$C(X[i:i+1]) = |X \to w_i|$$

$$C(X[i:j]) = \sum_{k=i+1}^{j-1} \sum_{X \to YZ} C(Y[i:k]) \times C(Z[k:j])$$

Where do grammars come from?

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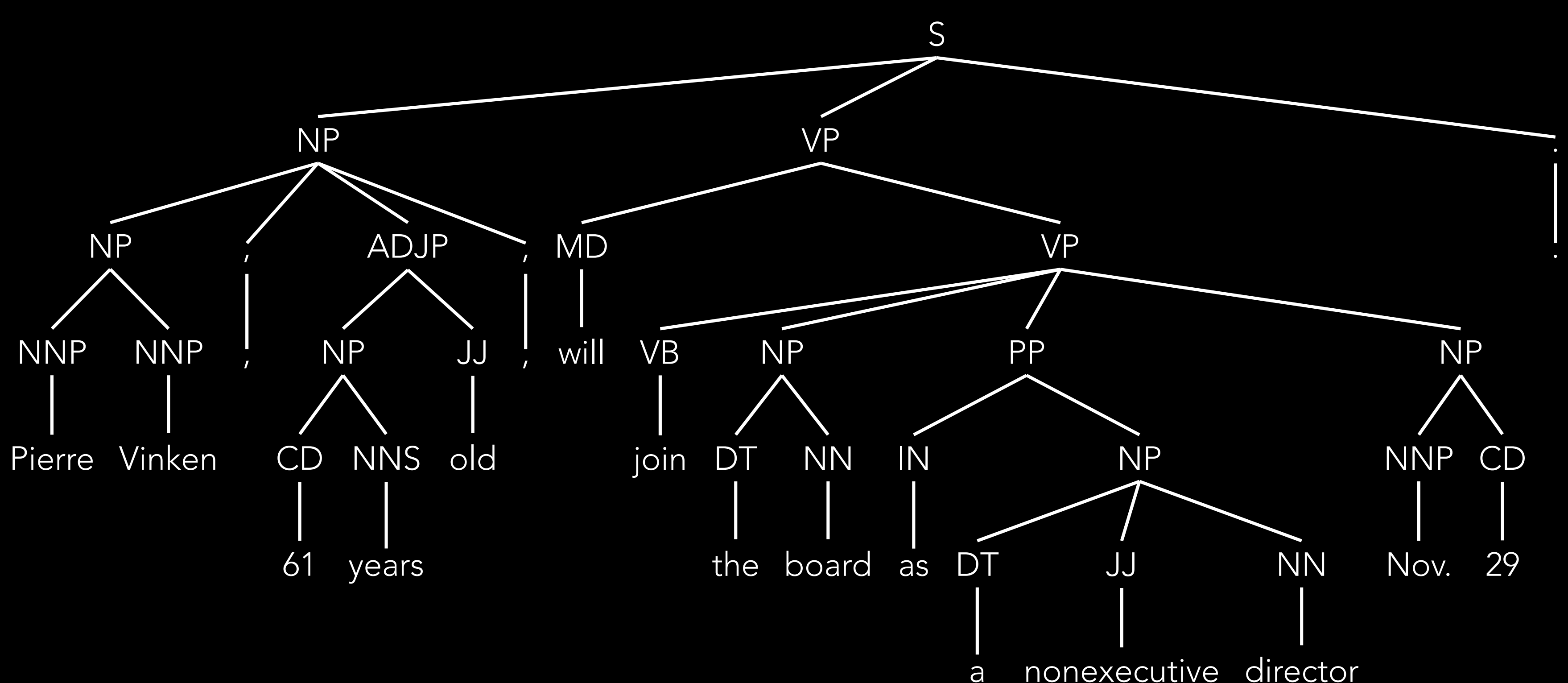

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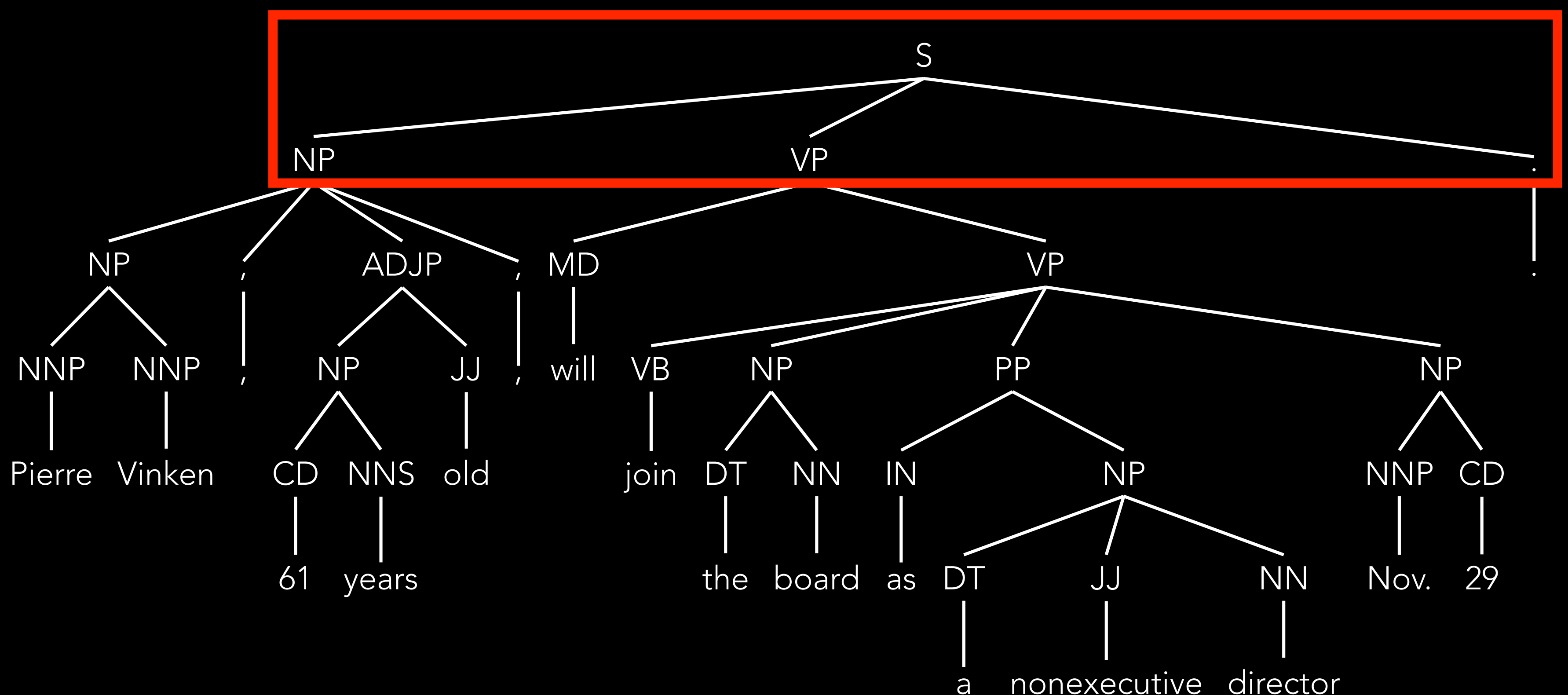

$S \rightarrow NP\ VP\ .$

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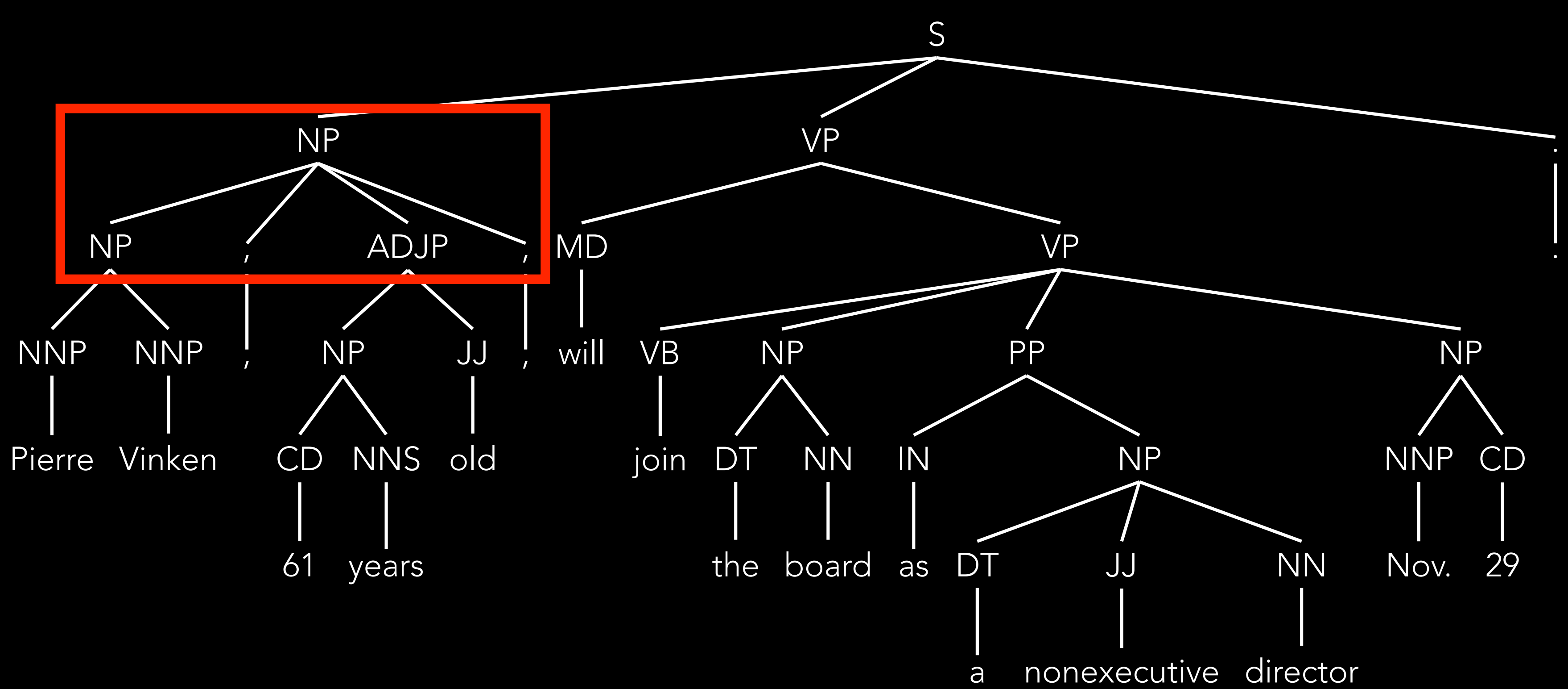

S → NP VP .

NP → NP , ADJP ,

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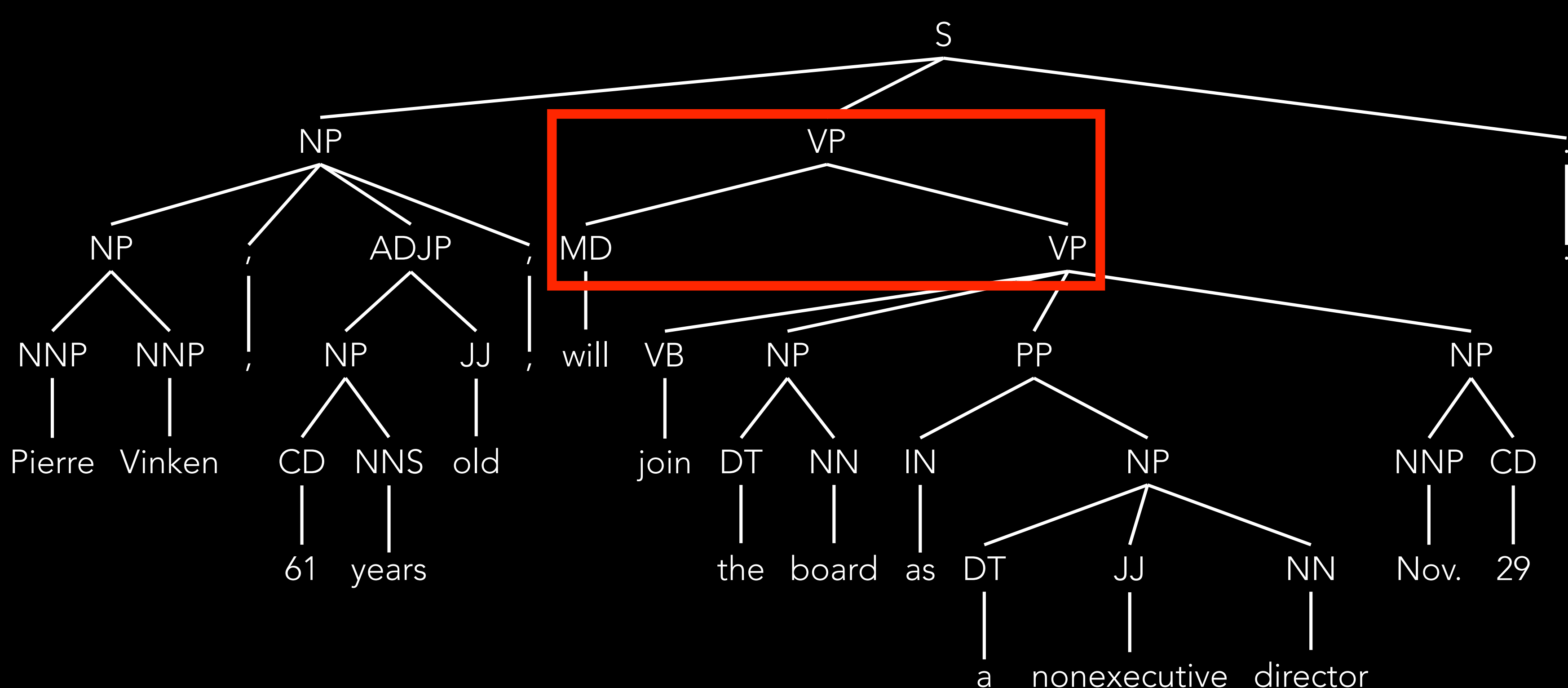

S → NP VP .

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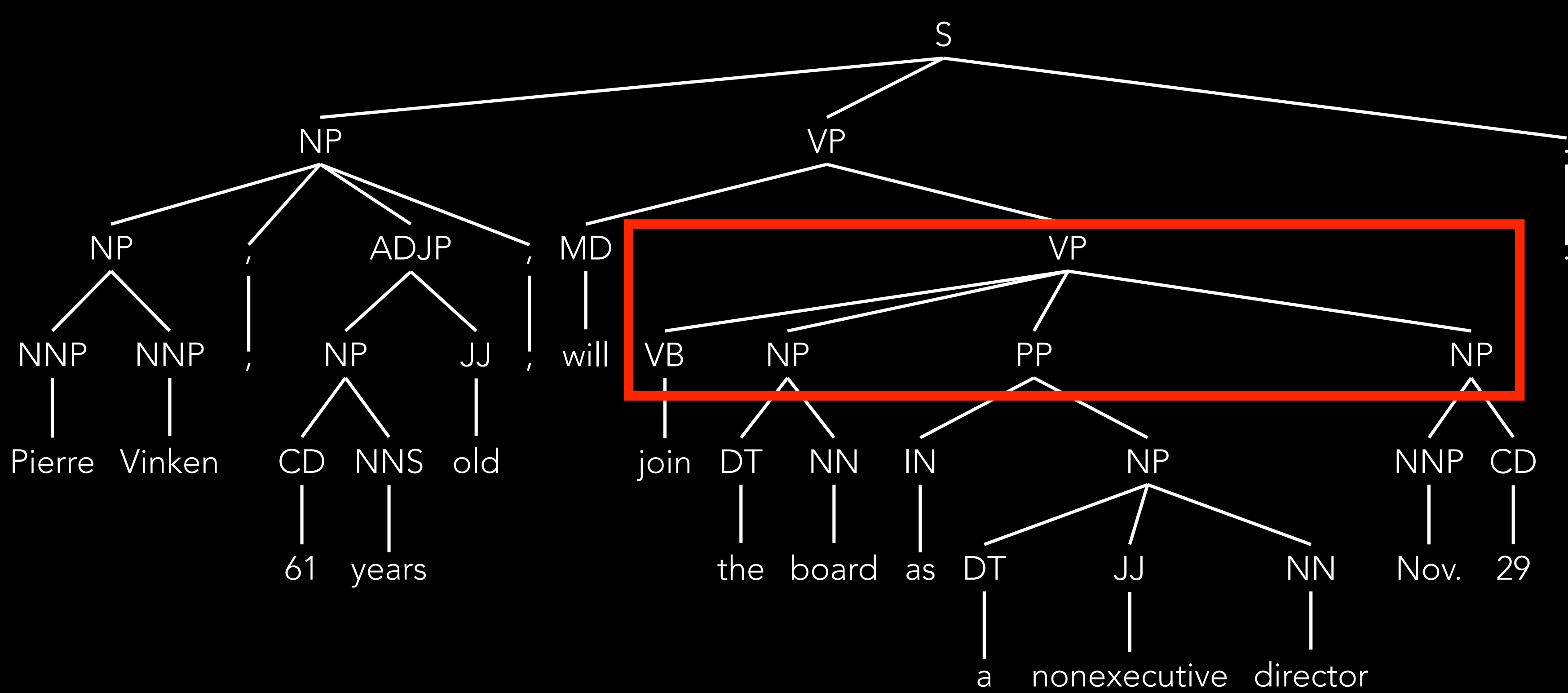

$$S \rightarrow NP\ VP\ .$$

$$NP \rightarrow NP\ ,\ ADJP\ ,$$

$$VP \rightarrow MD\ VP$$

$$VP \rightarrow VB\ NP\ PP\ NP$$

Where do grammars come from?

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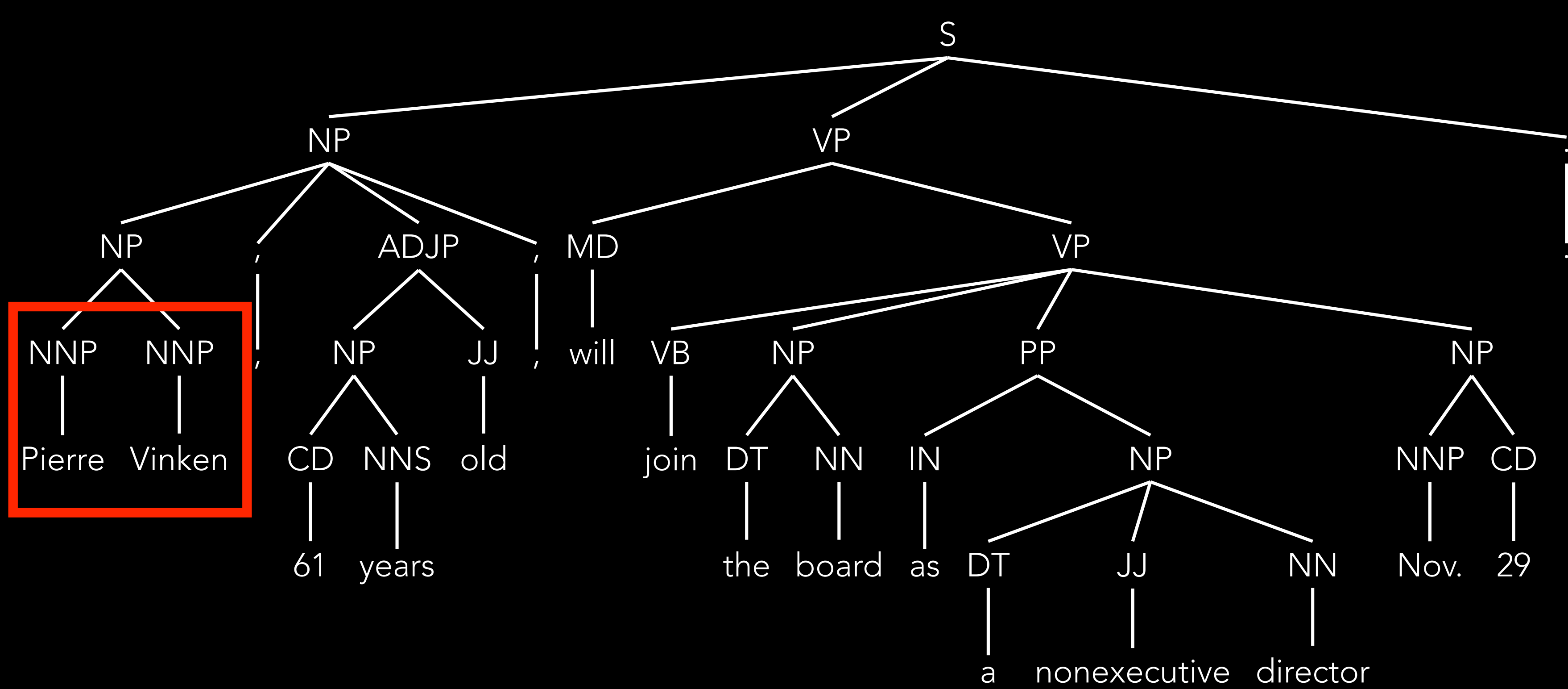

S → NP VP .

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…

NNP → Pierre

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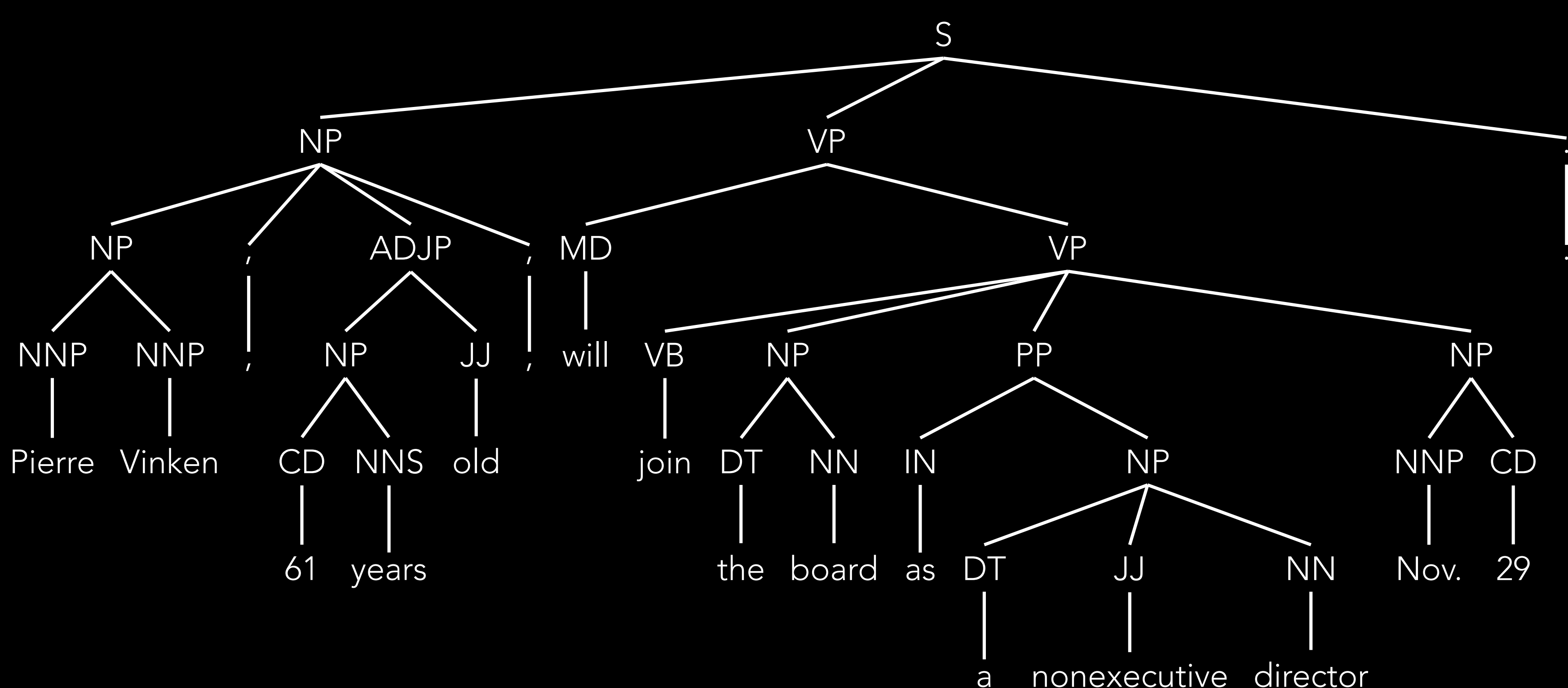

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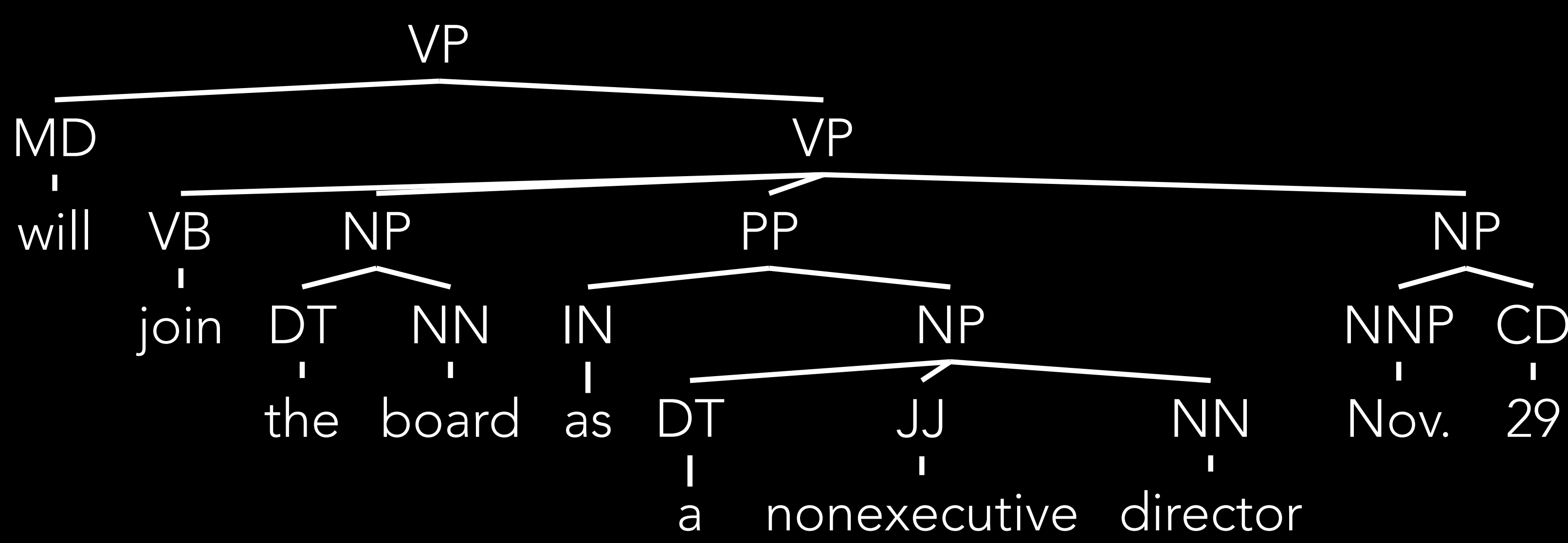
Chomsky Normal Form Violation!

CFG Normalization?

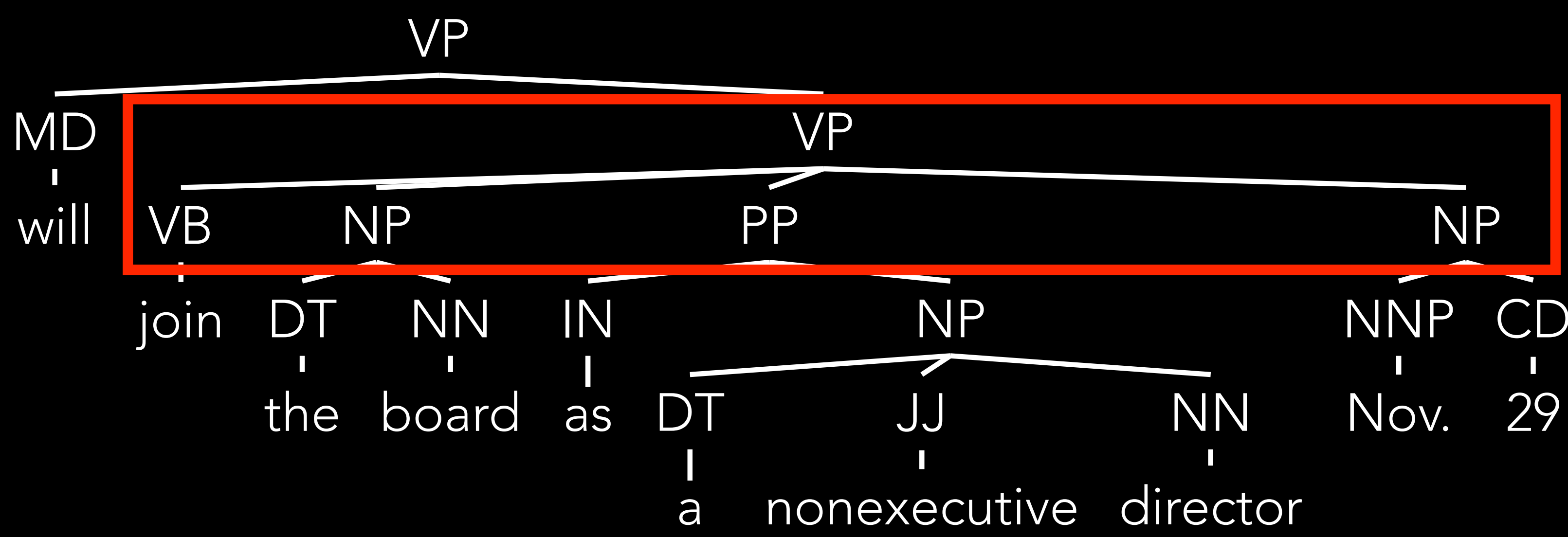
- There are well known approaches to normalizing CFGs into CNF
- However, it’s far simpler to just modify the *trees*

CFG Normalization

CFG Normalization



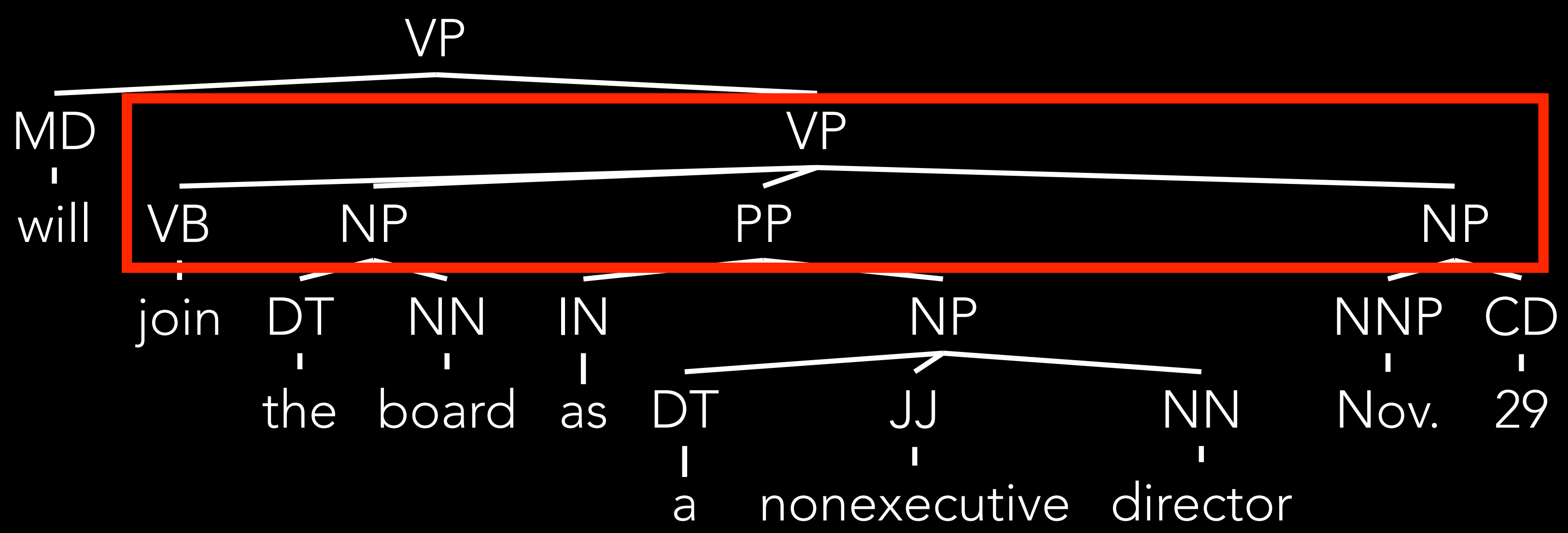
CFG Normalization



VP -> VB NP PP NP

not ok for CKY

CFG Normalization



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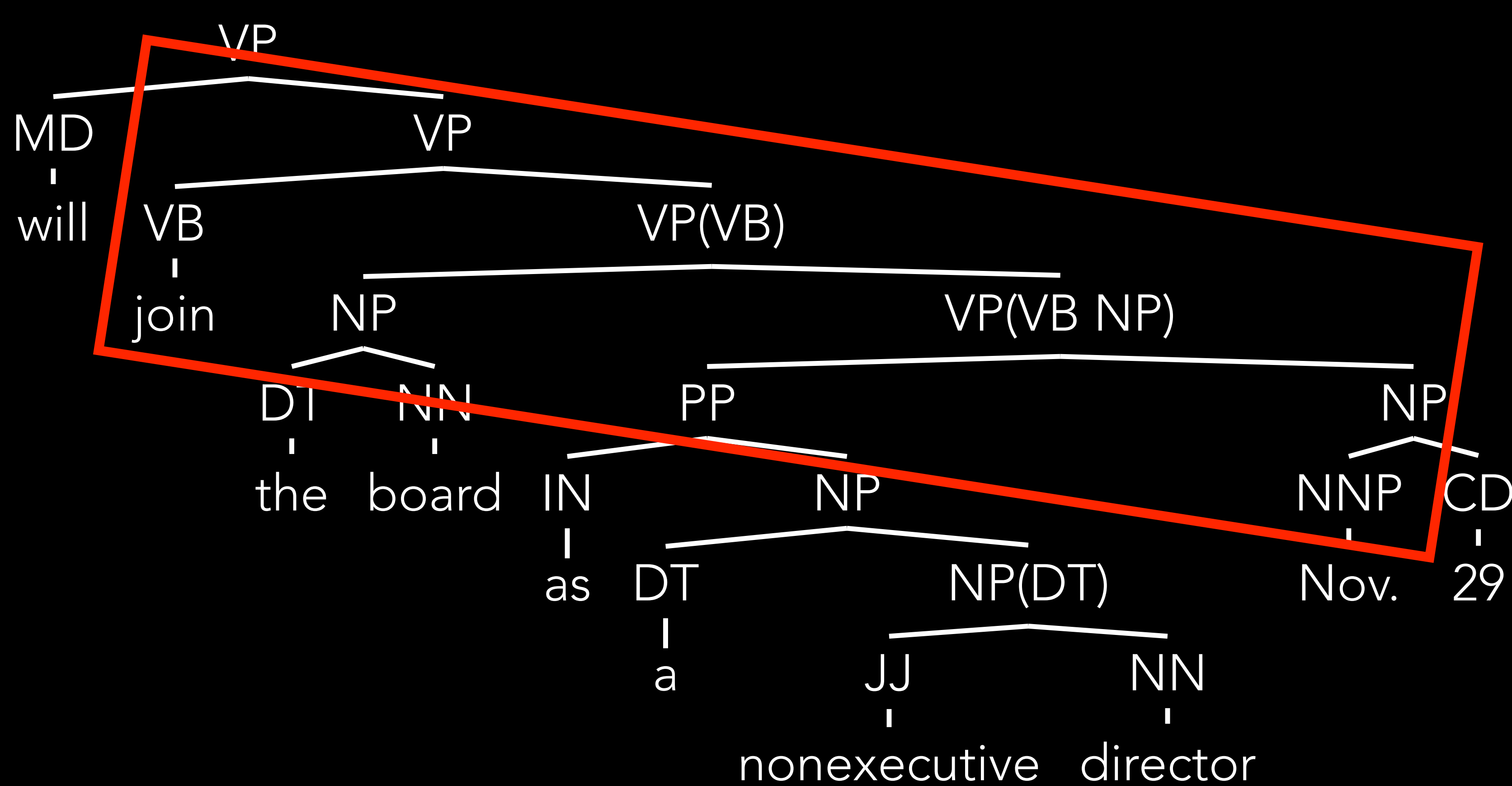
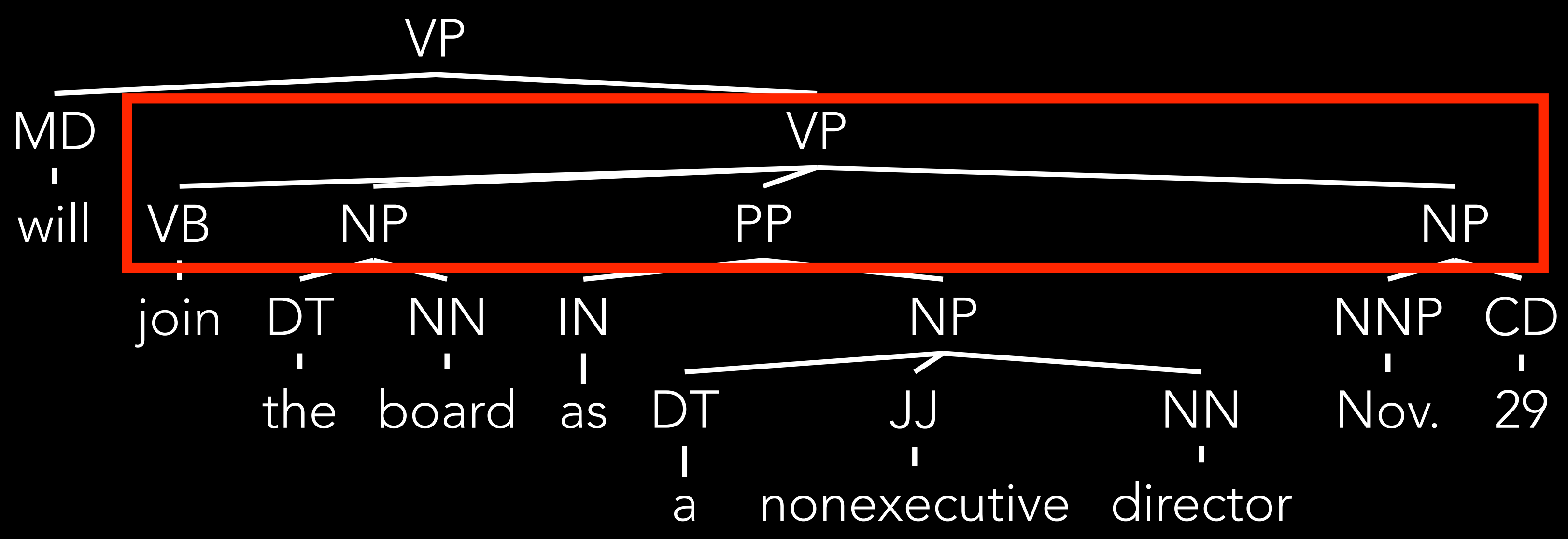


Three binary rules

ok for CKY

CFG Normalization



VP -> VB NP PP NP

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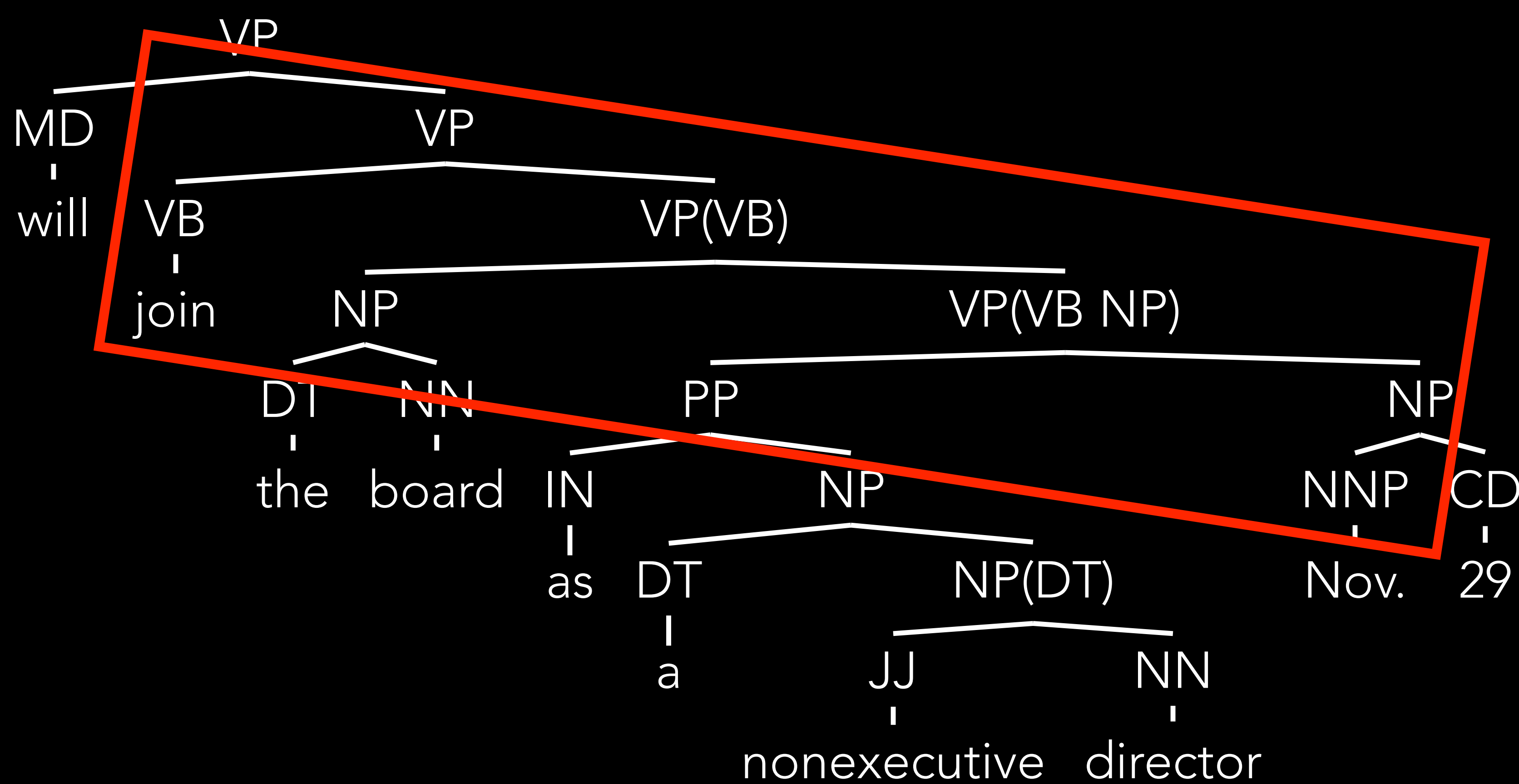

Three binary rules ok for CKY

Why are the labels important?

What about unary trees?

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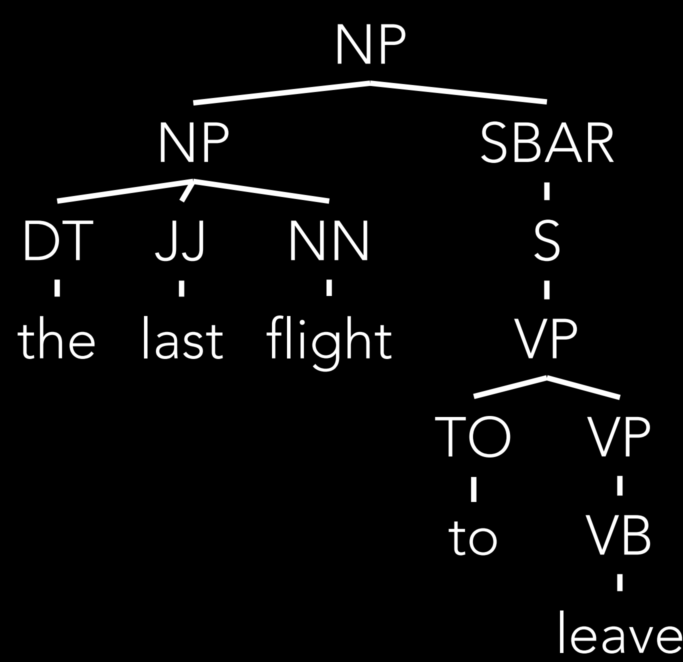
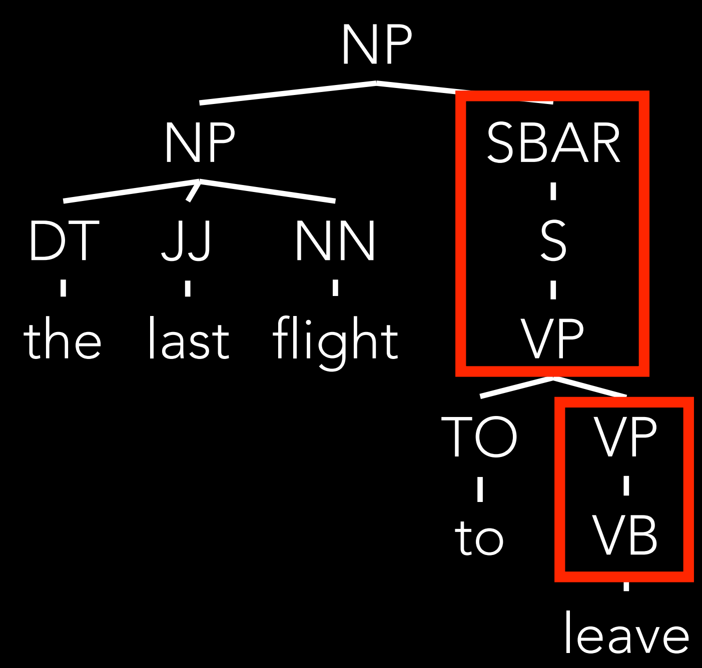
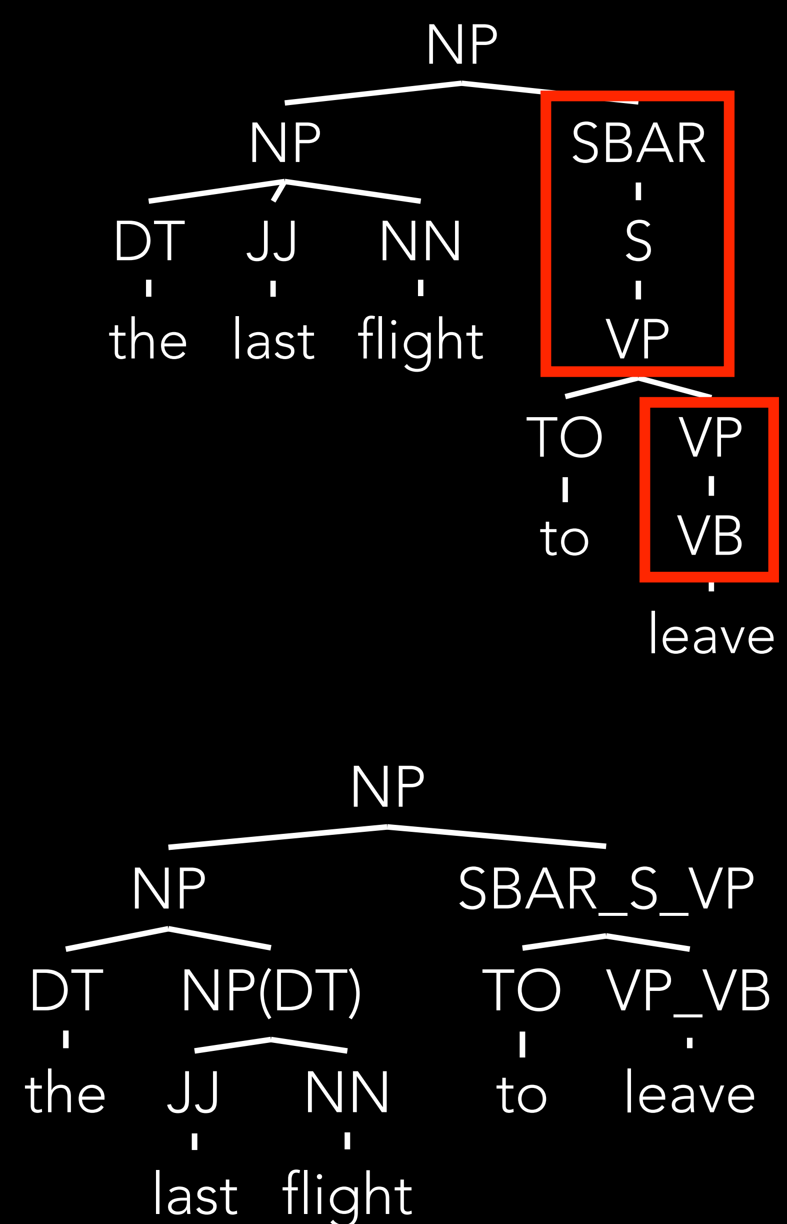


What about unary trees?



SBAR -> S, S->VP,
VP-> VB
not good for CKY

What about unary trees?



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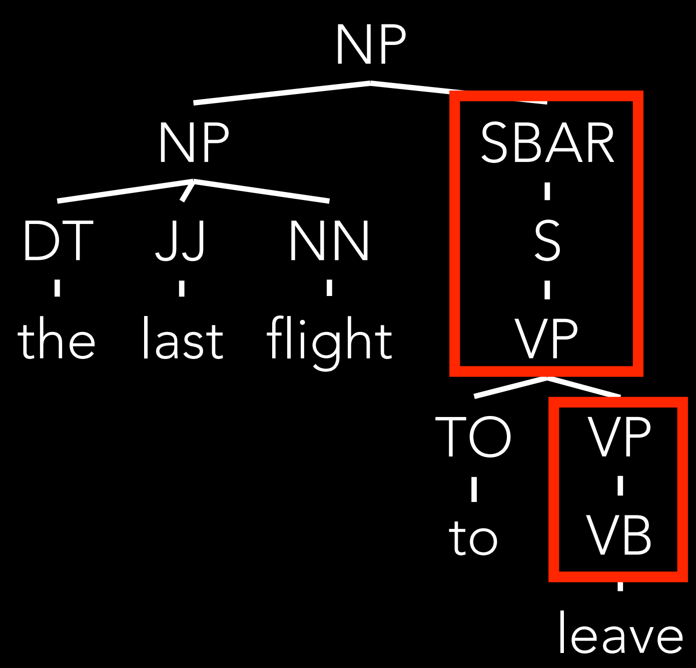

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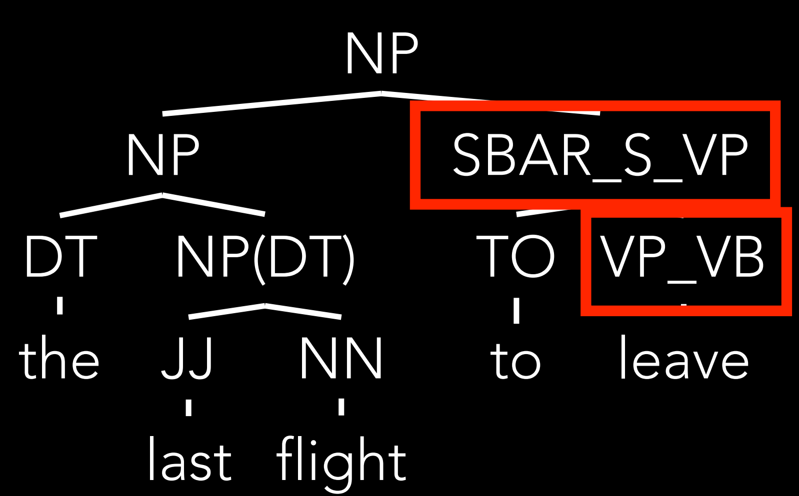

Collapse into single label

Review

Review

- Parsing (generating syntax trees) is a useful task

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- The Treebank is a resource of real-world syntax trees

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Alternate: Modify CKY!

- Initialize: build [X, i, i+1] for every lexical rule R = X -> w_i; add backpointer {R, ()}
- Recursively: build [X, i, j] for every nonlexical rule R = X -> Y Z and pair of states ([Y, i, k], [Z, k, j]) where i < k < j; add backpointer {R, k}
- If state is already built, just add backpointer

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- Initialize: build [X, i, i+1] for every lexical rule R = X -> w_i; add backpointer {R, ()}
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  - build [X, i, j] for every nonlexical rule R = X -> Y Z and pair of states ([Y, i, k], [Z, k, j]) where i < k < j; add backpointer {R, k}
  - build [X, i, j] for every nonlexical rule R = X -> Y and state [Y, i, j] **if [X, i, j] does not exist**; add backpointer {R, ()}
- If state is already built, just add backpointer

time	flies	like	an	arrow
[0,1]	[0,2]	[0,3]	[0,4]	[0,5]
	[1,2]	[1,3]	[1,4]	[1,5]
		[2,3]	[2,4]	[2,5]
			[3,4]	[3,5]
				[4,5]

S → NP VP
NP → DT NN
NP → time | fruit
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

time	flies	like	an	arrow
[0,1]	[0,2]	[0,3]	[0,4]	[0,5]
	[1,2]	[1,3]	[1,4]	[1,5]
		[2,3]	[2,4]	[2,5]
			[3,4]	[3,5]
				[4,5]

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NP → DT NN
NP → NN
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

More realistic!

time	flies	like	an	arrow
[0,1]	[0,2]	[0,3]	[0,4]	[0,5]
	[1,2]	[1,3]	[1,4]	[1,5]
		[2,3]	[2,4]	[2,5]
			[3,4]	[3,5]
				[4,5]

S → NP VP
NP → DT NN
NP → NN
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

PP → NP
VP → PP
NP → VP

Not typical, but for illustration.

	time	flies	like	an	arrow
	NN [0,1]	[0,2]	[0,3]	[0,4]	[0,5]
		VP NNS [1,2]	[1,3]	[1,4]	[1,5]
			IN VBP [2,3]	[2,4]	[2,5]
				DT [3,4]	[3,5]
					NN [4,5]

S → NP VP
NP → DT NN
NP → NN
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

PP → NP
VP → PP
NP → VP

After seeding the chart.
We need to check length-1 spans
for nonlexical rules

time	flies	like	an	arrow
NP NN [0,1]	[0,2]	[0,3]	[0,4]	[0,5]
	VP NNS [1,2]	[1,3]	[1,4]	[1,5]
		IN VBP [2,3]	[2,4]	[2,5]
			DT [3,4]	[3,5]
				NN [4,5]

S → NP VP
NP → DT NN
NP → NN
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

PP → NP
VP → PP
NP → VP

New state!

time	flies	like	an	arrow
NP PP NN [0,1]	[0,2]	[0,3]	[0,4]	[0,5]
	VP NNS [1,2]	[1,3]	[1,4]	[1,5]
		IN VBP [2,3]	[2,4]	[2,5]
			DT [3,4]	[3,5]
				NN [4,5]

S → NP VP
NP → DT NN
NP → NN
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

PP → NP
VP → PP
NP → VP

New state!

	time	flies	like	an	arrow
	NP PP NN VP [0,1]	[0,2]	[0,3]	[0,4]	[0,5]
		VP NNS [1,2]	[1,3]	[1,4]	[1,5]
			IN VBP [2,3]	[2,4]	[2,5]
				DT [3,4]	[3,5]
					NN [4,5]

S → NP VP
NP → DT NN
NP → NN
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

PP → NP
VP → PP
NP → VP

New state!

time	flies	like	an	arrow
NP PP NN VP [0,1]	[0,2]	[0,3]	[0,4]	[0,5]
	VP NNS [1,2]	[1,3]	[1,4]	[1,5]
		IN VBP [2,3]	[2,4]	[2,5]
			DT [3,4]	[3,5]
				NN [4,5]

S → NP VP
NP → DT NN
NP → NN
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

PP → NP
VP → PP
NP → VP

No new state, and no backpointer
(would lead to infinite loop)

	time	flies	like	an	arrow
	NP PP NN VP [0,1]	[0,2]	[0,3]	[0,4]	[0,5]
		PP VP NP NNS [1,2]	[1,3]	[1,4]	[1,5]
			IN VBP [2,3]	[2,4]	[2,5]
				DT [3,4]	[3,5]
					NN [4,5]

S → NP VP
NP → DT NN
NP → NN
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

$\boxed{\text{PP → NP}}$
VP → PP
$\boxed{\text{NP → VP}}$

Two new states!

time	flies	like	an	arrow
NP PP NN VP [0,1]	[0,2]	[0,3]	[0,4]	[0,5]
	PP VP NP NNS [1,2]	[1,3]	[1,4]	[1,5]
		IN VBP [2,3]	[2,4]	[2,5]
			DT [3,4]	[3,5]
				NP PP NN VP [4,5]

S → NP VP
NP → DT NN
NP → NN
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

PP → NP
VP → PP
NP → VP

Three new states!

time	flies	like	an	arrow
NP PP NN VP [0,1]	S NP [0,2]	[0,3]	[0,4]	[0,5]
	PP VP NP NNS [1,2]	[1,3]	[1,4]	[1,5]
		IN VBP [2,3]	[2,4]	[2,5]
			DT [3,4]	[3,5]
				NP PP NN VP [4,5]

S → NP VP
NP → DT NN
NP → NN
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

PP → NP
VP → PP
NP → VP

This is what we had before…

time	flies	like	an	arrow
NP PP NN VP [0,1]	S NP VP [0,2]	[0,3]	[0,4]	[0,5]
	PP VP NP NNS [1,2]	[1,3]	[1,4]	[1,5]
		IN VBP [2,3]	[2,4]	[2,5]
			DT [3,4]	[3,5]
				NP PP NN VP [4,5]

S → NP VP
NP → DT NN
NP → NN
NP → NN NNS
VP → VBP NP
VP → flies
$\boxed{\text{VP → VP PP}}$
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

PP → NP
VP → PP
NP → VP

…but now we can add one more
with a binary rule

time	flies	like	an	arrow
NP PP NN VP [0,1]	S NP VP PP [0,2]	[0,3]	[0,4]	[0,5]
	PP VP NP NNS [1,2]	[1,3]	[1,4]	[1,5]
		IN VBP [2,3]	[2,4]	[2,5]
			DT [3,4]	[3,5]
				NP PP NN VP [4,5]

S → NP VP

NP → DT NN

NP → NN

NP → NN NNS

VP → VBP NP

VP → flies

VP → VP PP

PP → IN NP

DT → a | an

NN → time | fruit | arrow | banana

NNS → flies

VBP → like

IN → like

$\boxed{\text{PP → NP}}$

VP → PP

NP → VP

…and can take a unary step

	time	flies	like	an	arrow
	NP PP NN VP [0,1]	S NP VP PP [0,2]	[0,3]	[0,4]	[0,5]
		PP VP NP NNS [1,2]	[1,3]	[1,4]	[1,5]
			IN VBP [2,3]	[2,4]	[2,5]
				DT [3,4]	NP [3,5]
					NP PP NN VP [4,5]

$S \rightarrow NP\ VP$

$\boxed{NP \rightarrow DT\ NN}$

$NP \rightarrow NN$

$NP \rightarrow NN\ NNS$

$VP \rightarrow VBP\ NP$

$VP \rightarrow$ flies

$VP \rightarrow VP\ PP$

$PP \rightarrow IN\ NP$

$DT \rightarrow$ a | an

$NN \rightarrow$ time | fruit | arrow | banana

$NNS \rightarrow$ flies

$VBP \rightarrow$ like

$IN \rightarrow$ like

$PP \rightarrow NP$

$VP \rightarrow PP$

$NP \rightarrow VP$

This is what we had before

	time	flies	like	an	arrow
	NP PP NN VP [0,1]	S NP VP PP [0,2]	[0,3]	[0,4]	[0,5]
		PP VP NP NNS [1,2]	[1,3]	[1,4]	[1,5]
			IN VBP [2,3]	[2,4]	[2,5]
				DT [3,4]	NP PP VP [3,5]
					NP PP NN VP [4,5]

S → NP VP
NP → DT NN
NP → NN
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

PP → NP
VP → PP
NP → VP

Now we have two more

time	flies	like	an	arrow
NP PP NN VP [0,1]	S NP VP PP [0,2]	[0,3]	[0,4]	[0,5]
	PP VP NP NNS [1,2]	[1,3]	[1,4]	[1,5]
		IN VBP [2,3]	[2,4]	PP VP [2,5]
			DT [3,4]	NP PP VP [3,5]
				NP PP NN VP [4,5]

S → NP VP
NP → DT NN
NP → NN
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

PP → NP
VP → PP
NP → VP

This is what we had before

	time	flies	like	an	arrow
	NP PP NN VP [0,1]	S NP VP PP [0,2]	[0,3]	[0,4]	[0,5]
		PP VP NP NNS [1,2]	[1,3]	[1,4]	[1,5]
			IN VBP [2,3]	[2,4]	PP VP NP [2,5]
				DT [3,4]	NP PP VP [3,5]
					NP PP NN VP [4,5]

S → NP VP
NP → DT NN
NP → NN
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

PP → NP
VP → PP
NP → VP

Can add one from unary step

time	flies	like	an	arrow
NP PP NN VP [0,1]	S NP VP PP [0,2]	[0,3]	[0,4]	[0,5]
	PP VP NP NNS [1,2]	[1,3]	[1,4]	VP [1,5]
		IN VBP [2,3]	[2,4]	PP NP VP [2,5]
			DT [3,4]	NP PP VP [3,5]
				NP PP NN VP [4,5]

S → NP VP
NP → DT NN
NP → NN
NP → NN NNS
VP → VBP NP
VP → flies
$\boxed{\text{VP → VP PP}}$
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

PP → NP
VP → PP
NP → VP

This is what we had before

time	flies	like	an	arrow
NP PP NN VP [0,1]	S NP VP PP [0,2]	[0,3]	[0,4]	[0,5]
	PP VP NP NNS [1,2]	[1,3]	[1,4]	VP S [1,5]
		IN VBP [2,3]	[2,4]	PP NP VP [2,5]
			DT [3,4]	NP PP VP [3,5]
				NP PP NN VP [4,5]

$\boxed{S \rightarrow NP\ VP}$

NP → DT NN

NP → NN

NP → NN NNS

VP → VBP NP

VP → flies

VP → VP PP

PP → IN NP

DT → a | an

NN → time | fruit | arrow | banana

NNS → flies

VBP → like

IN → like

PP → NP

VP → PP

NP → VP

We can add one more non-unary now

time	flies	like	an	arrow
NP PP NN VP [0,1]	S NP VP PP [0,2]	[0,3]	[0,4]	[0,5]
	PP VP NP NNS [1,2]	[1,3]	[1,4]	VP S PP NP [1,5]
		IN VBP [2,3]	[2,4]	PP NP VP [2,5]
			DT [3,4]	NP PP VP [3,5]
				NP PP NN VP [4,5]

S → NP VP
NP → DT NN
NP → NN
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

PP → NP
VP → PP
NP → VP

And two more with unary steps.

time	flies	like	an	arrow
NP PP NN VP [0,1]	S NP VP PP [0,2]	[0,3]	[0,4]	S [0,5]
	PP VP NP NNS [1,2]	[1,3]	[1,4]	VP S PP NP [1,5]
		IN VBP [2,3]	[2,4]	PP NP VP [2,5]
			DT [3,4]	NP PP VP [3,5]
				NP PP NN VP [4,5]

$\boxed{S \rightarrow NP\ VP}$

$NP \rightarrow DT\ NN$

$NP \rightarrow NN$

$NP \rightarrow NN\ NNS$

$VP \rightarrow VBP\ NP$

$VP \rightarrow$ flies

$VP \rightarrow VP\ PP$

$PP \rightarrow IN\ NP$

$DT \rightarrow$ a | an

$NN \rightarrow$ time | fruit | arrow | banana

$NNS \rightarrow$ flies

$VBP \rightarrow$ like

$IN \rightarrow$ like

$PP \rightarrow NP$

$VP \rightarrow PP$

$NP \rightarrow VP$

We built S this way before

time	flies	like	an	arrow
NP PP NN VP [0,1]	S NP VP PP [0,2]	[0,3]	[0,4]	S VP [0,5]
	PP VP NP NNS [1,2]	[1,3]	[1,4]	VP S PP NP [1,5]
		IN VBP [2,3]	[2,4]	PP NP VP [2,5]
			DT [3,4]	NP PP VP [3,5]
				NP PP NN VP [4,5]

S → NP VP
NP → DT NN
NP → NN
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

PP → NP
VP → PP
NP → VP

We can also build a VP at this split point.

time	flies	like	an	arrow
NP PP NN VP [0,1]	S NP VP PP [0,2]	[0,3]	[0,4]	S VP [0,5]
	PP VP NP NNS [1,2]	[1,3]	[1,4]	VP S PP NP [1,5]
		IN VBP [2,3]	[2,4]	PP NP VP [2,5]
			DT [3,4]	NP PP VP [3,5]
				NP PP NN VP [4,5]

S → NP VP

NP → DT NN

NP → NN

NP → NN NNS

VP → VBP NP

VP → flies

VP → VP PP

PP → IN NP

DT → a | an

NN → time | fruit | arrow | banana

NNS → flies

VBP → like

IN → like

PP → NP

VP → PP

NP → VP

Before, we built a second backpointer to S

time	flies	like	an	arrow
NP PP NN VP [0,1]	S NP VP PP [0,2]	[0,3]	[0,4]	S VP [0,5]
	PP VP NP NNS [1,2]	[1,3]	[1,4]	VP S PP NP [1,5]
		IN VBP [2,3]	[2,4]	PP NP VP [2,5]
			DT [3,4]	NP PP VP [3,5]
				NP PP NN VP [4,5]

S → NP VP
NP → DT NN
NP → NN
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

PP → NP
VP → PP
NP → VP

Now we have a second backpointer to VP, too

time	flies	like	an	arrow
NP PP NN VP [0,1]	S NP VP PP [0,2]	[0,3]	[0,4]	S VP NP PP [0,5]
	PP VP NP NNS [1,2]	[1,3]	[1,4]	VP S PP NP [1,5]
		IN VBP [2,3]	[2,4]	PP NP VP [2,5]
			DT [3,4]	NP PP VP [3,5]
				NP PP NN VP [4,5]

S → NP VP
NP → DT NN
NP → NN
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

$\boxed{\text{PP → NP}}$
VP → PP
$\boxed{\text{NP → VP}}$

Finally, we have new states from unary steps.

time	flies	like	an	arrow
NP PP NN VP [0,1]	S NP VP PP [0,2]	[0,3]	[0,4]	S VP NP PP [0,5]
	PP VP NP NNS [1,2]	[1,3]	[1,4]	VP S PP NP [1,5]
		IN VBP [2,3]	[2,4]	PP NP VP [2,5]
			DT [3,4]	NP PP VP [3,5]
				NP PP NN VP [4,5]

S → NP VP
NP → DT NN
NP → NN
NP → NN NNS
VP → VBP NP
VP → flies
VP → VP PP
PP → IN NP
DT → a | an
NN → time | fruit | arrow | banana
NNS → flies
VBP → like
IN → like

PP → NP
VP → PP
NP → VP

Do we have any new trees?
Actually, no,
because S is the only start symbol.

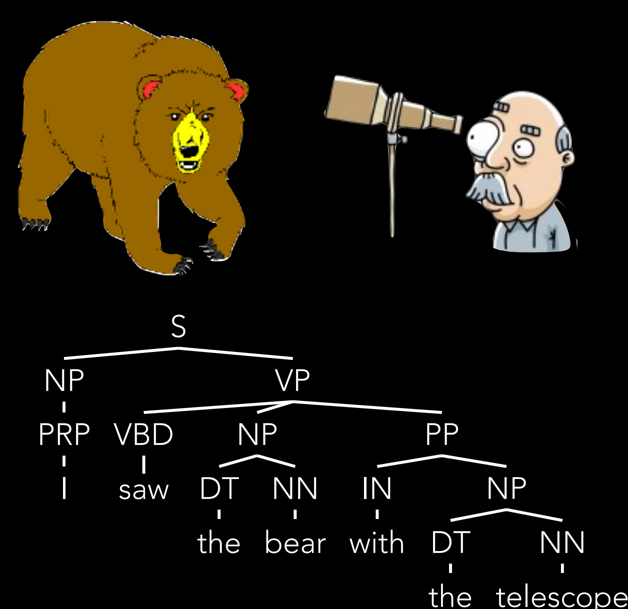
But Which Parse Is Best?

But Which Parse Is Best?

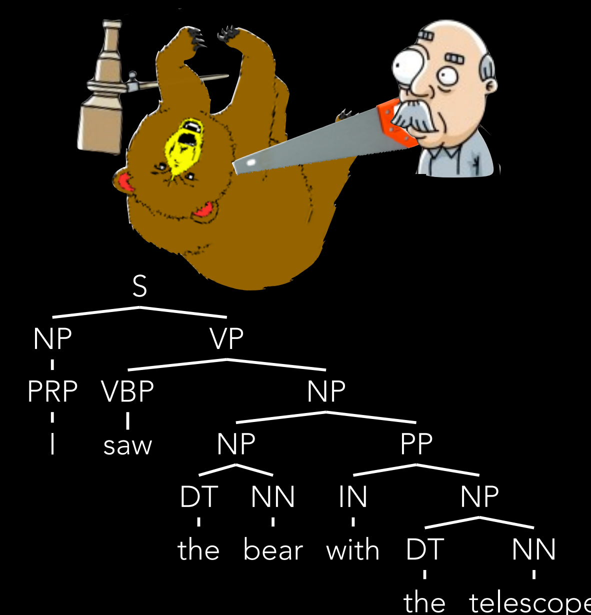
- How does our parser make decisions about which tree to produce?

But Which Parse Is Best?

- How does our parser make decisions about which tree to produce?

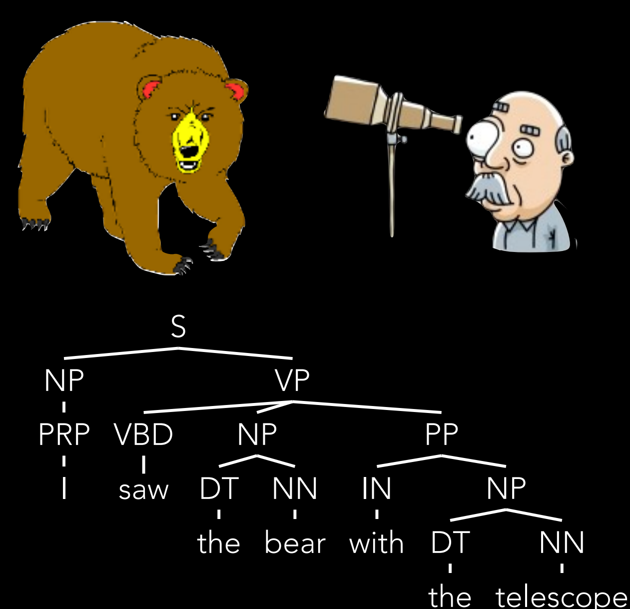


VS

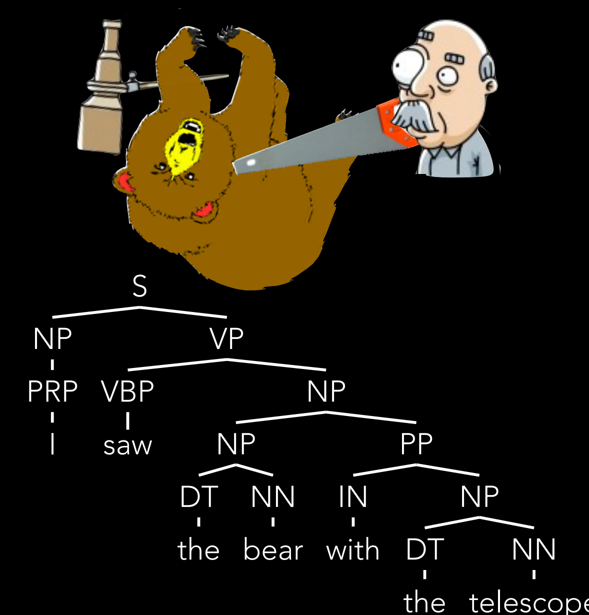


But Which Parse Is Best?

- How does our parser make decisions about which tree to produce?



VS



- We need a probabilistic CFG and a probability model of trees

Probabilistic Context-Free Grammars

S NP
VP NNS
PP
VB
DT
…

Nonterminals
(start)

cats I
mice the
telescope
… eat

Terminals

S → NP VP
VP → VB NP
NP → NNS
NP → DT NNS
NNS → cats
NNS → mice
VB → eat

Rules

Probabilistic Context-Free Grammars

S NP
VP NNS
PP
VB
DT
…

Nonterminals
(start)

cats I
mice the
telescope
eat
…

Terminals

$S \rightarrow NP\ VP$		1.0
$VP \rightarrow VB\ NP$		1.0
$NP \rightarrow NNS$		0.2
$NP \rightarrow DT\ NNS$		0.8
$NNS \rightarrow$ cats		0.6
$NNS \rightarrow$ mice		0.4
$VB \rightarrow$ eat		1.0

Rules

Probabilistic Context-Free Grammars

S NP
VP NNS
PP
DT VB
…

Nonterminals (start)

cats I
mice the
telescope
… eat

Terminals

S → NP VP	1.0
VP → VB NP	1.0
NP → NNS	0.2
NP → DT NNS	0.8
NNS → cats	0.6
NNS → mice	0.4
VB → eat	1.0

Rules

Each rule has a weight w, 0 < w <= 1

Probabilistic Context-Free Grammars

Nonterminals (start)	Terminals	Rules	
S, NP, VP, NNS, PP, VB, DT, …	cats, I, mice, the, telescope, eat, …	$S \rightarrow NP\ VP$	1.0
		$VP \rightarrow VB\ NP$	1.0
		$NP \rightarrow NNS$	0.2
		$NP \rightarrow DT\ NNS$	0.8
		$NNS \rightarrow$ cats	0.6
		$NNS \rightarrow$ mice	0.4
		$VB \rightarrow$ eat	1.0

Each rule has a weight w, 0 < w <= 1

Weights of all rules with the same LHS sum to 1

Probabilistic Context-Free Grammars

S NP
VP NNS
PP
VB
… DT

Nonterminals
(start)

cats I
mice the
telescope
… eat

Terminals

S →	NP VP	1.0
VP →	VB NP	1.0
NP →	NNS	0.2
NP →	DT NNS	0.8
NNS →	cats	0.6
NNS →	mice	0.4
VB →	eat	1.0

Rules

Each rule has a weight w, $0 < w <= 1$

Weights of all rules with the same LHS sum to 1

Probability of tree is product of
probability of rules in its derivation

Probabilistic Context-Free Grammars

S NP
VP NNS
PP
VB
DT
…

Nonterminals
(start)

cats I
mice the
telescope
eat
…

Terminals

S →	NP VP	1.0
VP →	VB NP	1.0
NP →	NNS	0.2
NP →	DT NNS	0.8
NNS →	cats	0.6
NNS →	mice	0.4
VB →	eat	1.0

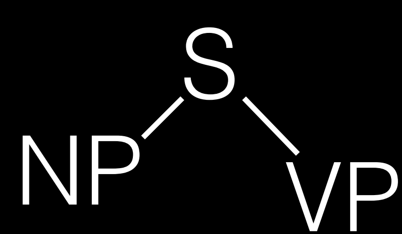
Rules

S

1.0

Probabilistic Context-Free Grammars

Nonterminals (start)	Terminals	Rules
S, NP, VP, NNS, PP, VB, DT, …	cats, I, mice, the, telescope, eat, …	S → NP VP 1.0 VP → VB NP 1.0 NP → NNS 0.2 NP → DT NNS 0.8 NNS → cats 0.6 NNS → mice 0.4 VB → eat 1.0



1.0

Probabilistic Context-Free Grammars

S NP
VP NNS
PP
VB
… DT

Nonterminals
(start)

cats I
mice the
telescope
… eat

Terminals

S → NP VP	1.0
VP → VB NP	1.0
NP → NNS	0.2
NP → DT NNS	0.8
NNS → cats	0.6
NNS → mice	0.4
VB → eat	1.0

Rules

S
NP VP
NNS

0.2

Probabilistic Context-Free Grammars

S NP VP NNS PP VB DT …

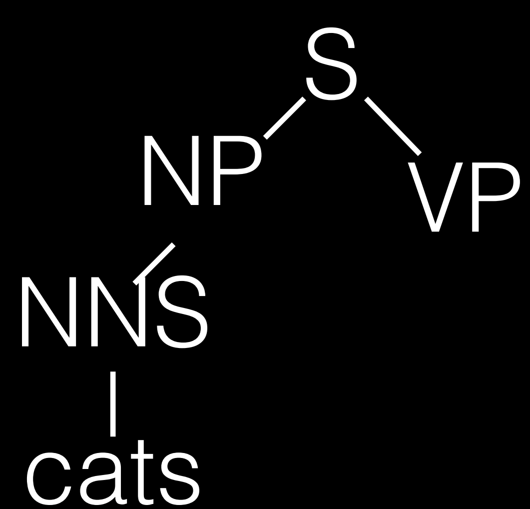
Nonterminals (start)

cats I mice the telescope eat …

Terminals

S → NP VP		1.0
VP → VB NP		1.0
NP → NNS		0.2
NP → DT NNS		0.8
NNS → cats		0.6
NNS → mice		0.4
VB → eat		1.0

Rules



0.12

Probabilistic Context-Free Grammars

S NP
VP NNS
PP
VB
… DT

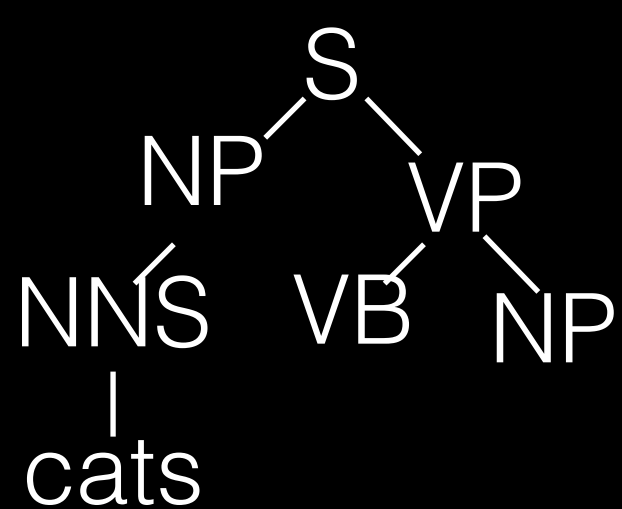
Nonterminals
(start)

cats I
mice the
telescope
… eat

Terminals

S	→ NP VP	1.0
VP	→ VB NP	1.0
NP	→ NNS	0.2
NP	→ DT NNS	0.8
NNS	→ cats	0.6
NNS	→ mice	0.4
VB	→ eat	1.0

Rules



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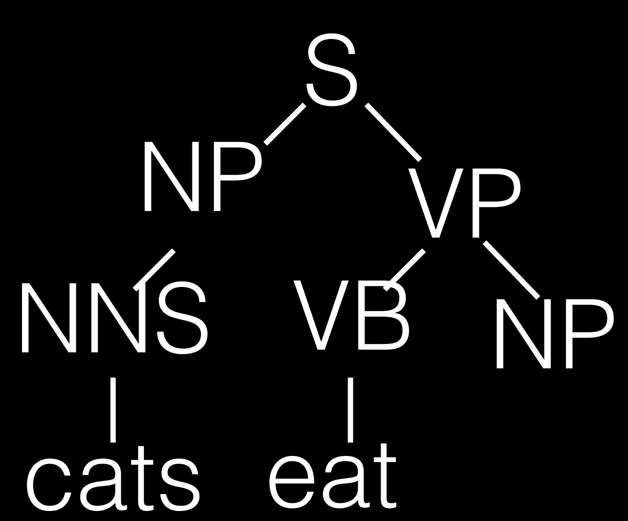

0.12

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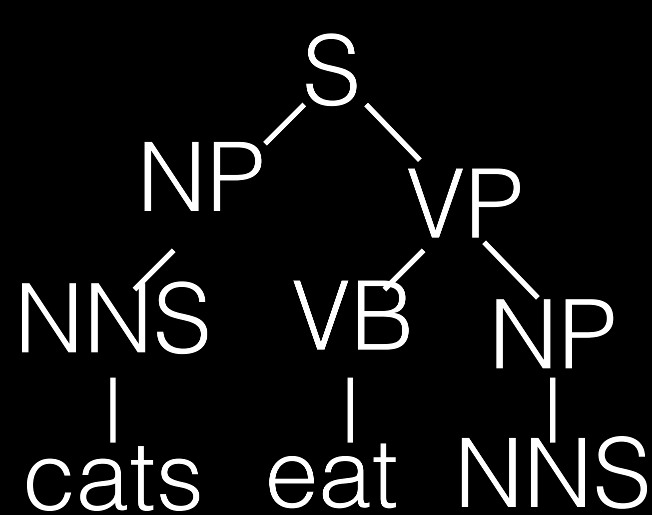


0.024

Probabilistic Context-Free Grammars

S NP VP NNS PP VB DT …

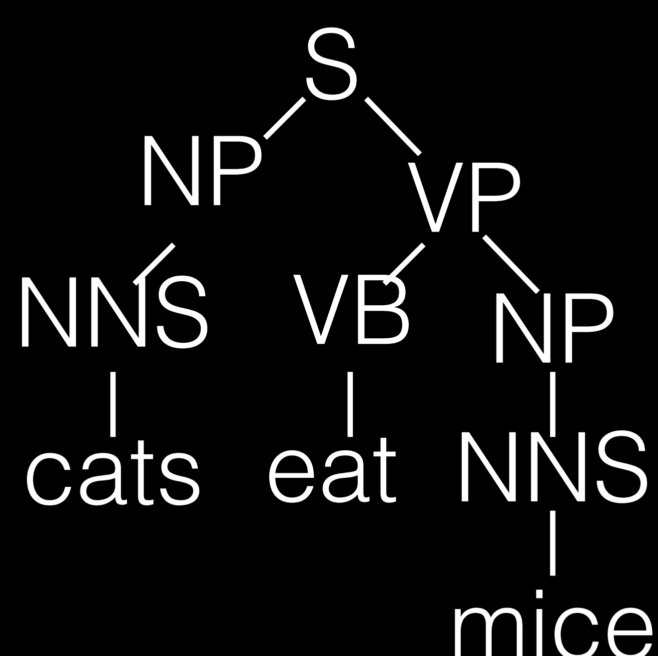
Nonterminals (start)

cats I mice the telescope eat …

Terminals

S → NP VP		1.0
VP → VB NP		1.0
NP → NNS		0.2
NP → DT NNS		0.8
NNS → cats		0.6
NNS → mice		0.4
VB → eat		1.0

Rules



0.0096

Viterbi (one-best) CKY for PCFG

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- Before:
  - we built states [X, i, j] denoting coverage of span from i to j with symbol X
  - we stored all {X->YZ, k} backpointer

Viterbi (one-best) CKY for PCFG

- Before:
    - we built states [X, i, j] denoting coverage of span from i to j with symbol X
    - we stored all {X->YZ, k} backpointer
- New:
    - when deriving via {R, k}, set best([X, i, j]) = p(R) * best([Y, i, k]) * best([Z, k, j]) if this is greater than current value for best([X, i, j])
    - only keep backpointer if best is updated
    - chart contains only the best derivation at end of algorithm

time	flies	like	an	arrow
[0,1]	[0,2]	[0,3]	[0,4]	[0,5]
	[1,2]	[1,3]	[1,4]	[1,5]
		[2,3]	[2,4]	[2,5]
			[3,4]	[3,5]
				[4,5]

$S \rightarrow NP\ VP$ 1.0

$NP \rightarrow DT\ NN$ 0.3

$NP \rightarrow time$ 0.05 $|$ $fruit$ 0.05

$NP \rightarrow NN\ NNS$ 0.6

$VP \rightarrow VBP\ NP$ 0.7

$VP \rightarrow flies$ 0.1

$VP \rightarrow VP\ PP$ 0.2

$PP \rightarrow IN\ NP$ 1.0

$DT \rightarrow a$ 0.5 $|$ an 0.5

$NN \rightarrow time$ 0.25 $|$ $fruit$ 0.25 $|$ $arrow$ 0.25 $|$ $banana$ 0.25

$NNS \rightarrow flies$ 1.0

$VBP \rightarrow like$ 1.0

$IN \rightarrow like$ 1.0

time	flies	like	an	arrow
NP 0.05 NN 0.25 [0,1]	[0,2]	[0,3]	[0,4]	[0,5]
	[1,2]	[1,3]	[1,4]	[1,5]
		[2,3]	[2,4]	[2,5]
			[3,4]	[3,5]
				[4,5]

S → NP VP 1.0
NP → DT NN 0.3
NP → $\boxed{\text{time}^{0.05}}$ | fruit 0.05
NP → NN NNS 0.6
VP → VBP NP 0.7
VP → flies 0.1
VP → VP PP 0.2
PP → IN NP 1.0
DT → a 0.5 | an 0.5
NN → $\boxed{\text{time}^{0.25}}$ | fruit 0.25 | arrow 0.25 | banana 0.25
NNS → flies 1.0
VBP → like 1.0
IN → like 1.0

best() for bottom of the chart
is simply the rule probability

time	flies	like	an	arrow
NP 0.05 NN 0.25 [0,1]	[0,2]	[0,3]	[0,4]	[0,5]
	VP 0.1 NNS 1.0 [1,2]	[1,3]	[1,4]	[1,5]
		[2,3]	[2,4]	[2,5]
			[3,4]	[3,5]
				[4,5]

- $S \rightarrow NP\ VP$ 1.0
- $NP \rightarrow DT\ NN$ 0.3
- $NP \rightarrow$ time (0.05) | fruit (0.05)
- $NP \rightarrow NN\ NNS$ 0.6
- $VP \rightarrow VBP\ NP$ 0.7
- $\boxed{VP \rightarrow \text{flies}}$ 0.1
- $VP \rightarrow VP\ PP$ 0.2
- $PP \rightarrow IN\ NP$ 1.0
- $DT \rightarrow$ a (0.5) | an (0.5)
- $NN \rightarrow$ time (0.25) | fruit (0.25) | arrow (0.25) | banana (0.25)
- $\boxed{NNS \rightarrow \text{flies}}$ 1.0
- $VBP \rightarrow$ like 1.0
- $IN \rightarrow$ like 1.0

best() for bottom of the chart
is simply the rule probability

time	flies	like	an	arrow
NP $^{0.05}$ NN $^{0.25}$ [0,1]	[0,2]	[0,3]	[0,4]	[0,5]
	VP $^{0.1}$ NNS $^{1.0}$ [1,2]	[1,3]	[1,4]	[1,5]
		IN $^{1.0}$ VBP $^{1.0}$ [2,3]	[2,4]	[2,5]
			[3,4]	[3,5]
				[4,5]

S → NP VP $^{1.0}$

NP → DT NN $^{0.3}$

NP → time $^{0.05}$ | fruit $^{0.05}$

NP → NN NNS $^{0.6}$

VP → VBP NP $^{0.7}$

VP → flies $^{0.1}$

VP → VP PP $^{0.2}$

PP → IN NP $^{1.0}$

DT → a $^{0.5}$ | an $^{0.5}$

NN → time $^{0.25}$ | fruit $^{0.25}$ | arrow $^{0.25}$ | banana $^{0.25}$

NNS → flies $^{1.0}$

VBP → like $^{1.0}$

IN → like $^{1.0}$

best() for bottom of the chart is simply the rule probability

time	flies	like	an	arrow
NP $^{0.05}$ NN $^{0.25}$ [0,1]	[0,2]	[0,3]	[0,4]	[0,5]
	VP $^{0.1}$ NNS $^{1.0}$ [1,2]	[1,3]	[1,4]	[1,5]
		IN $^{1.0}$ VBP $^{1.0}$ [2,3]	[2,4]	[2,5]
			DT $^{0.5}$ [3,4]	[3,5]
				[4,5]

$S \rightarrow NP\ VP^{1.0}$

$NP \rightarrow DT\ NN^{0.3}$

$NP \rightarrow time^{0.05} \mid fruit^{0.05}$

$NP \rightarrow NN\ NNS^{0.6}$

$VP \rightarrow VBP\ NP^{0.7}$

$VP \rightarrow flies^{0.1}$

$VP \rightarrow VP\ PP^{0.2}$

$PP \rightarrow IN\ NP^{1.0}$

$DT \rightarrow a^{0.5} \mid \boxed{an}^{0.5}$

$NN \rightarrow time^{0.25} \mid fruit^{0.25} \mid arrow^{0.25} \mid banana^{0.25}$

$NNS \rightarrow flies^{1.0}$

$VBP \rightarrow like^{1.0}$

$IN \rightarrow like^{1.0}$

best() for bottom of the chart is simply the rule probability

time	flies	like	an	arrow
NP 0.05 NN 0.25 [0,1]	[0,2]	[0,3]	[0,4]	[0,5]
	VP 0.1 NNS 1.0 [1,2]	[1,3]	[1,4]	[1,5]
		IN 1.0 VBP 1.0 [2,3]	[2,4]	[2,5]
			DT 0.5 [3,4]	[3,5]
				NN 0.25 [4,5]

$S \rightarrow NP\ VP$ 1.0

$NP \rightarrow DT\ NN$ 0.3

$NP \rightarrow$ time 0.05 | fruit 0.05

$NP \rightarrow NN\ NNS$ 0.6

$VP \rightarrow VBP\ NP$ 0.7

$VP \rightarrow$ flies 0.1

$VP \rightarrow VP\ PP$ 0.2

$PP \rightarrow IN\ NP$ 1.0

$DT \rightarrow$ a 0.5 | an 0.5

$NN \rightarrow$ time 0.25 | fruit 0.25 | arrow 0.25 | banana 0.25

$NNS \rightarrow$ flies 1.0

$VBP \rightarrow$ like 1.0

$IN \rightarrow$ like 1.0

best() for bottom of the chart is simply the rule probability

	time	flies	like	an	arrow
	NP $^{0.05}$ NN $^{0.25}$ [0,1]	[0,2]	[0,3]	[0,4]	[0,5]
		VP $^{0.1}$ NNS $^{1.0}$ [1,2]	[1,3]	[1,4]	[1,5]
			IN $^{1.0}$ VBP $^{1.0}$ [2,3]	[2,4]	[2,5]
				DT $^{0.5}$ [3,4]	[3,5]
					NN $^{0.25}$ [4,5]

S → NP VP $^{1.0}$

NP → DT NN $^{0.3}$

NP → time $^{0.05}$ | fruit $^{0.05}$

NP → NN NNS $^{0.6}$

VP → VBP NP $^{0.7}$

VP → flies $^{0.1}$

VP → VP PP $^{0.2}$

PP → IN NP $^{1.0}$

DT → a $^{0.5}$ | an $^{0.5}$

NN → time $^{0.25}$ | fruit $^{0.25}$ | arrow $^{0.25}$ | banana $^{0.25}$

NNS → flies $^{1.0}$

VBP → like $^{1.0}$

IN → like $^{1.0}$

Now multiply rule by best() of descendants

time	flies	like	an	arrow
NP 0.05 NN 0.25 [0,1]	S 0.005 NP 0.15 [0,2]	[0,3]	[0,4]	[0,5]
	VP 0.1 NNS 1.0 [1,2]	[1,3]	[1,4]	[1,5]
		IN 1.0 VBP 1.0 [2,3]	[2,4]	[2,5]
			DT 0.5 [3,4]	[3,5]
				NN 0.25 [4,5]

$\boxed{S \rightarrow NP\ VP}$ 1.0
NP → DT NN 0.3
NP → time 0.05 | fruit 0.05
$\boxed{NP \rightarrow NN\ NNS}$ 0.6
VP → VBP NP 0.7
VP → flies 0.1
VP → VP PP 0.2
PP → IN NP 1.0
DT → a 0.5 | an 0.5
NN → time 0.25 | fruit 0.25 | arrow 0.25 | banana 0.25
NNS → flies 1.0
VBP → like 1.0
IN → like 1.0

$$1.0 * .05 * .1 = .005$$
$$.6 * .25 * 1.0 = .15$$

	time	flies	like	an	arrow
	NP 0.05 NN 0.25 [0,1]	S 0.005 NP 0.15 [0,2]	[0,3]	[0,4]	0.0000375 S [0,5]
		VP 0.1 NNS 1.0 [1,2]	[1,3]	[1,4]	0.00075 VP [1,5]
			IN 1.0 VBP 1.0 [2,3]	[2,4]	PP 0.0375 VP 0.02625 [2,5]
				DT 0.5 [3,4]	0.0375 NP [3,5]
					NN 0.25 [4,5]

$S \rightarrow NP\ VP$ 1.0

$NP \rightarrow DT\ NN$ 0.3

$NP \rightarrow$ time 0.05 | fruit 0.05

$NP \rightarrow NN\ NNS$ 0.6

$VP \rightarrow VBP\ NP$ 0.7

$VP \rightarrow$ flies 0.1

$VP \rightarrow VP\ PP$ 0.2

$PP \rightarrow IN\ NP$ 1.0

$DT \rightarrow$ a 0.5 | an 0.5

$NN \rightarrow$ time 0.25 | fruit 0.25 | arrow 0.25 | banana 0.25

$NNS \rightarrow$ flies 1.0

$VBP \rightarrow$ like 1.0

$IN \rightarrow$ like 1.0

best(S) = 1*.05*.00075 = .0000375

time	flies	like	an	arrow
NP 0.05 NN 0.25 [0,1]	S 0.005 NP 0.15 [0,2]	[0,3]	[0,4]	0.0039375 S [0,5]
	VP 0.1 NNS 1.0 [1,2]	[1,3]	[1,4]	0.00075 VP [1,5]
		IN 1.0 VBP 1.0 [2,3]	[2,4]	PP 0.0375 VP 0.02625 [2,5]
			DT 0.5 [3,4]	0.0375 NP [3,5]
				NN 0.25 [4,5]

$\boxed{S \rightarrow NP\ VP}$ 1.0

NP → DT NN 0.3

NP → time 0.05 | fruit 0.05

NP → NN NNS 0.6

VP → VBP NP 0.7

VP → flies 0.1

VP → VP PP 0.2

PP → IN NP 1.0

DT → a 0.5 | an 0.5

NN → time 0.25 | fruit 0.25 | arrow 0.25 | banana 0.25

NNS → flies 1.0

VBP → like 1.0

IN → like 1.0

can also derive as

1*.15*.02625 = .0039375

so update best and change backpointer

time	flies	like	an	arrow
NP 0.05 NN 0.25 [0,1]	S 0.005 NP 0.15 [0,2]	[0,3]	[0,4]	S 0.0039375 [0,5]
	VP 0.1 NNS 1.0 [1,2]	[1,3]	[1,4]	VP 0.00075 [1,5]
		IN 1.0 VBP 1.0 [2,3]	[2,4]	PP 0.0375 VP 0.02625 [2,5]
			DT 0.5 [3,4]	NP 0.0375 [3,5]
				NN 0.25 [4,5]

S → NP VP 1.0

NP → DT NN 0.3

NP → time 0.05 | fruit 0.05

NP → NN NNS 0.6

VP → VBP NP 0.7

VP → flies 0.1

VP → VP PP 0.2

PP → IN NP 1.0

DT → a 0.5 | an 0.5

NN → time 0.25 | fruit 0.25 | arrow 0.25 | banana 0.25

NNS → flies 1.0

VBP → like 1.0

IN → like 1.0

If we wanted the probability of ALL parses of this sentence, sum multiple derivations instead of max (= .0039375+ .0000375)

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- If we see NP 1000 times in training, and we see NP -> DT NN 150 times, then p(NP -> DT NN) = 150/1000 = .15

Problems with PCFGs

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- Using the approach just described ("vanilla PCFG"), a CKY parser scores about 73% F1. State of the art parsers are in the mid-90s

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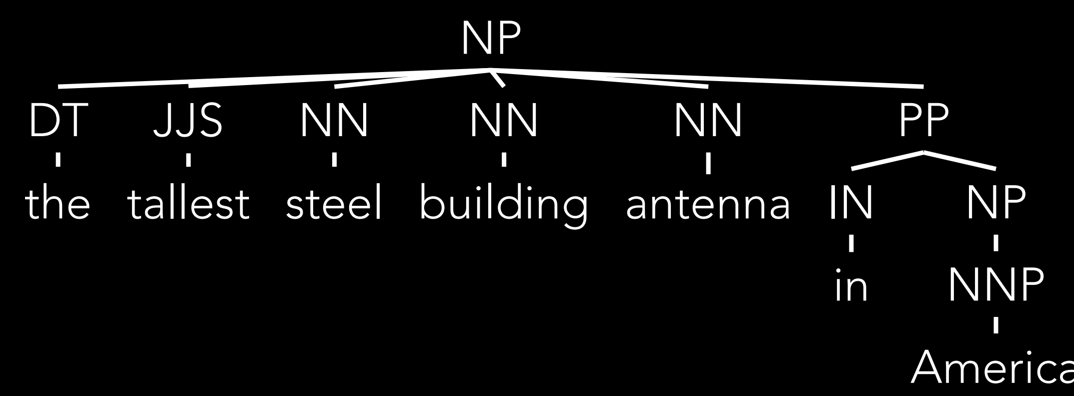
- Using the approach just described ("vanilla PCFG"), a CKY parser scores about 73% F1. State of the art parsers are in the mid-90s

- Why so bad?

  - Rules are too specific

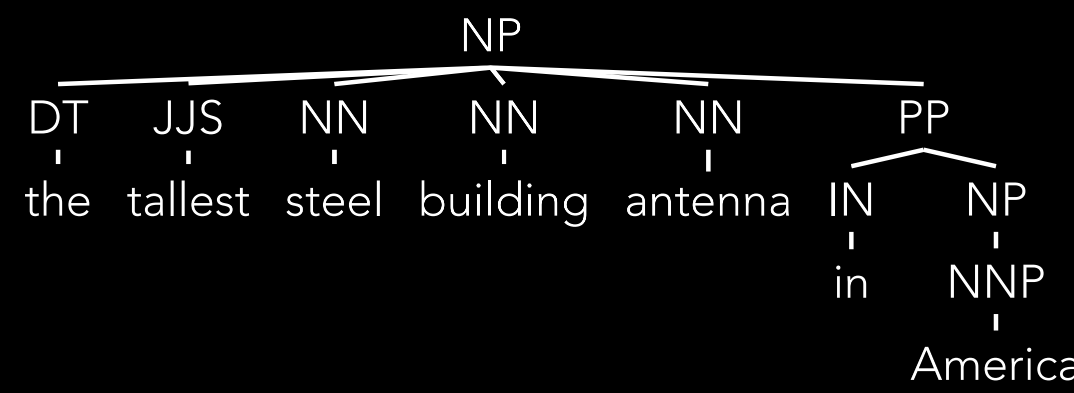
  - Rules are not specific enough

Too Specific



Too Specific

If we see this tree:



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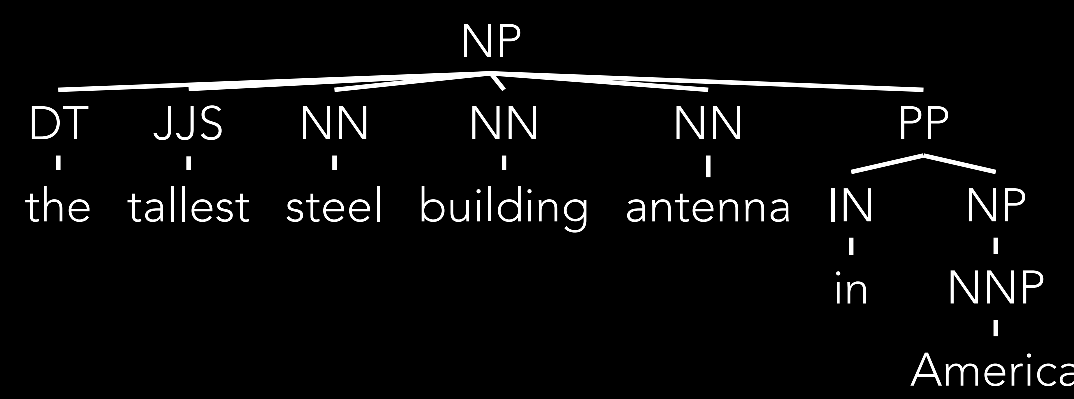
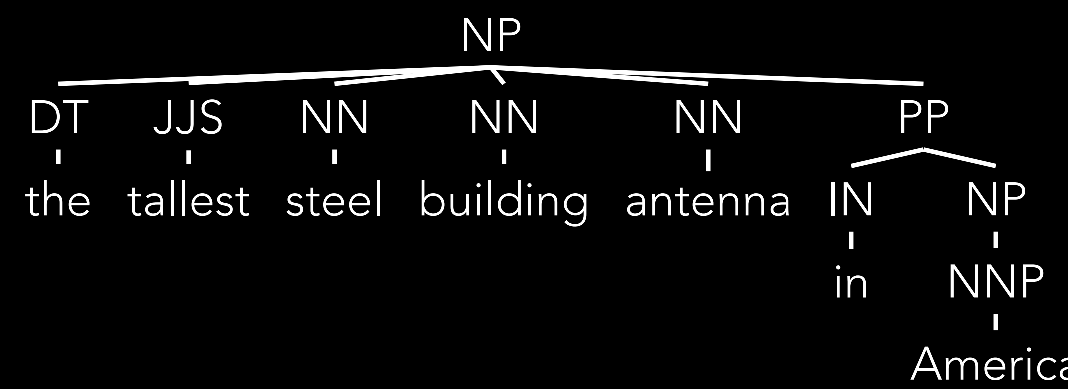


We get this rule: NP -> DT JJS NN NN NN PP

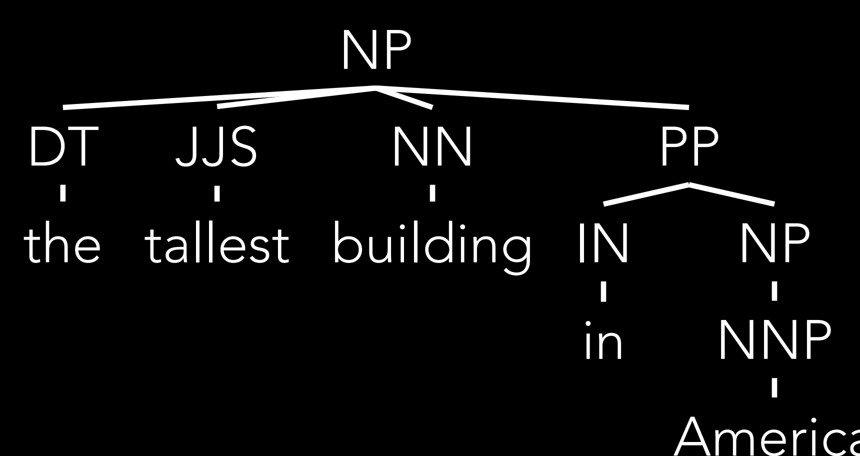
Too Specific

If we see this tree:



We get this rule: NP -> DT JJS NN NN NN PP

But we can't parse this tree:



Too Specific

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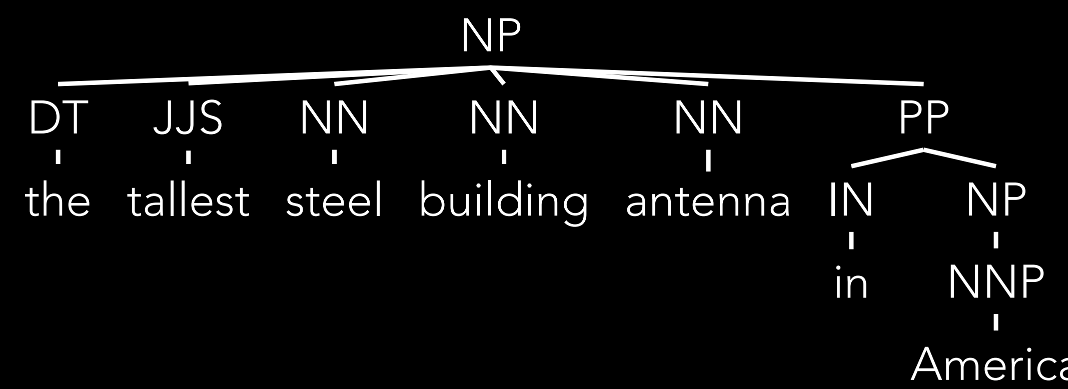
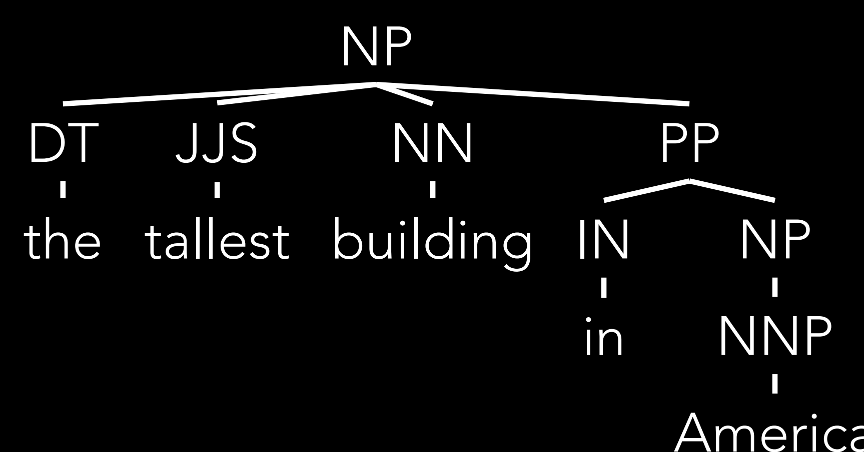


We get this rule: NP -> DT JJS NN NN NN PP

But we can't parse this tree:



without this rule: NP -> DT JJS NN PP

Too Specific

Too Specific

Recall that for
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Too Specific

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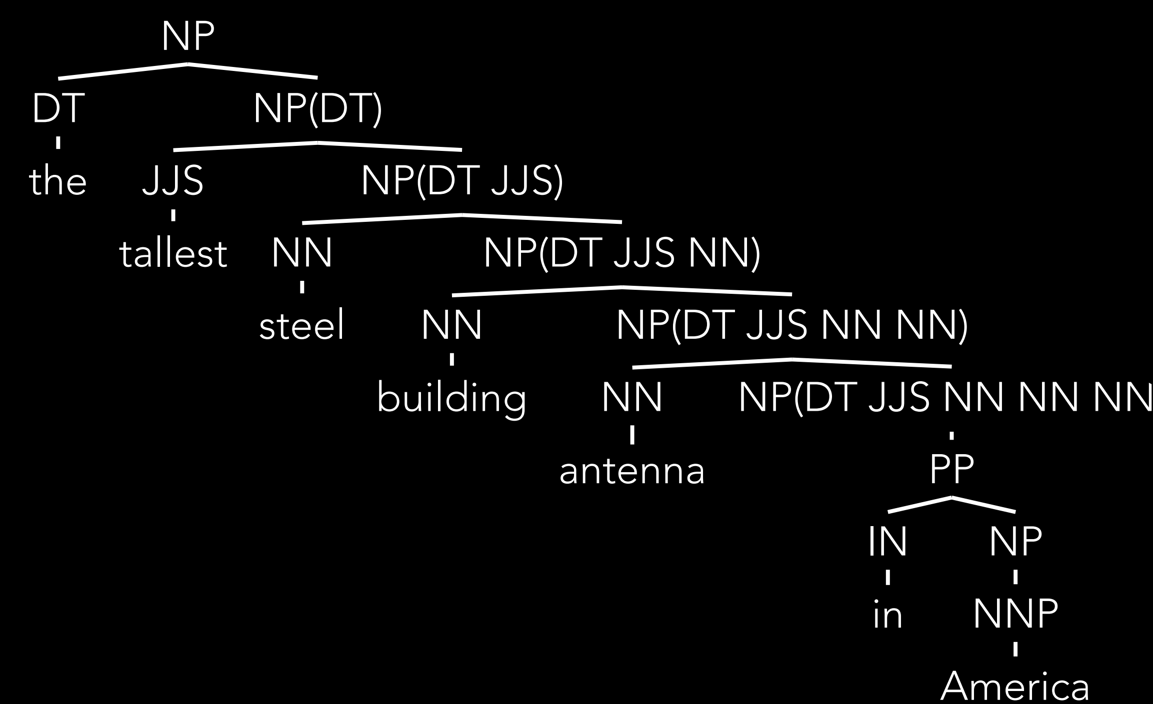

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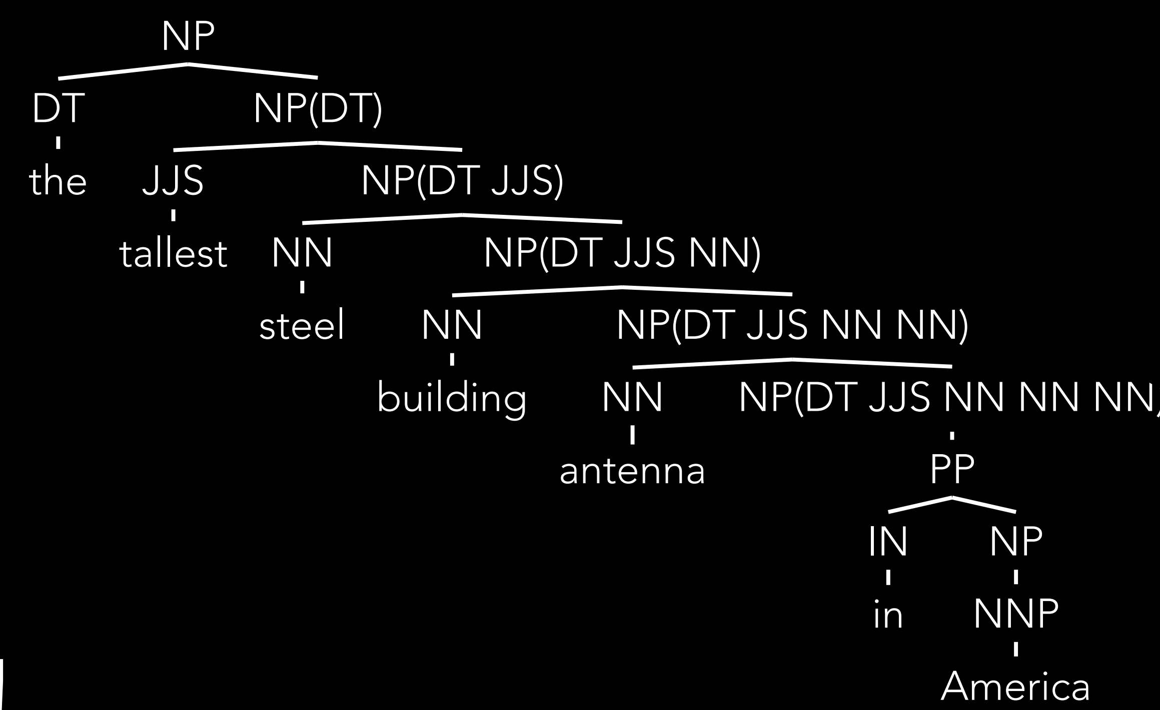

That still doesn't help!

Too Specific

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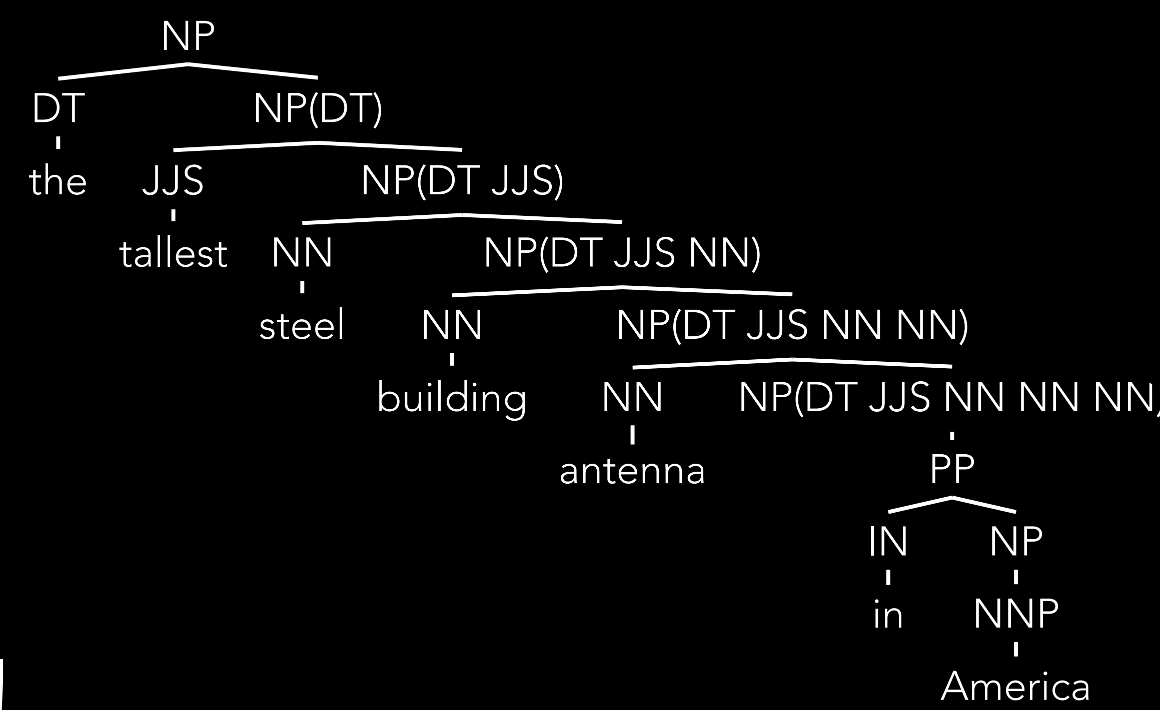

That still doesn't help!

What if we only remembered one sibling?

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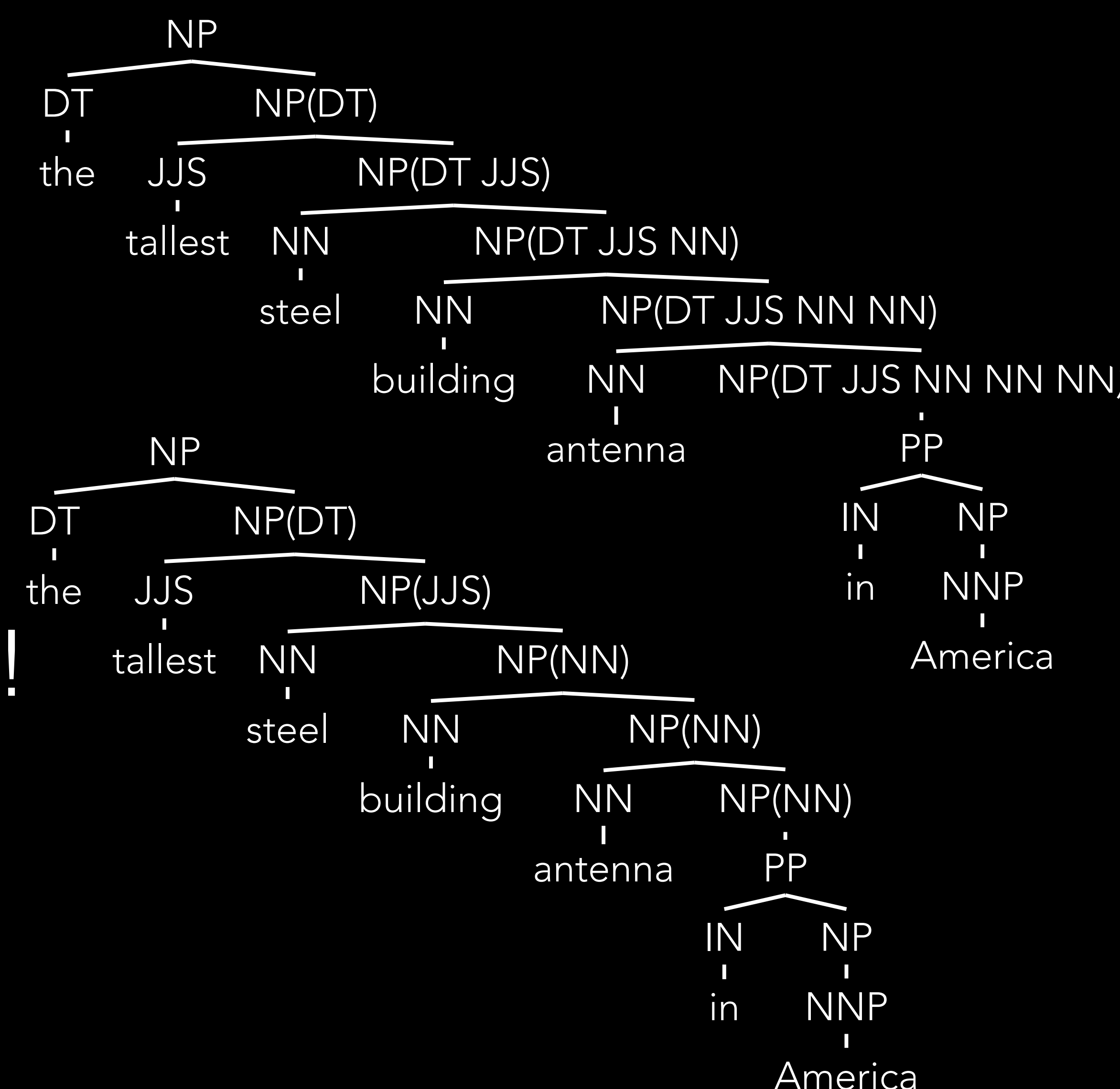

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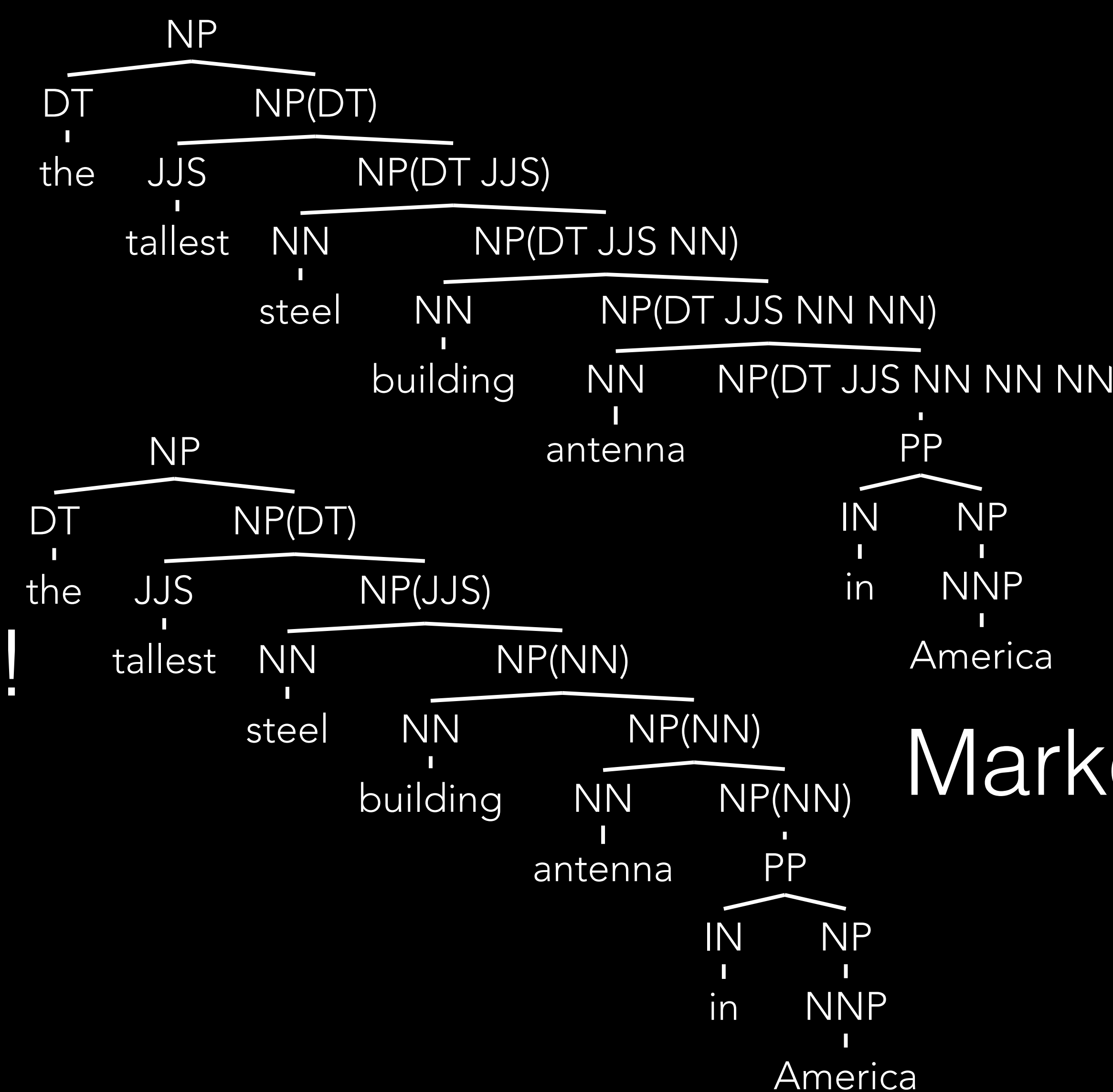
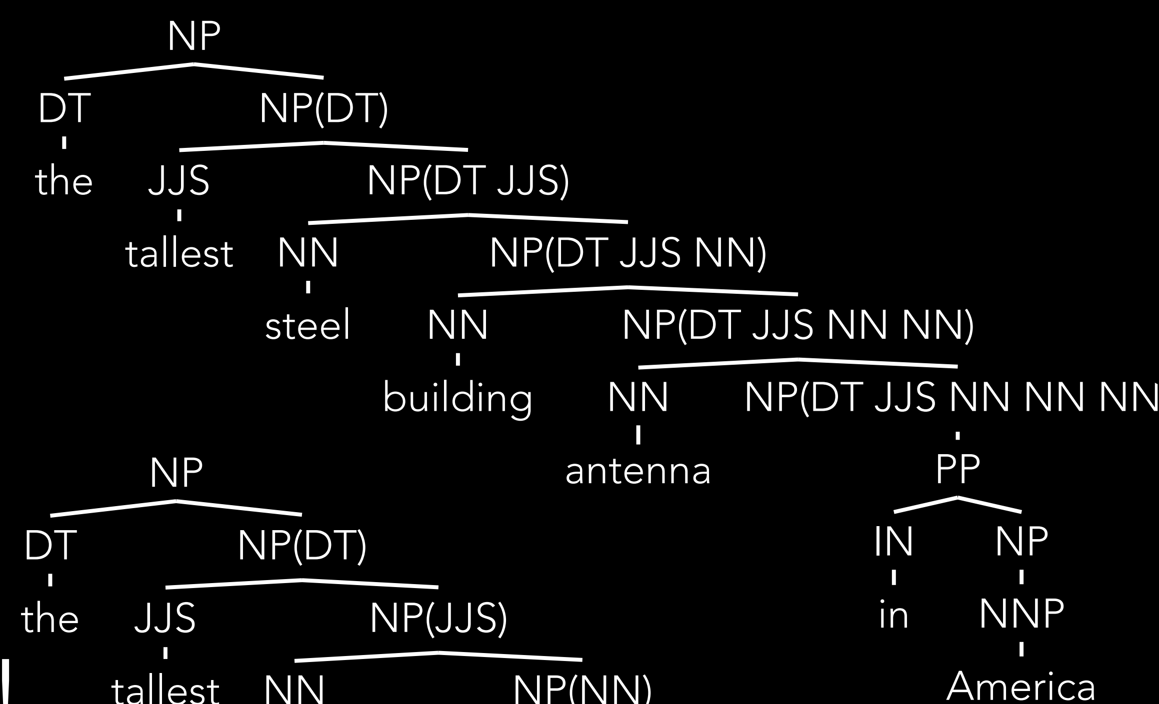


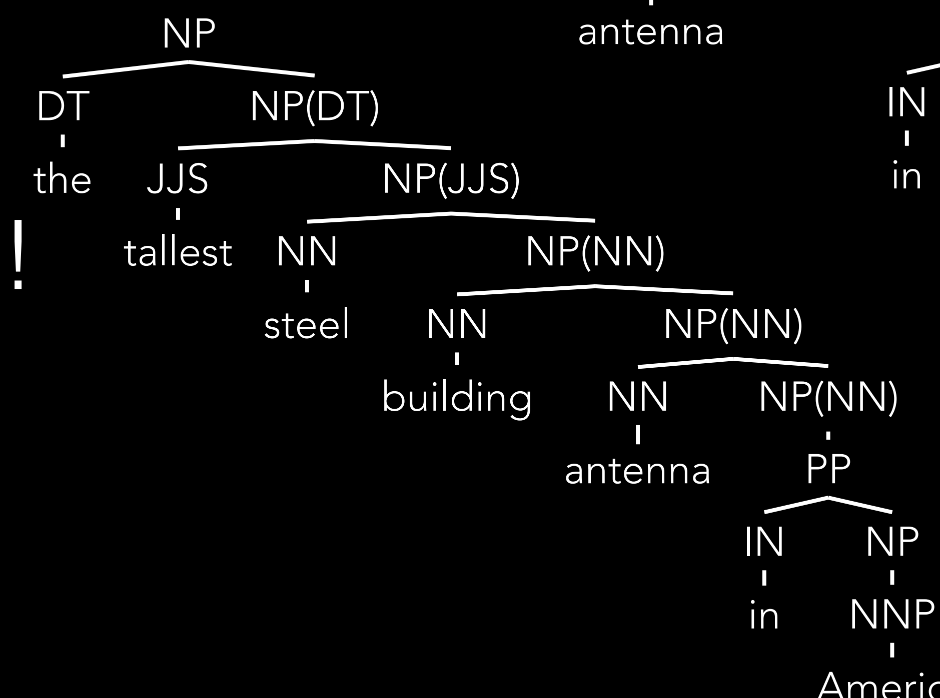
Markovization!

Too Specific

Recall that for CKY purposes we binarized



That still doesn't help!



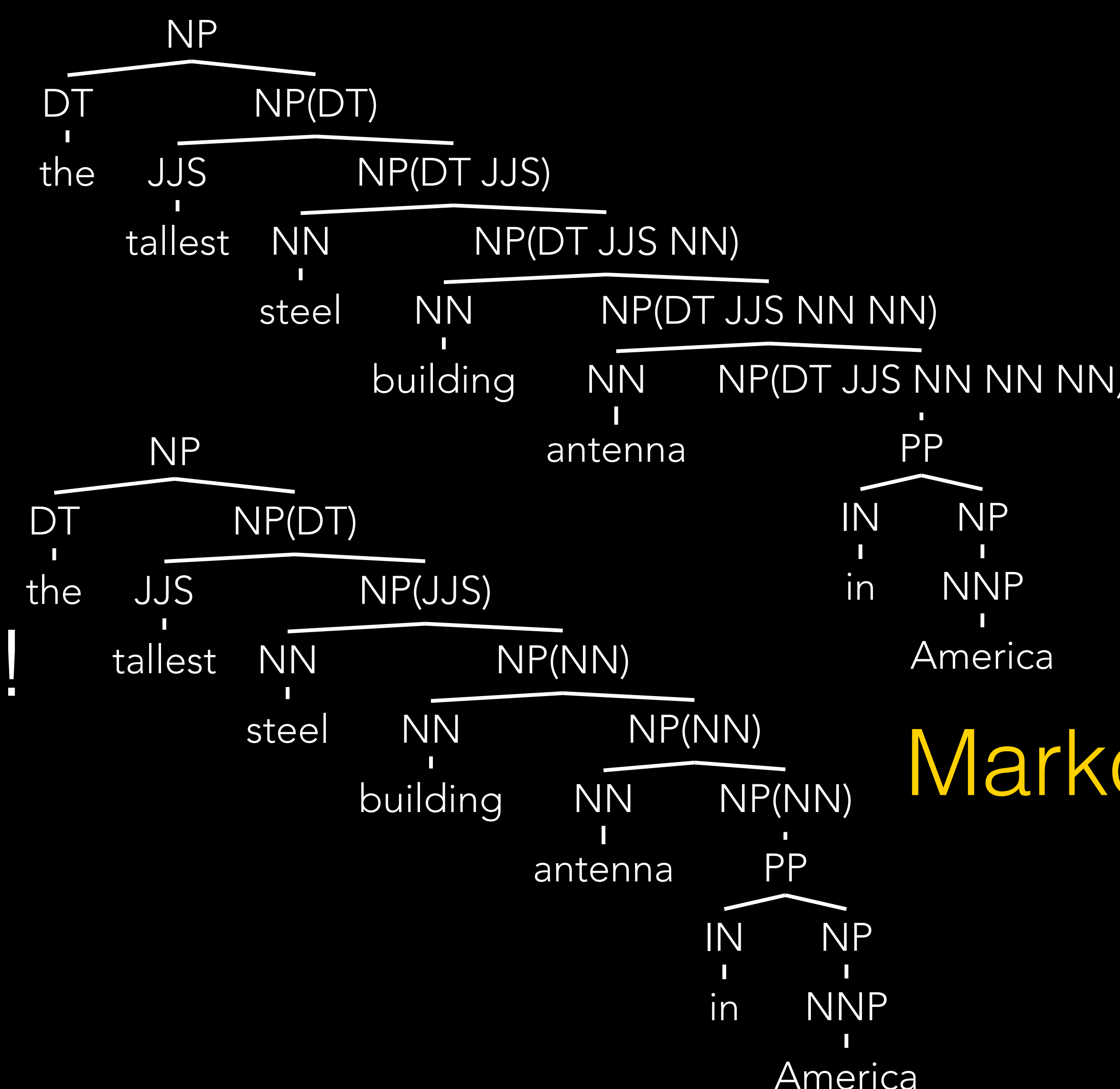
Markovization!

What if we only remembered one sibling?

Now we have the rules we need

Too Specific

Recall that for CKY purposes we binarized



That still doesn't help!

What if we only remembered one sibling?

Markovization!

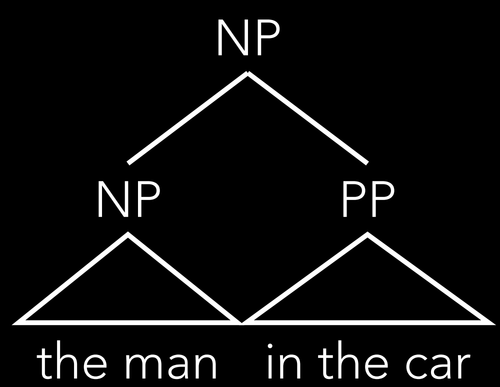
Now we have the rules we need

Can experiment with keeping more or less context

Not Specific Enough (I)

If we saw

Not Specific Enough (I)

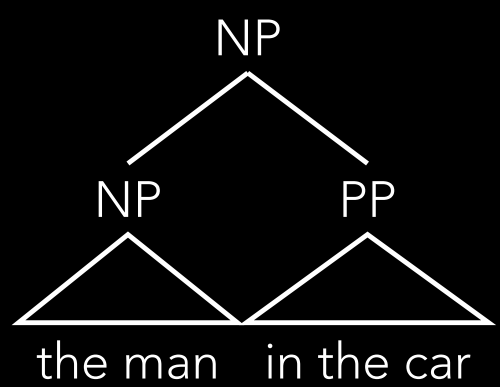


If we saw

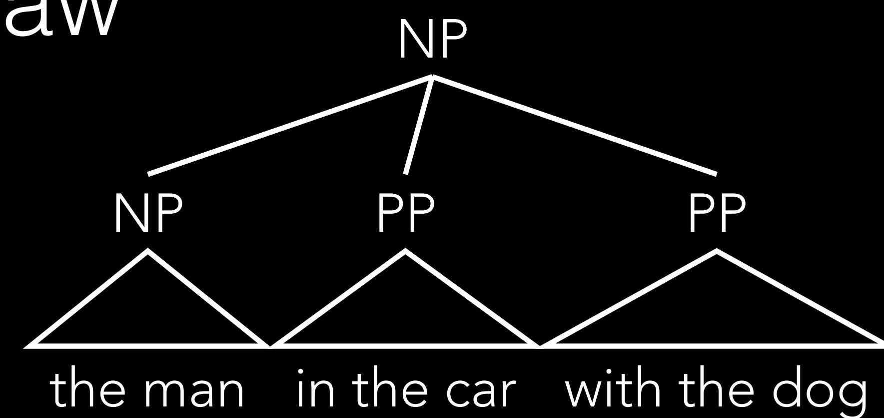
90
times

Not Specific Enough (I)

If we saw



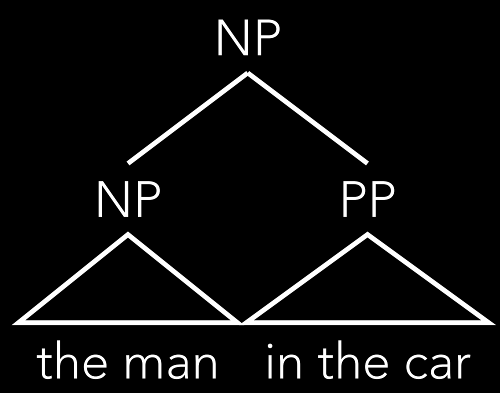
90 times



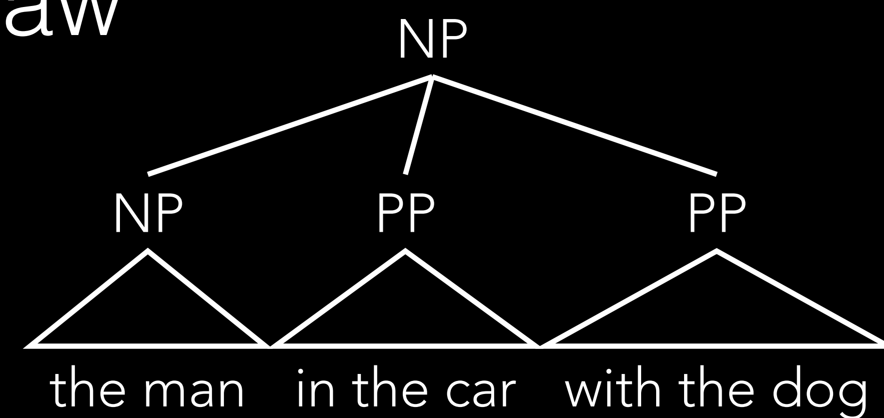
10 times

Not Specific Enough (I)

If we saw



90 times

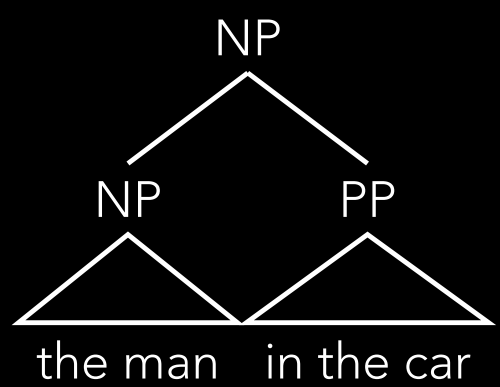


10 times

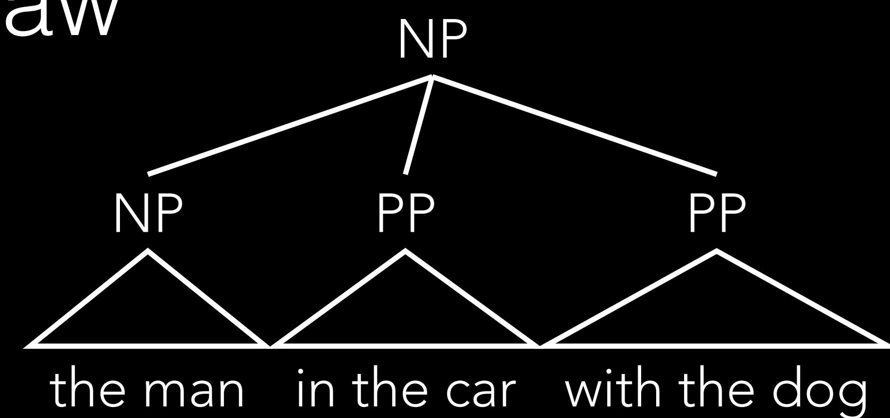
p(NP -> NP PP)
= 90/200 = .45

Not Specific Enough (I)

If we saw



90 times



10 times

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p(NP -> NP PP PP)
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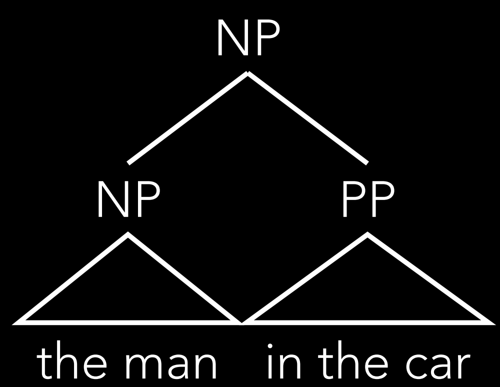

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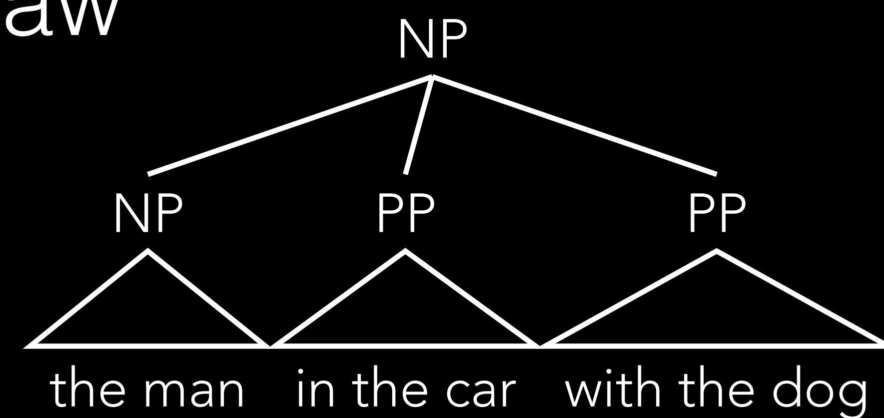

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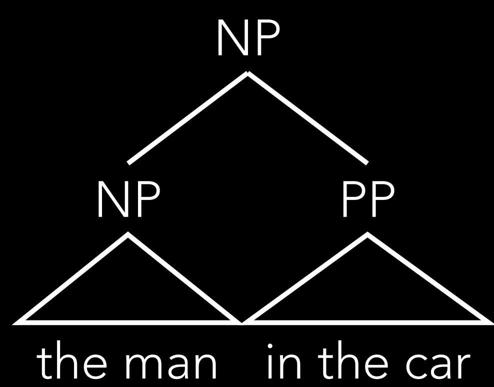

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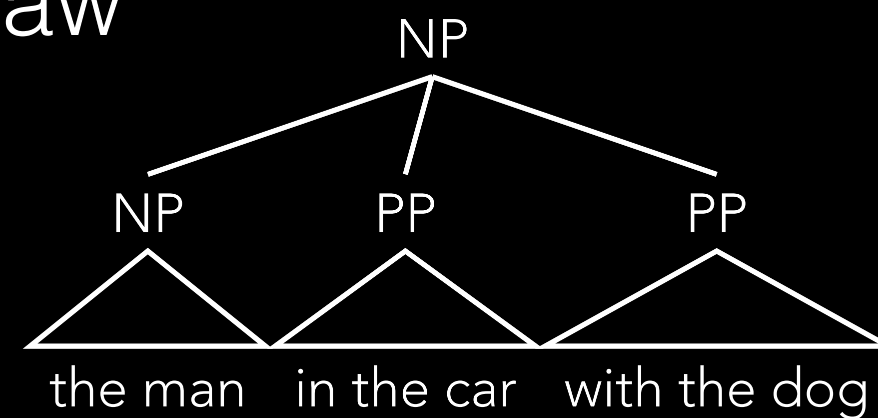

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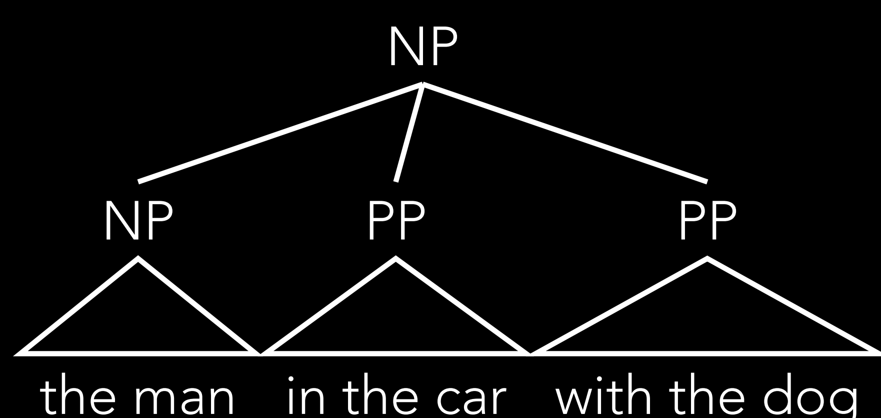

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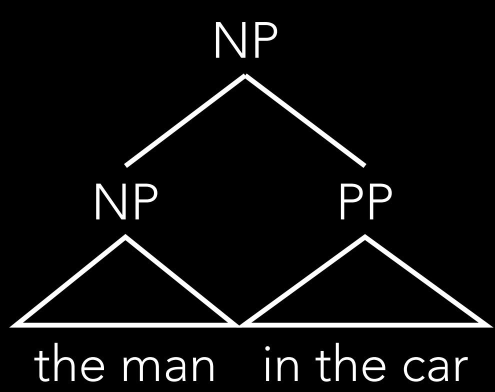

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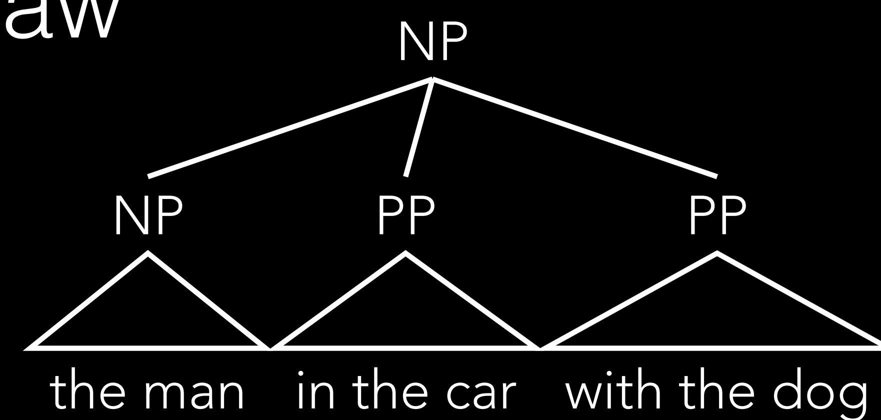

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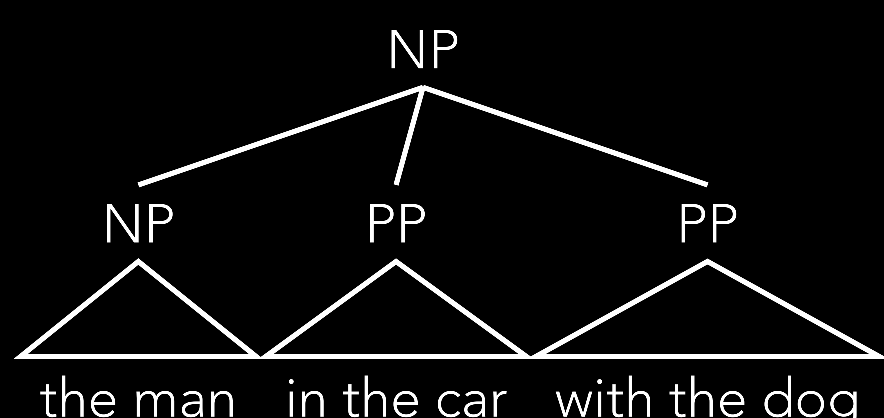

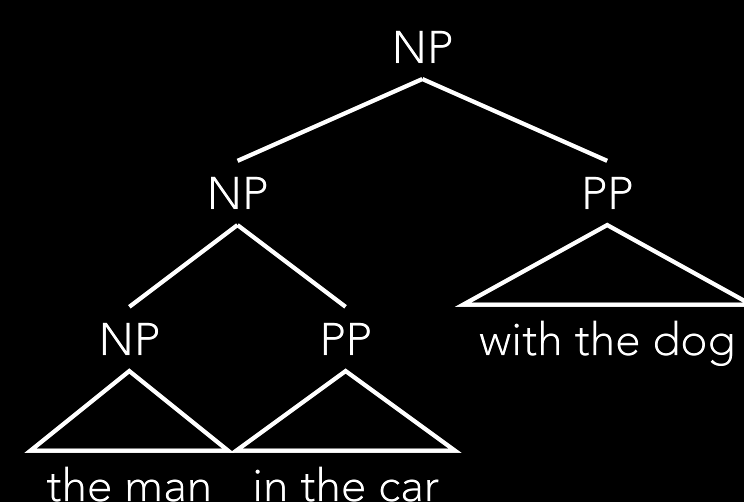

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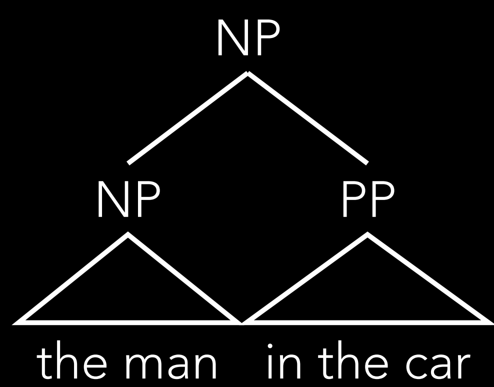

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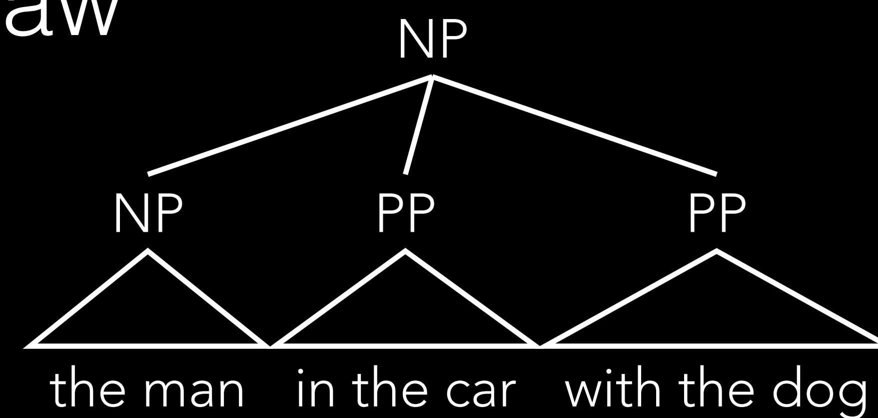

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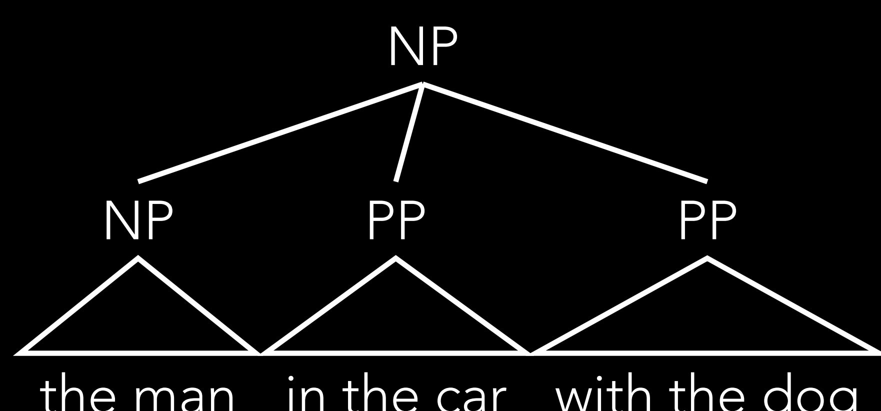

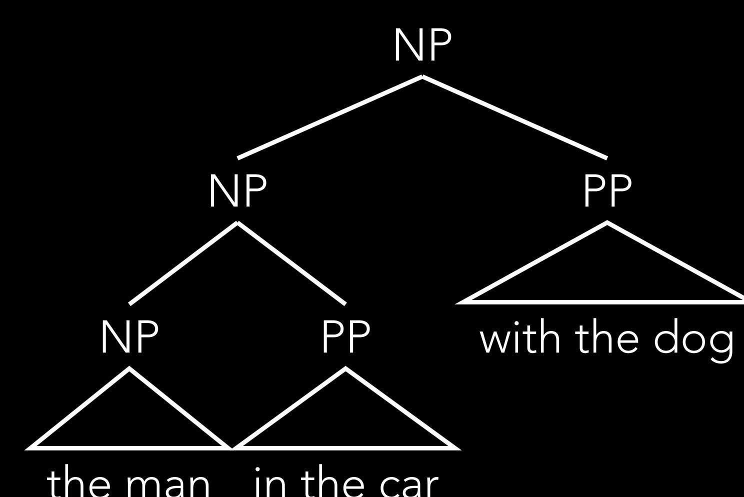

.05x…

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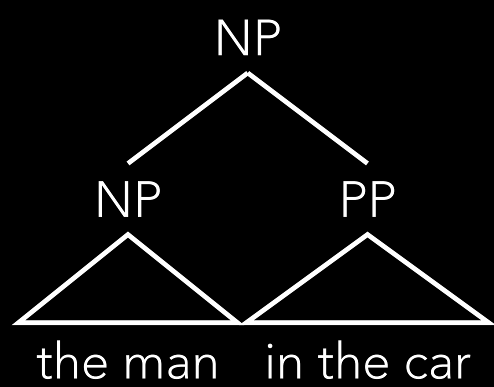

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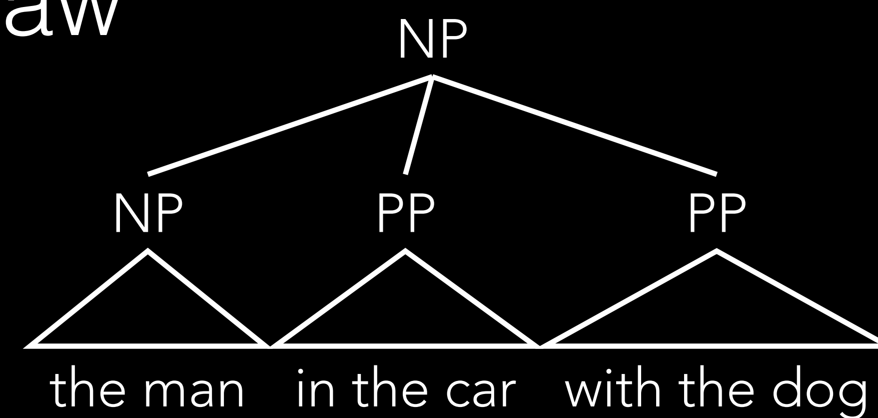

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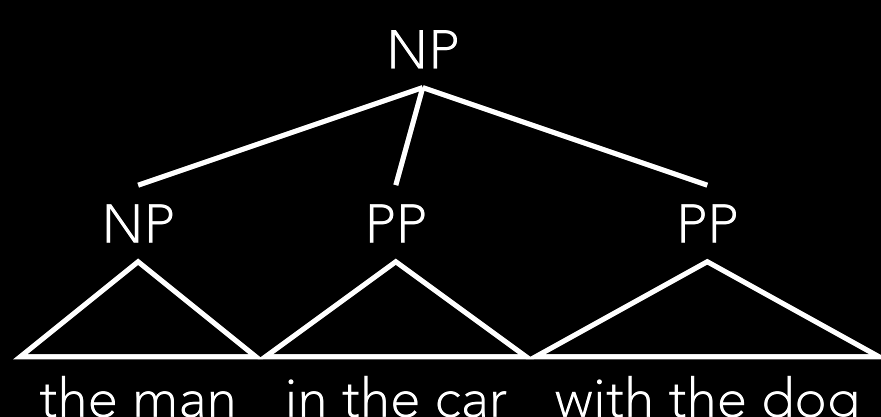

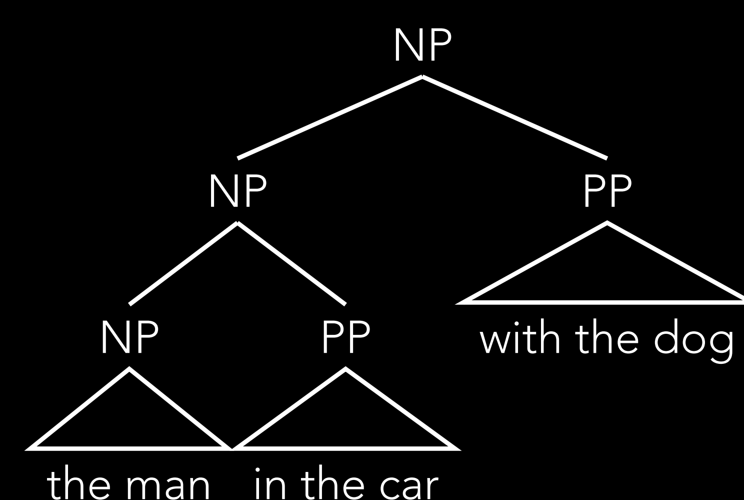

.05x…

.45x.45x… = .2025x…

Not Specific Enough (I)

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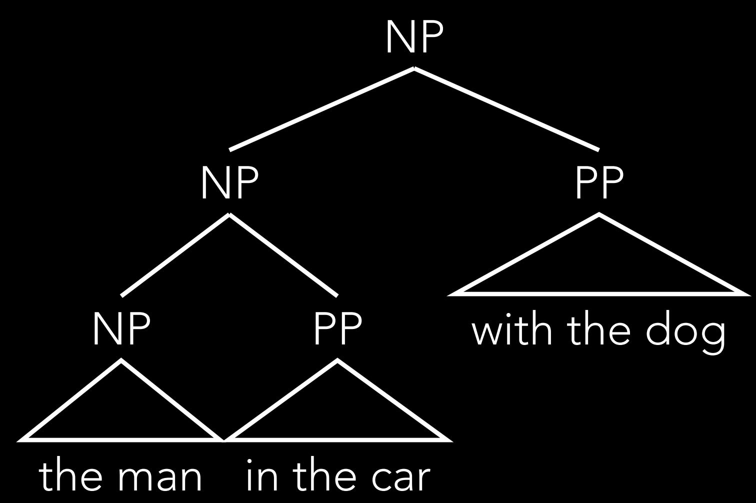
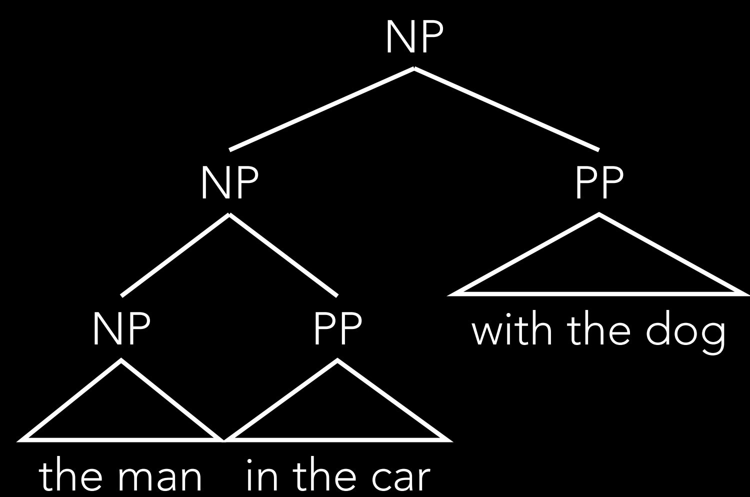
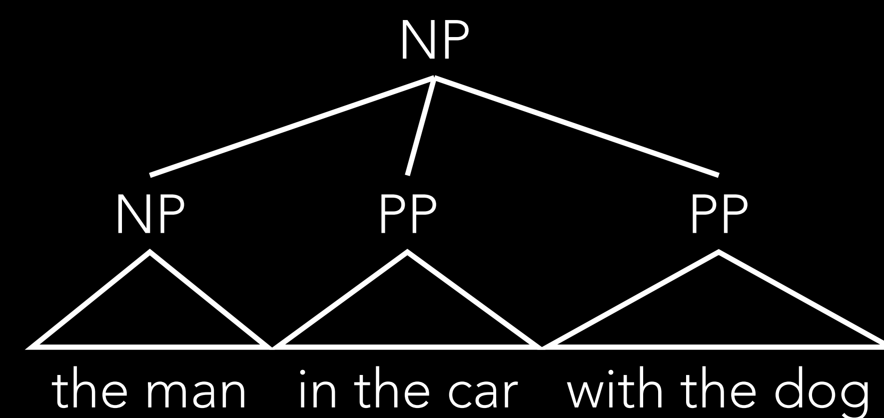


This was never seen in training

Not Specific Enough (I)





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This was!

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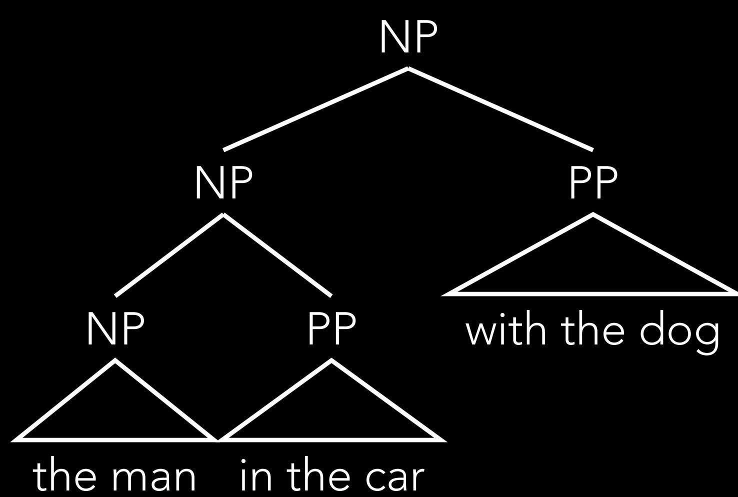
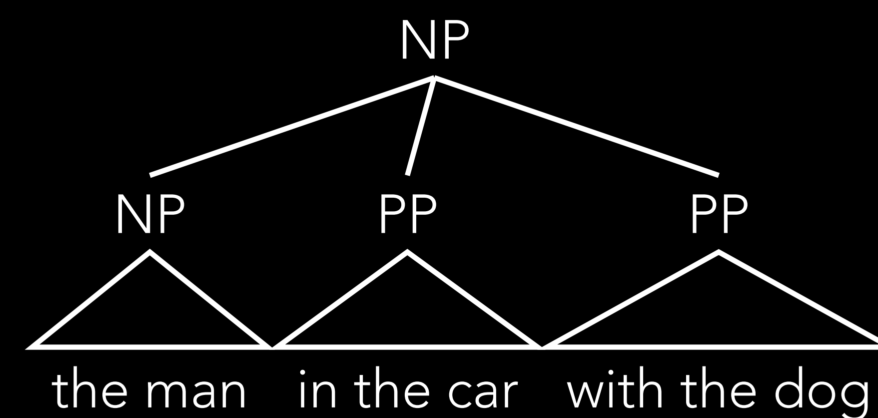


.2025

This was never seen in training



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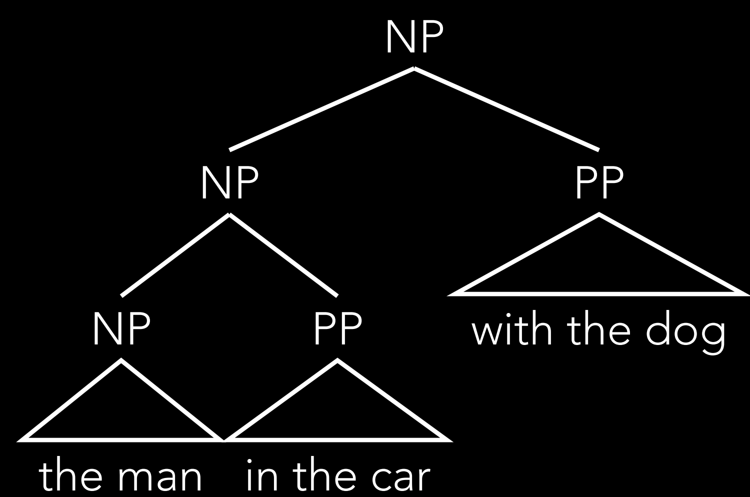

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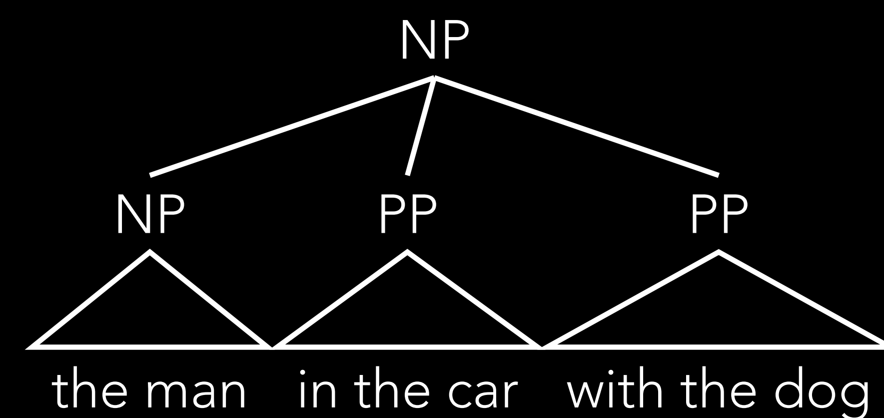

.05

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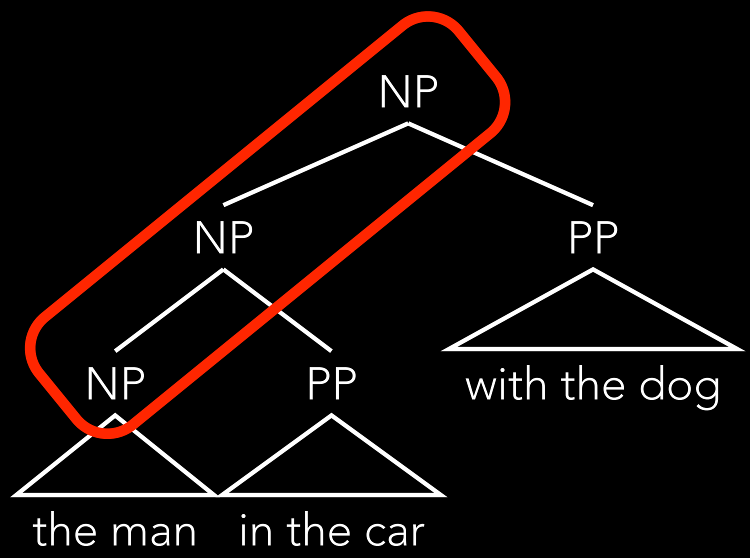

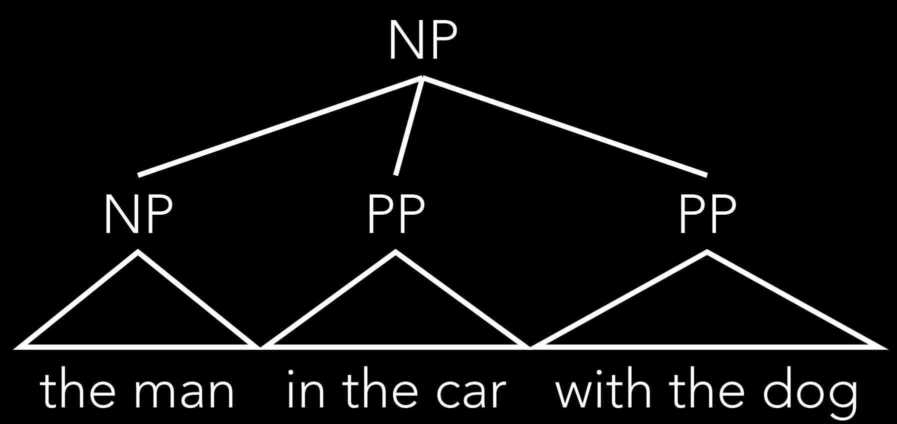

.2025

This was never seen in training

.05

This was!

We should model parent-child behavior

Not Specific Enough (I)

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Add parent symbol annotation

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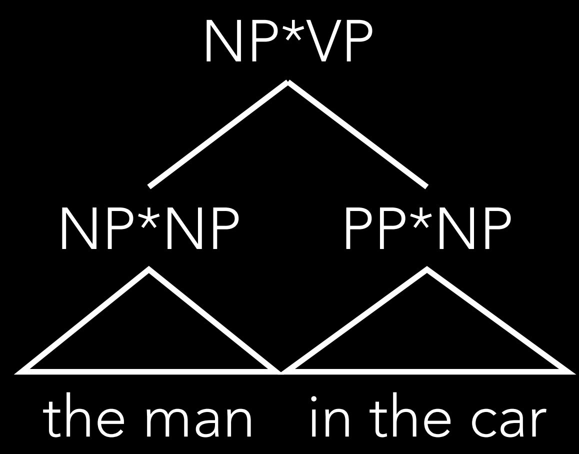

90 times

Not Specific Enough (I)

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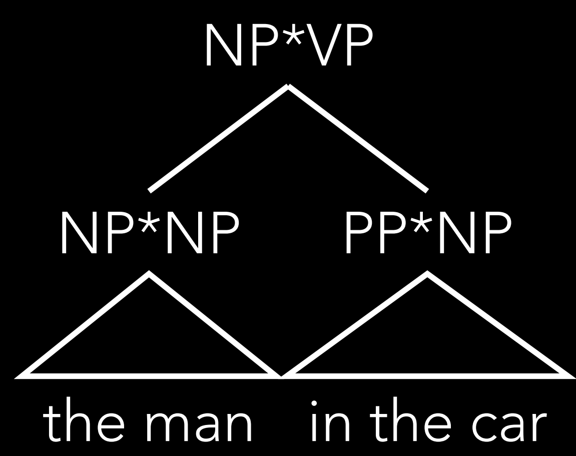

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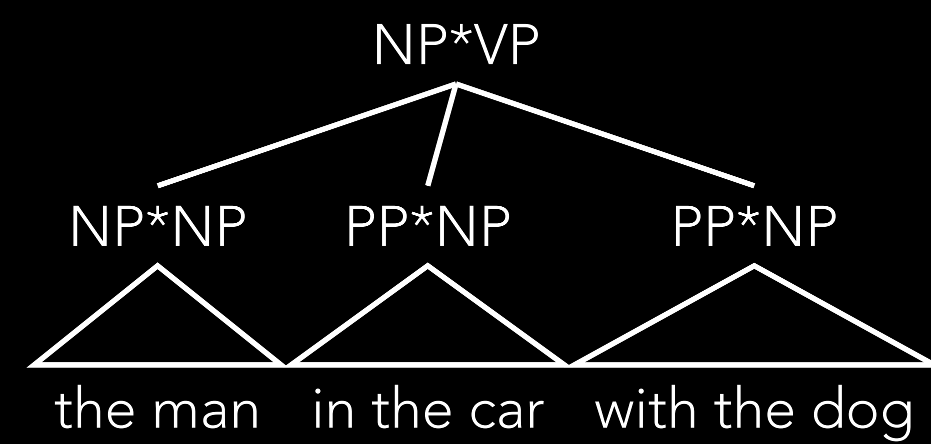

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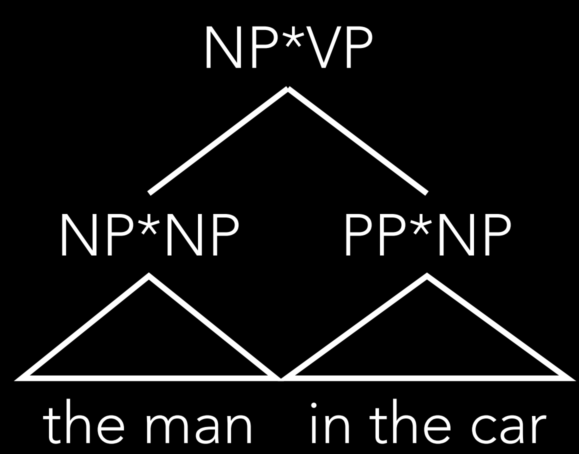

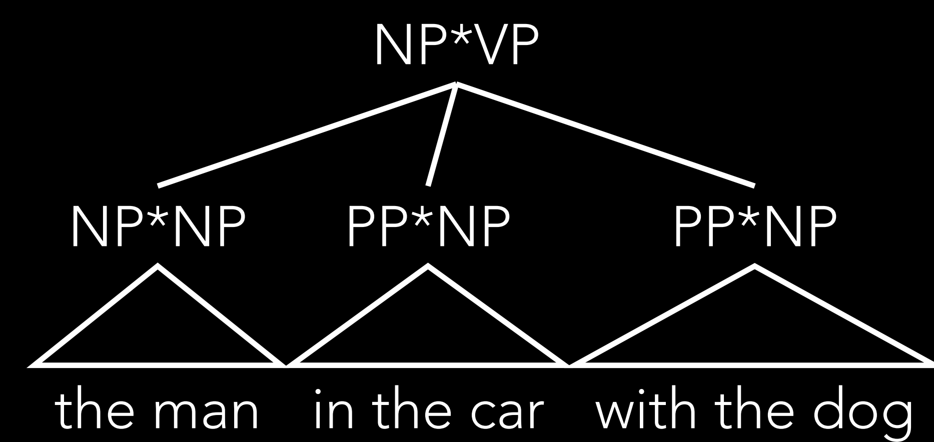

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p(NP*VP -> NP*NP PP*NP)
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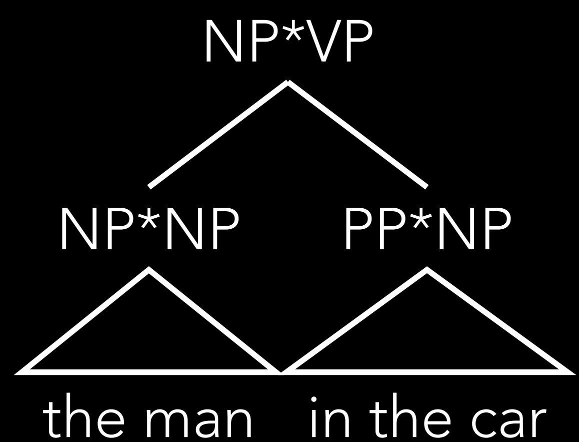

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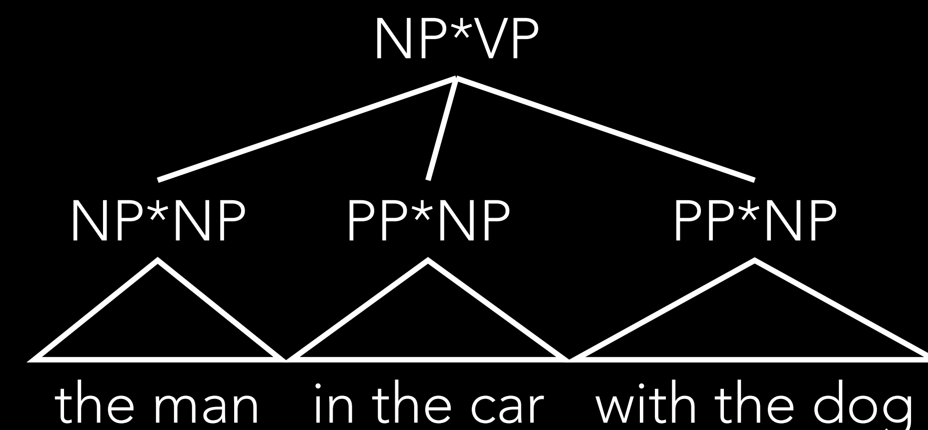

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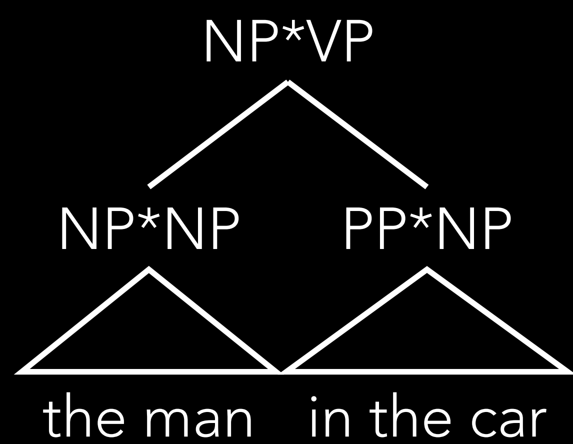

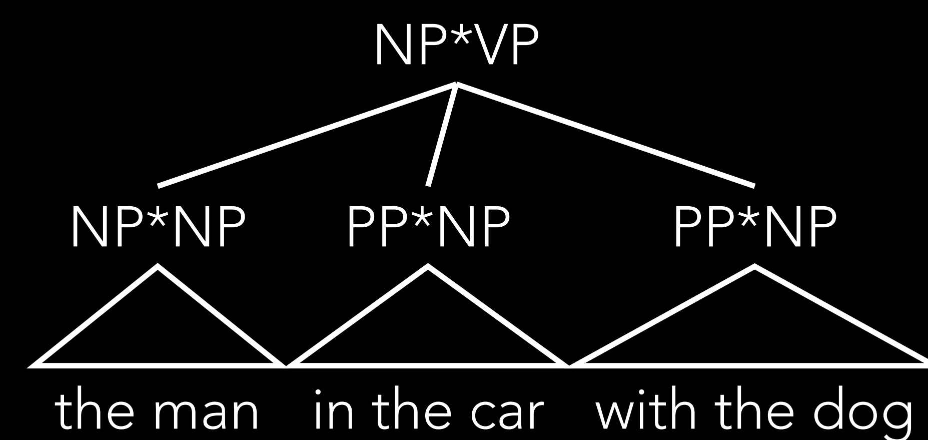

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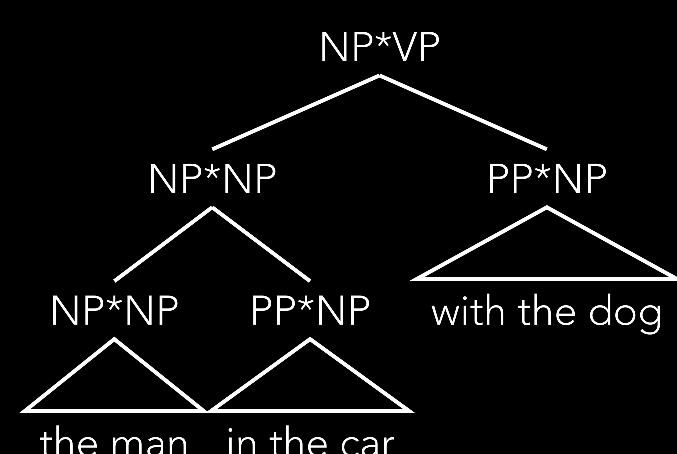

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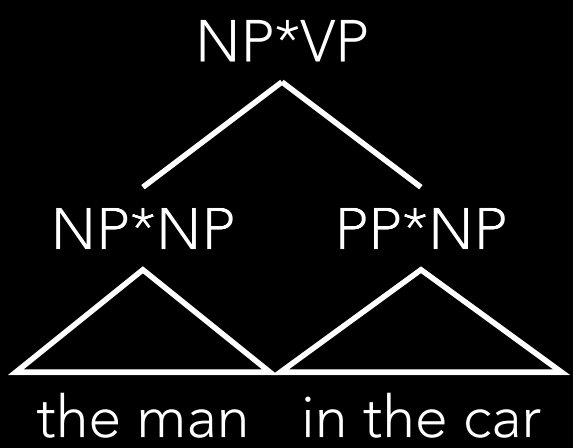

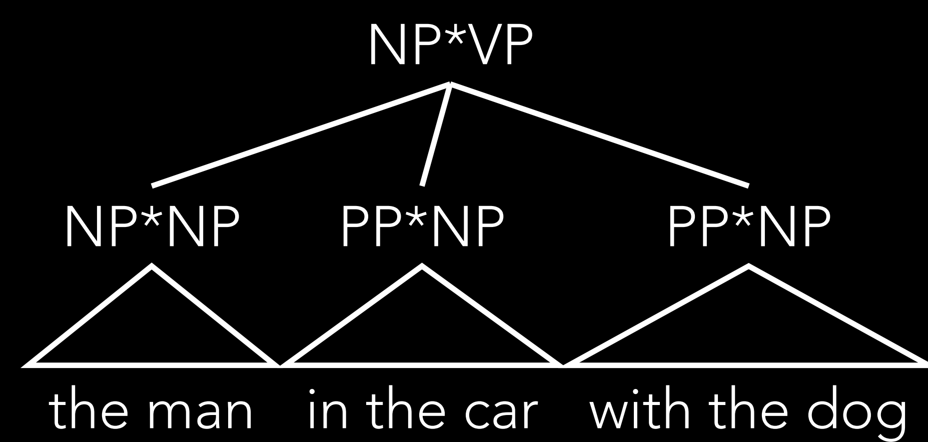

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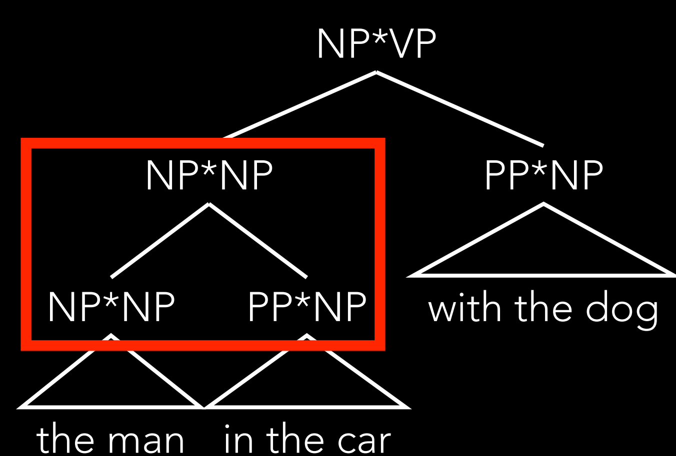

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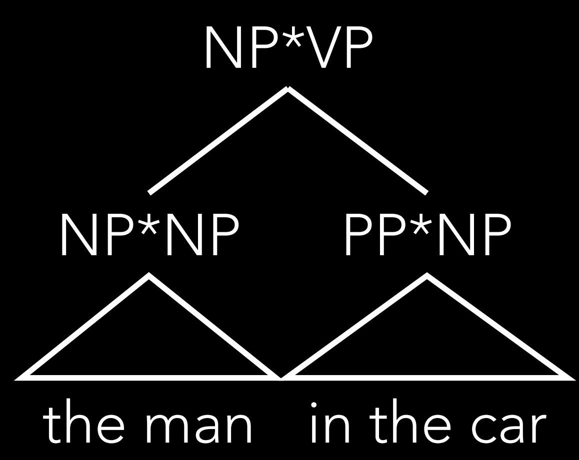

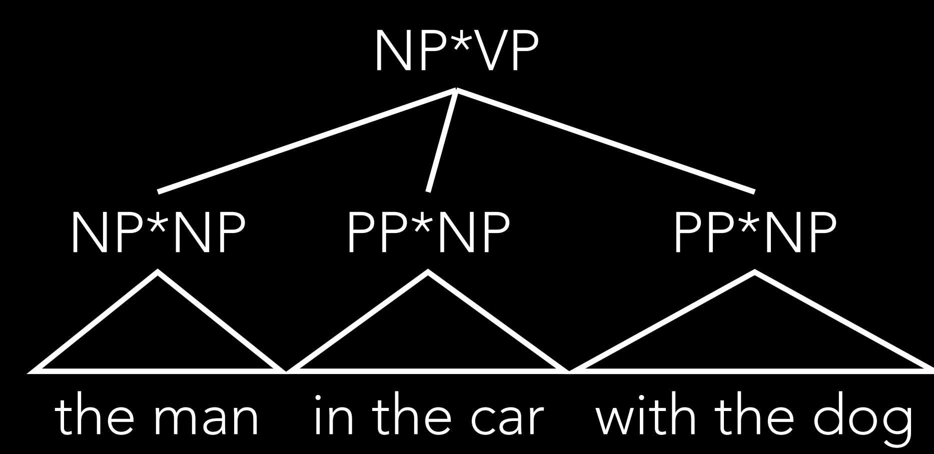

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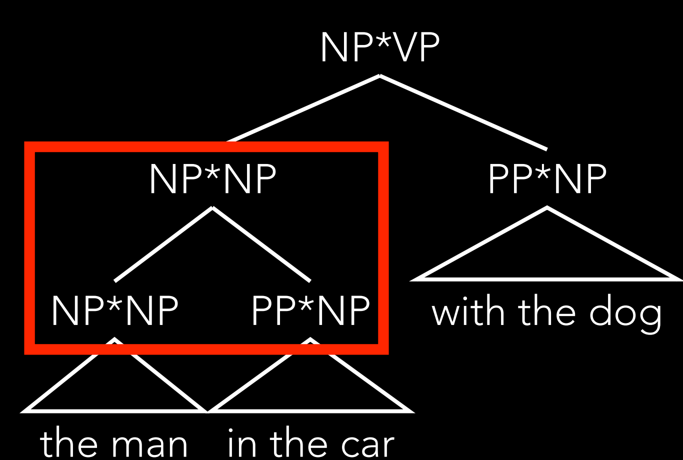
p(NP*NP -> NP*NP PP*NP) = 0



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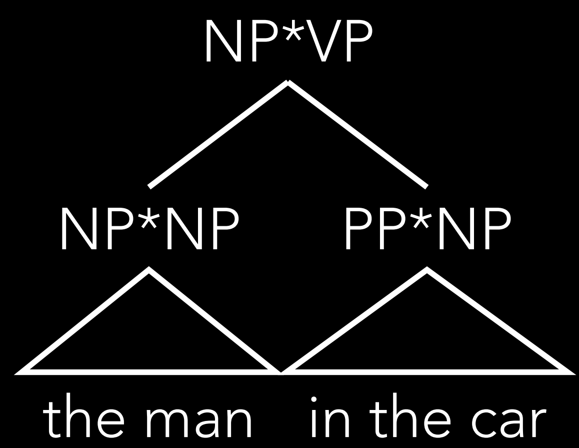

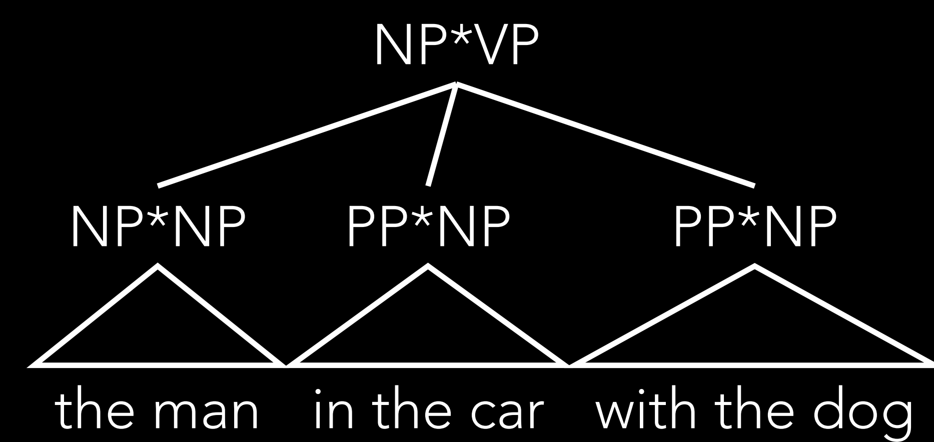

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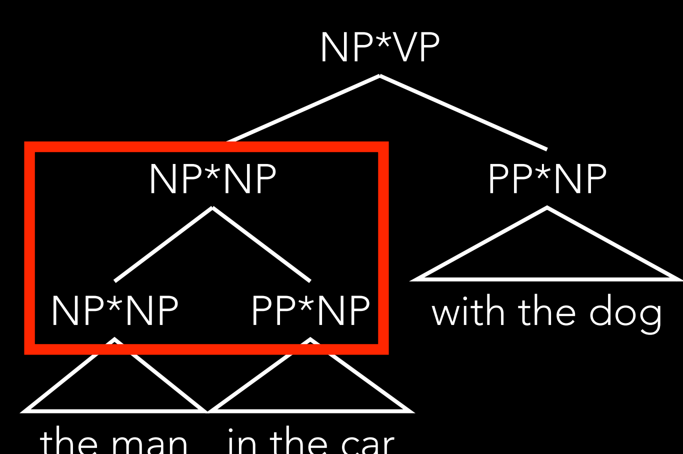
Not possible!



Other Useful Category Splits

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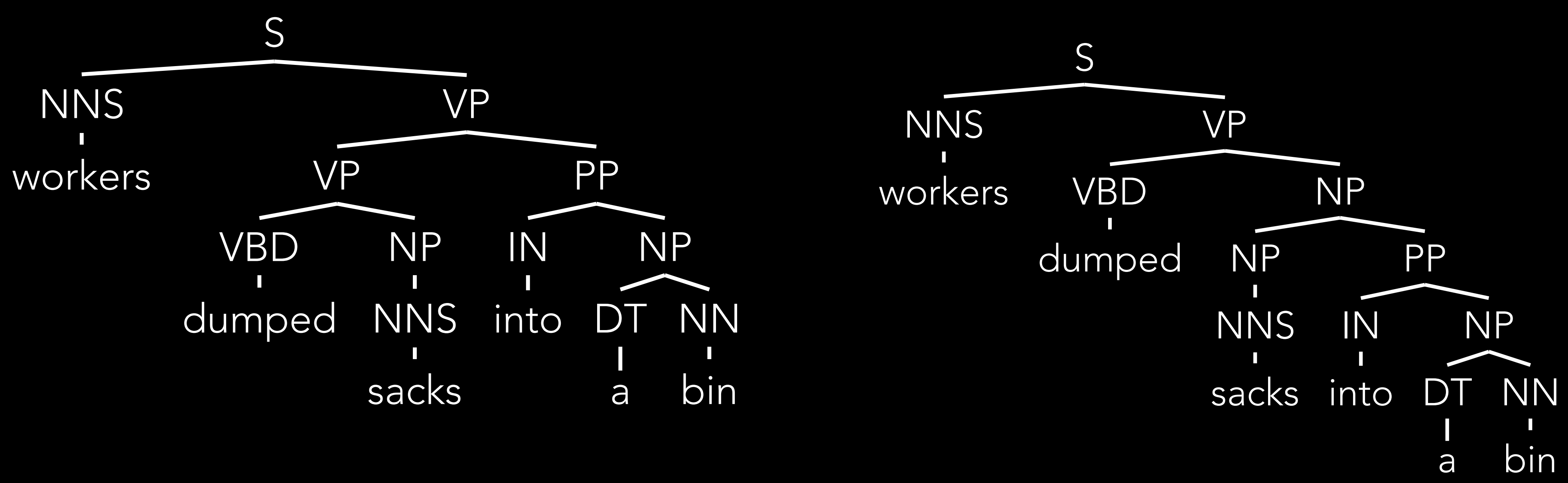
- Subdivide IN, CC, “have” vs “be” auxiliary
- See “Accurate Unlexicalized Parsing” (Klein & Manning, 2003)

Not Specific Enough (II)



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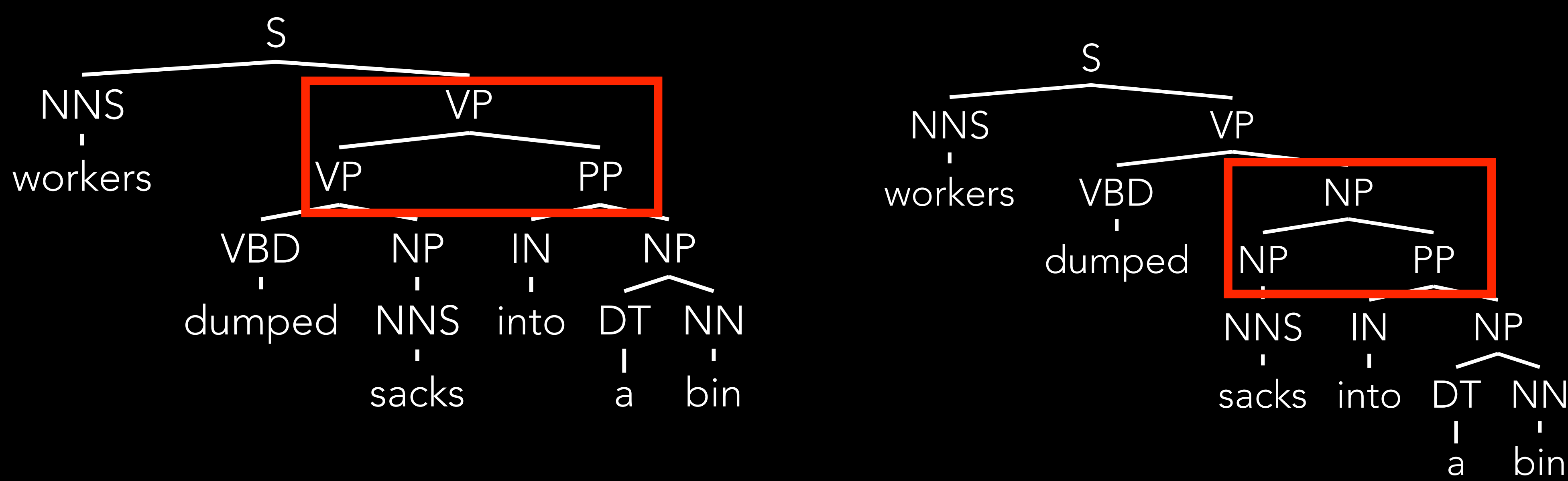

These derivations only differ by the highlighted rules

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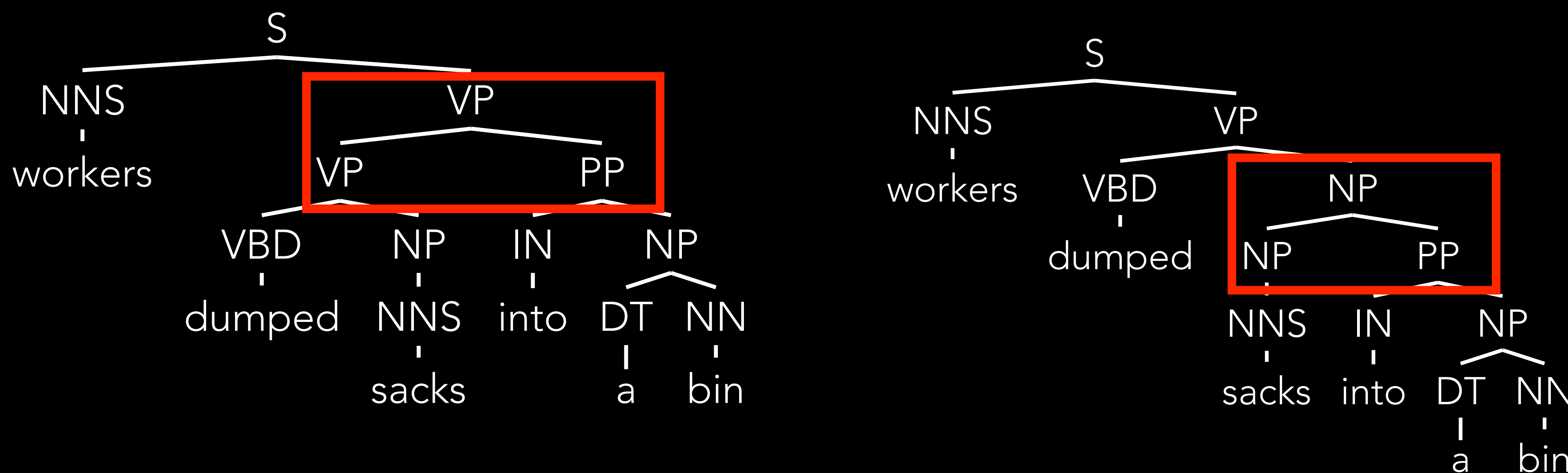

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If p(VP -> VP PP) > p(NP -> NP PP) then
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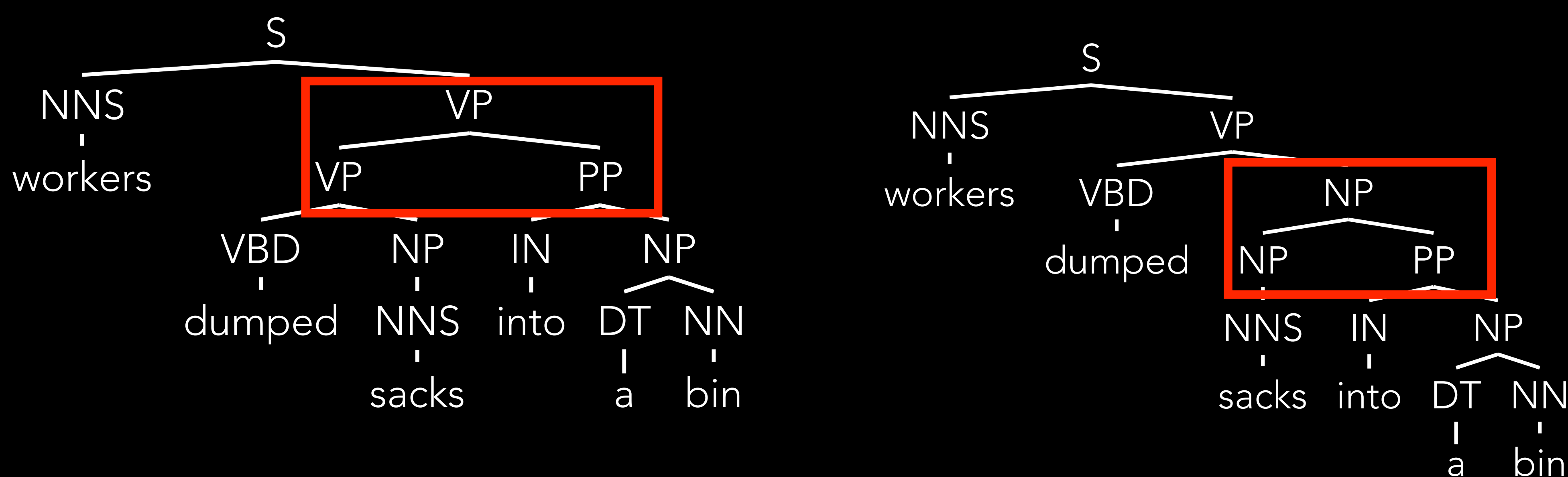

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If p(VP -> VP PP) > p(NP -> NP PP) then
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The words (particularly “into”) are not considered. PPs with “into” are much more likely to attach to VP than NP.

Head lexicalization

Head lexicalization

Annotate tree labels with their “head” word

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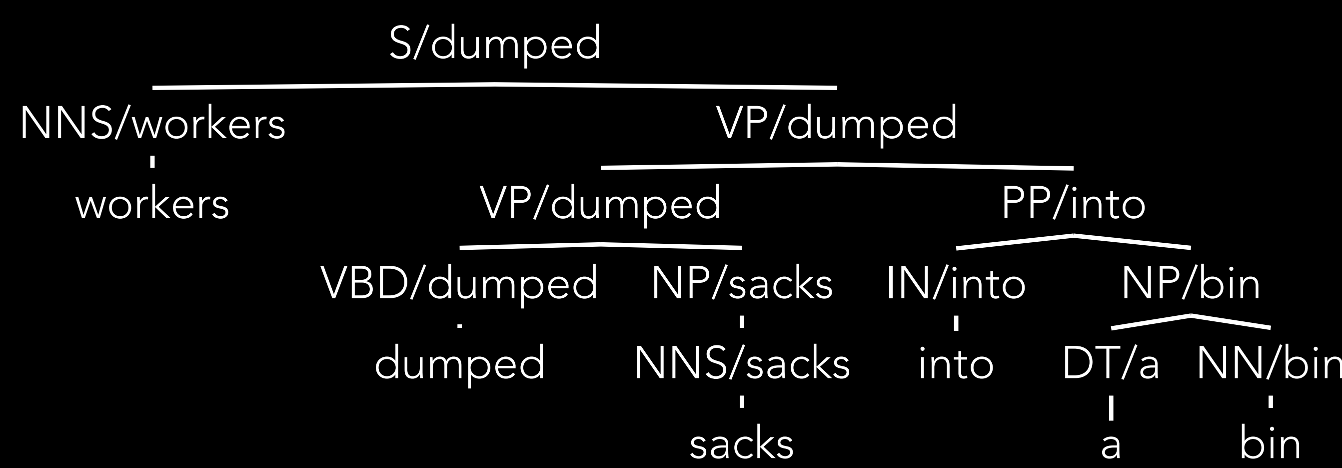

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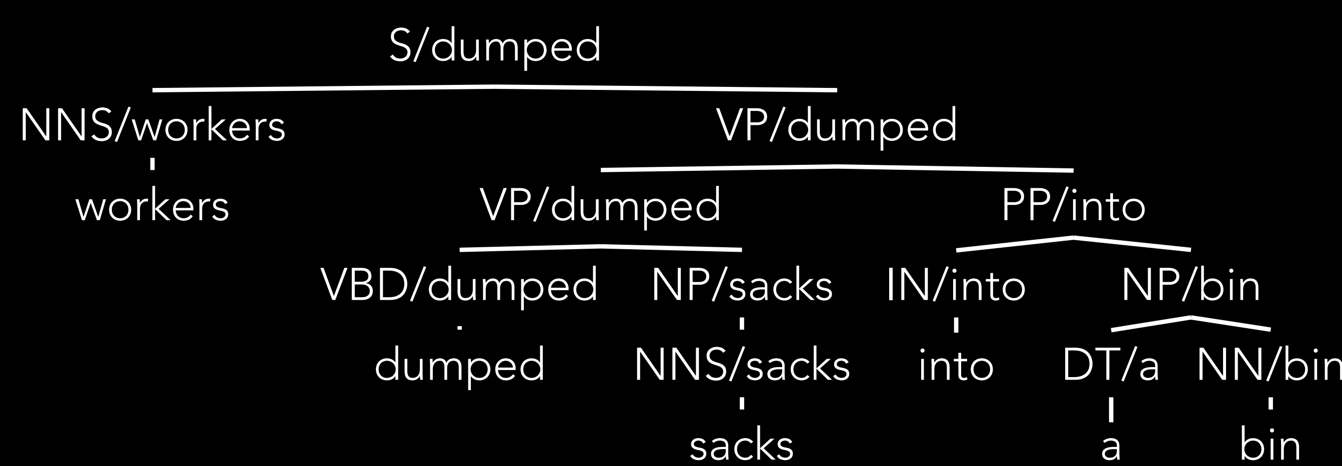

Heads are the “important” word in a phrase

Head lexicalization

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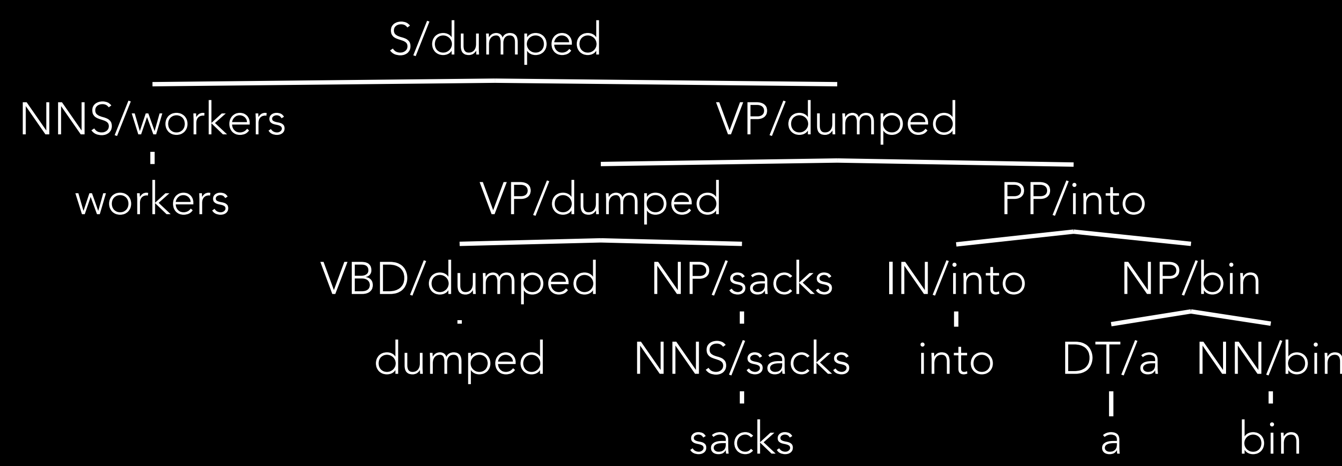

Heads are the "important" word in a phrase

They could be provided by annotators

Head lexicalization

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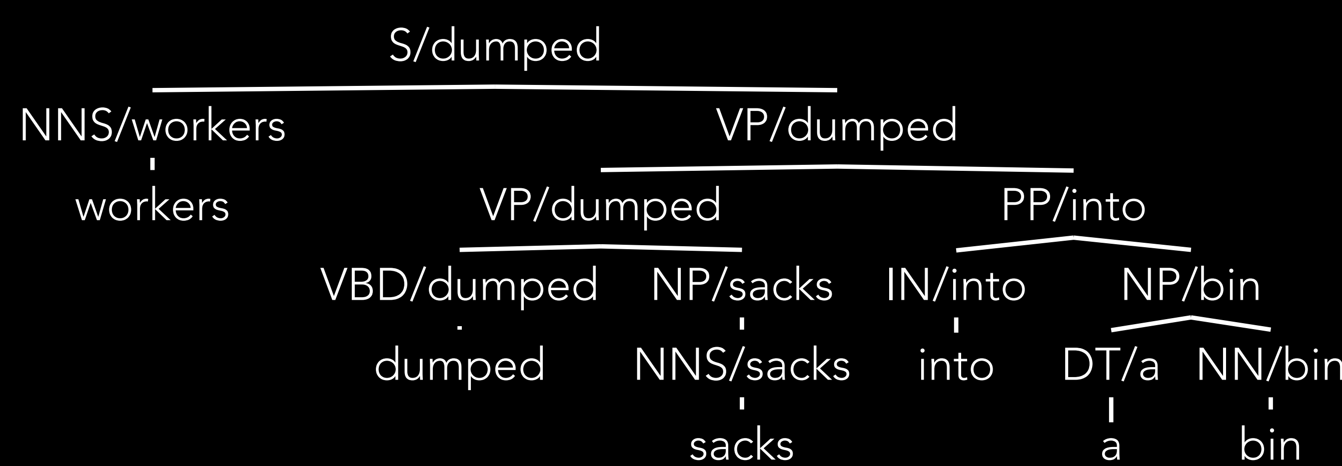

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In practice, for English, some heuristics work well

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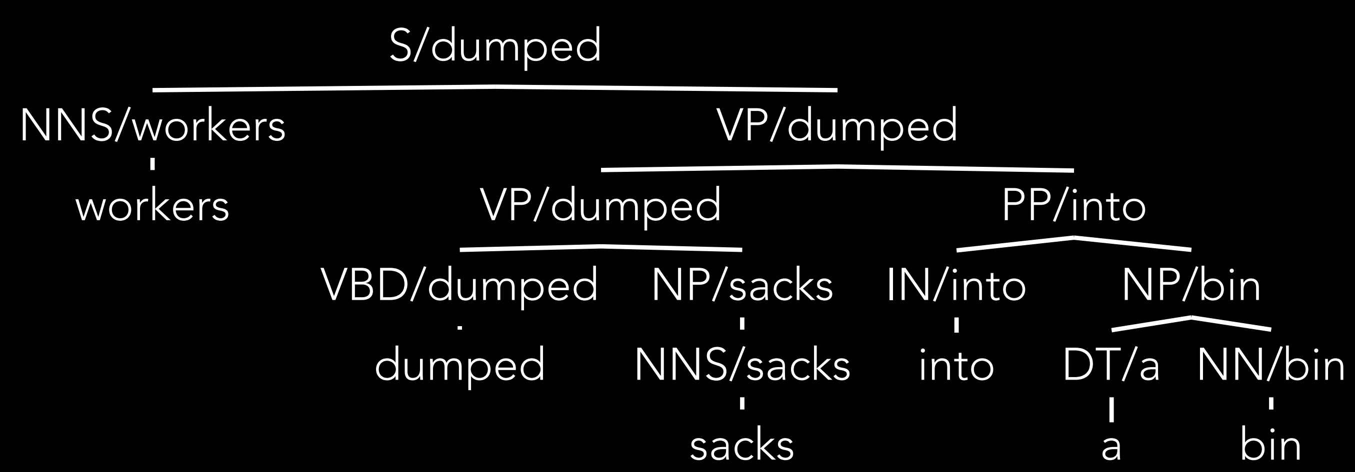

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http://www.cs.columbia.edu/~mcollins/papers/heads

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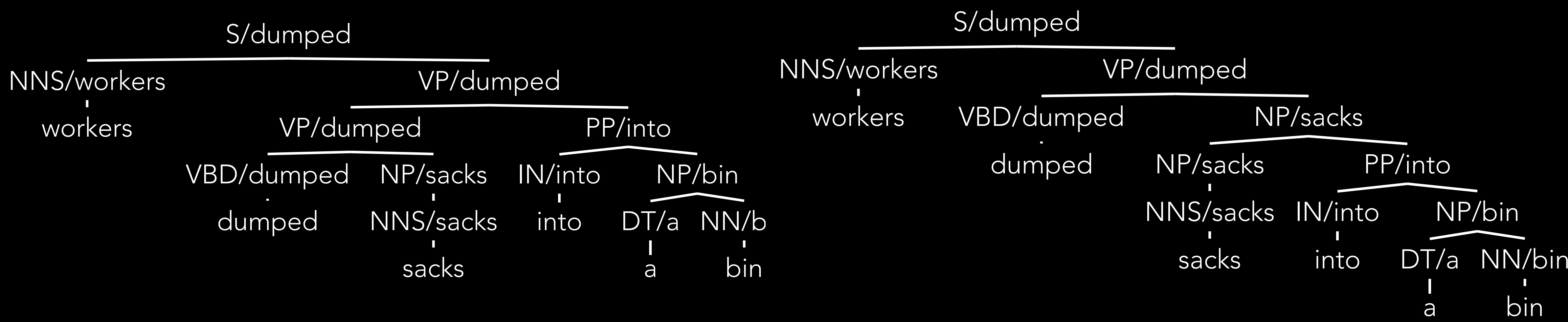

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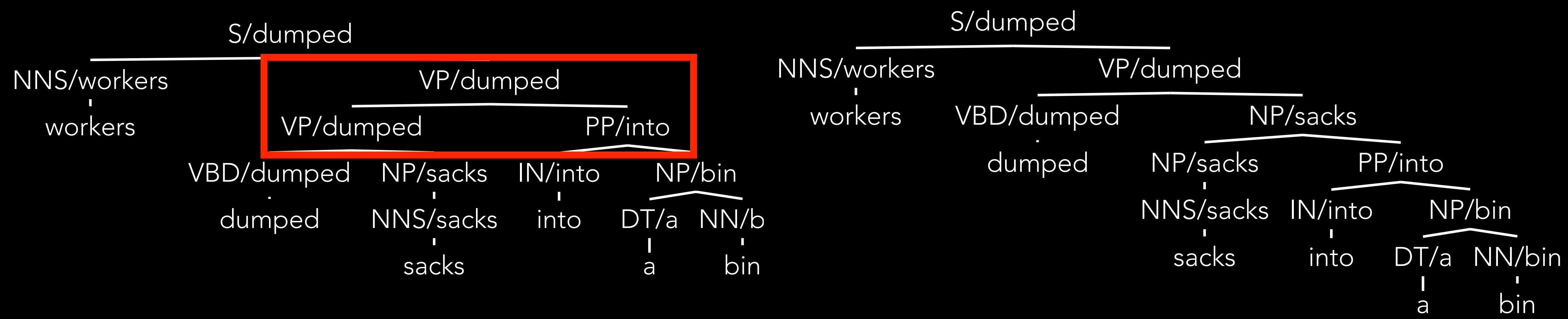
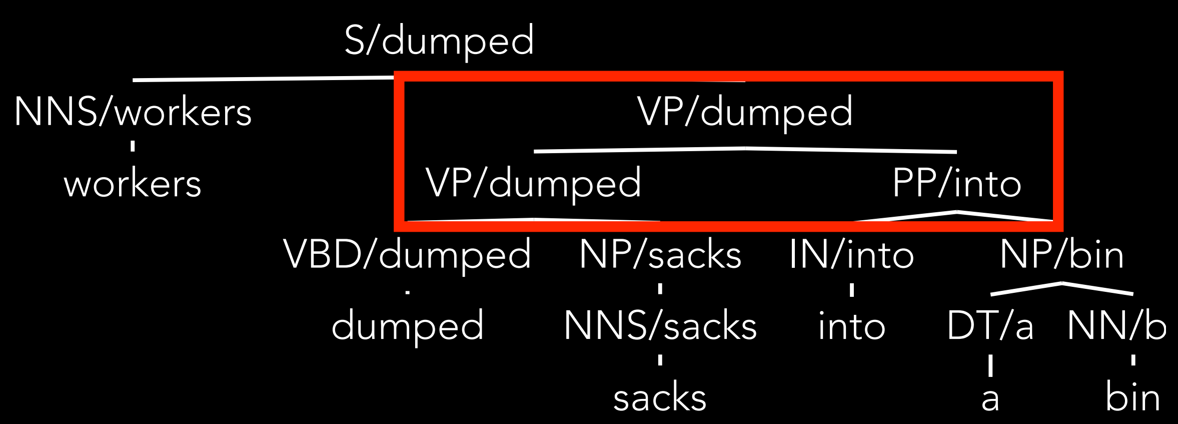
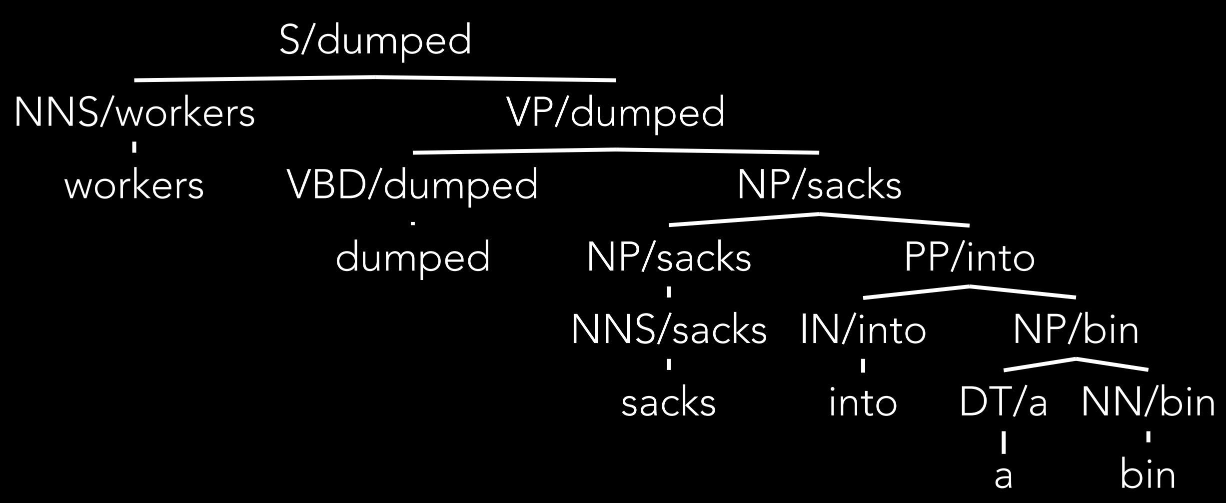


VP/dumped -> VP/dumped PP/into

Head lexicalization





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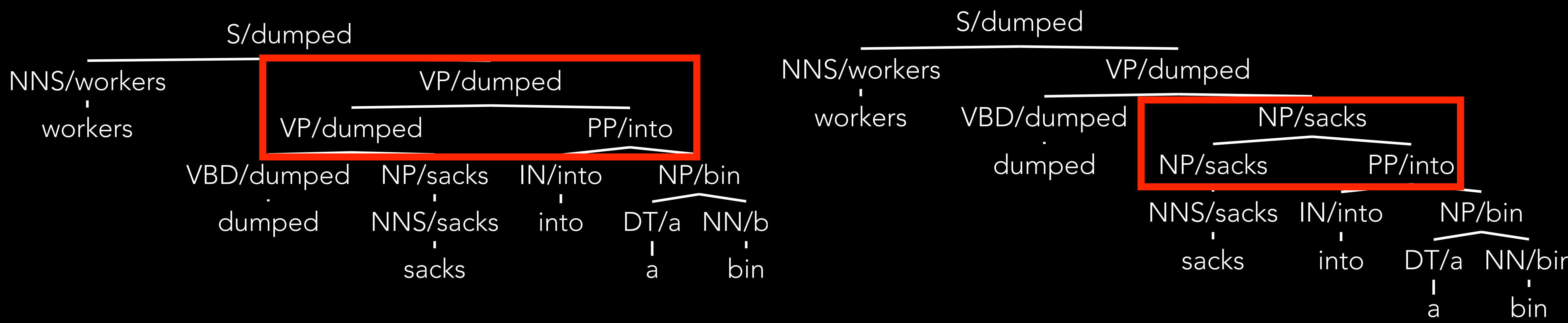
more likely than

Head lexicalization



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NP/sacks-> NP/sacks PP/into

Lexicalization and Binarization

Lexicalization and Binarization

- Want to keep meaningful head at every point

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- Want to keep meaningful head at every point
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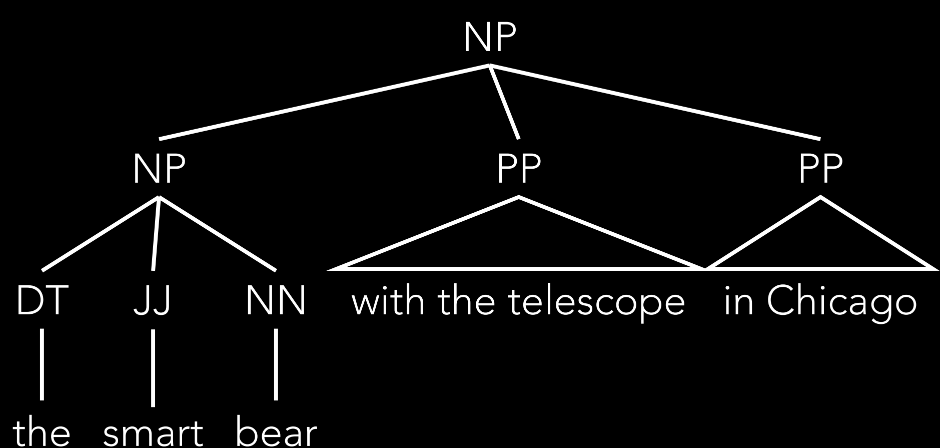

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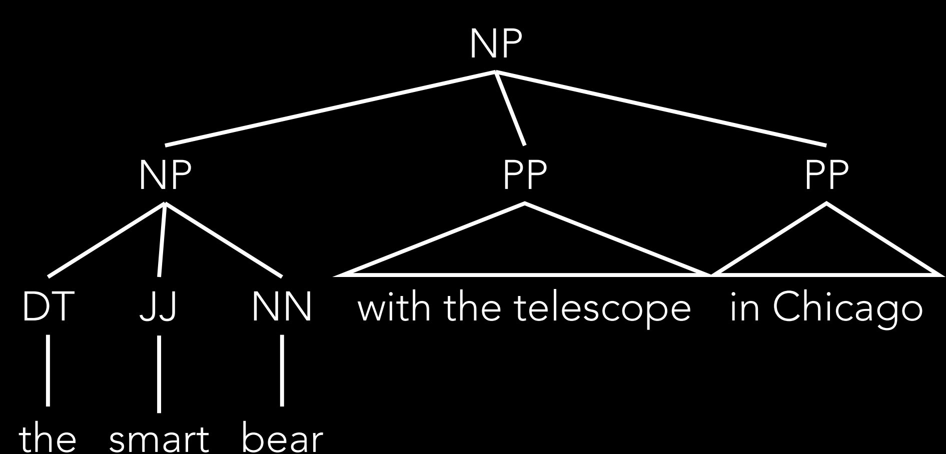

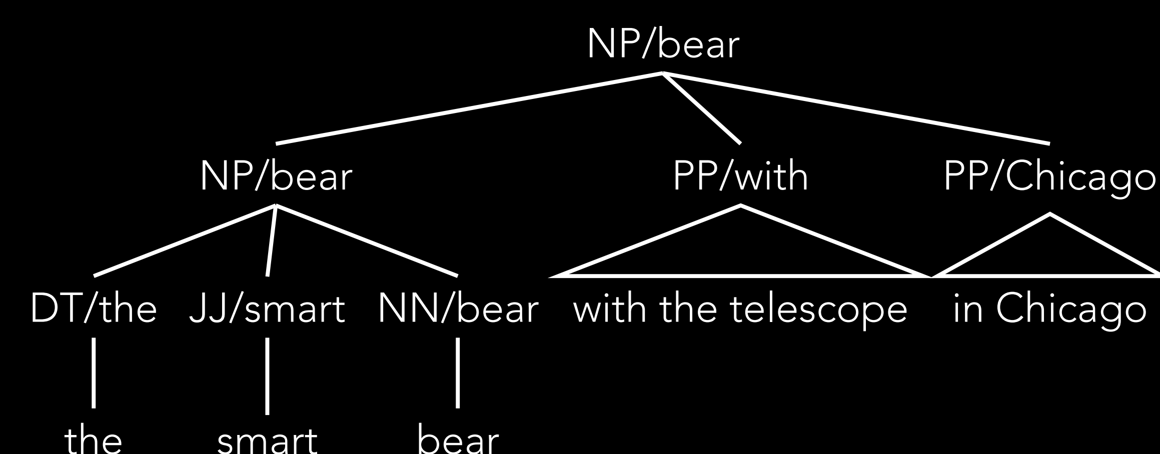

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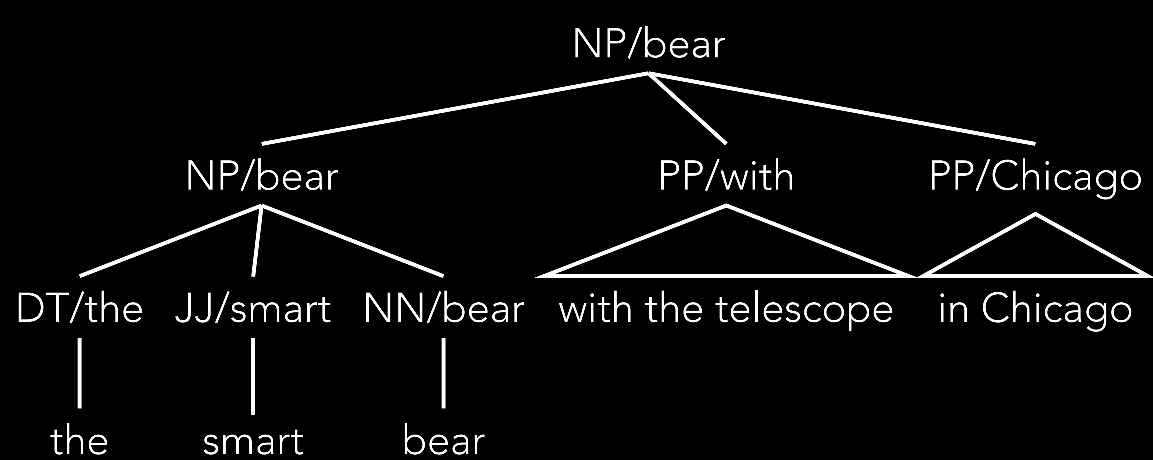

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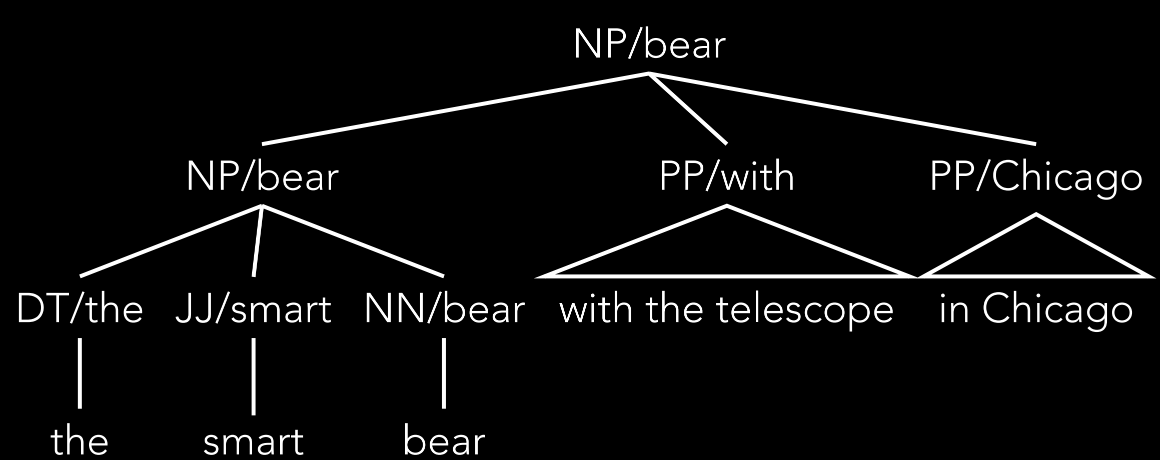

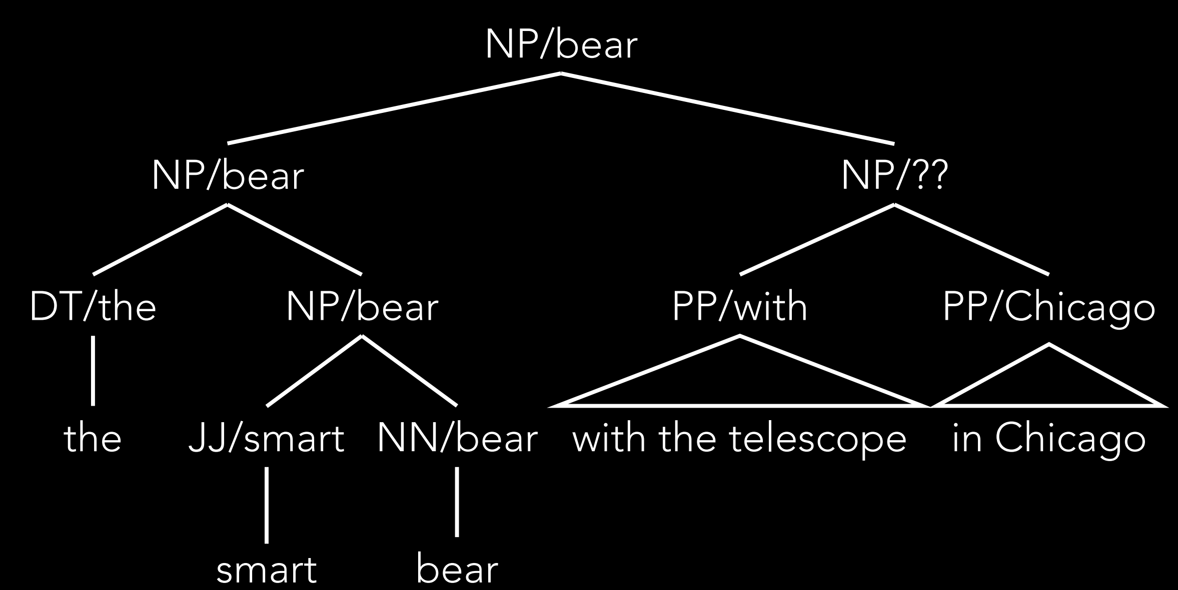

Right binarization

Lexicalization and Binarization

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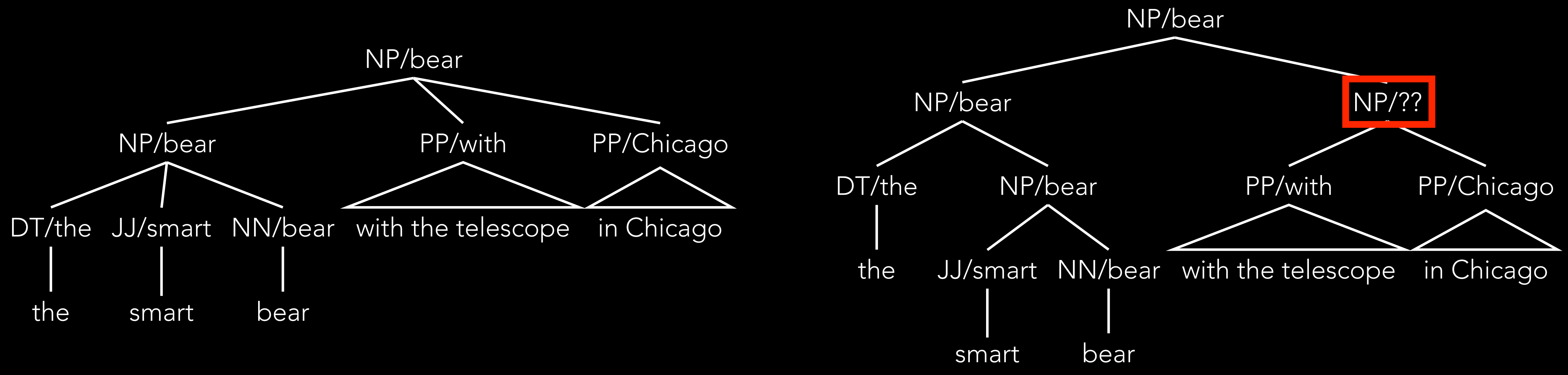

Right binarization

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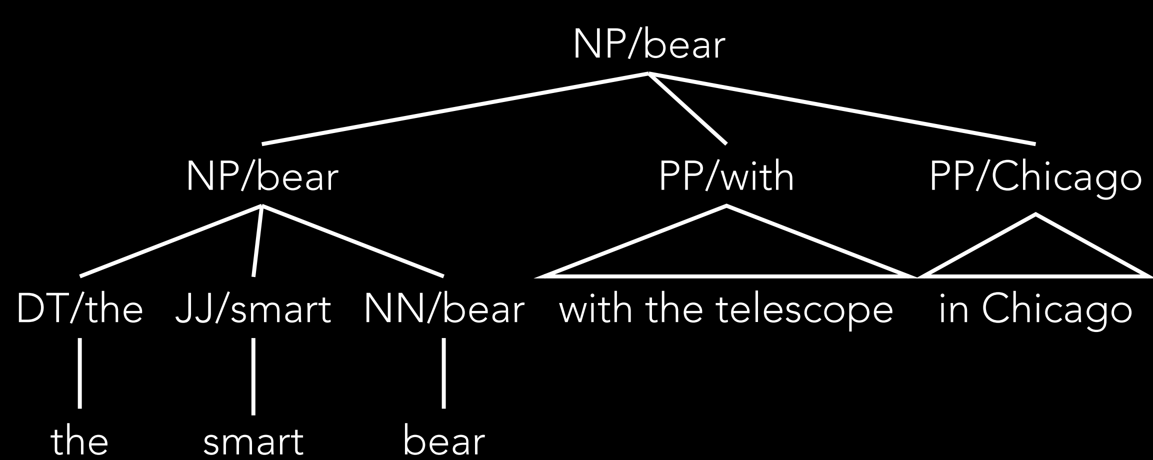

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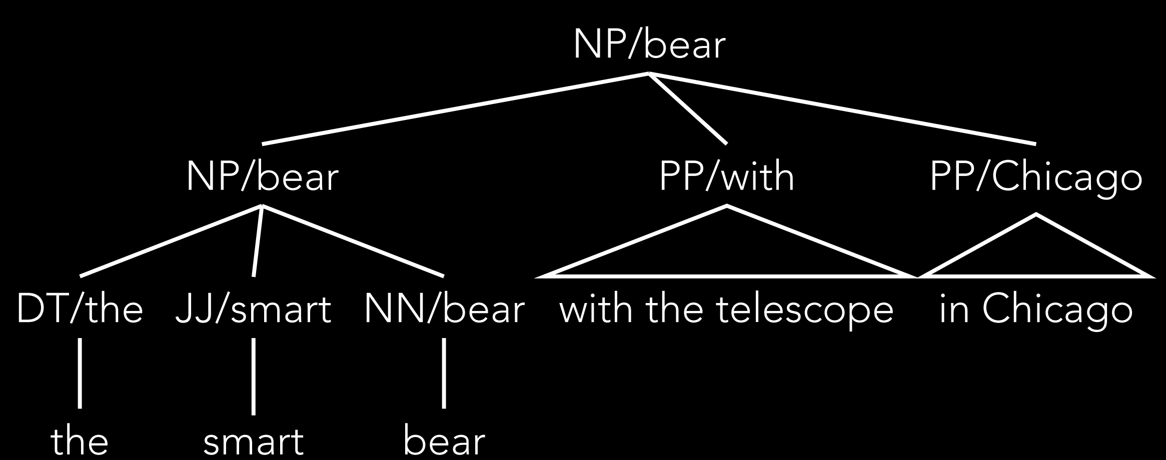

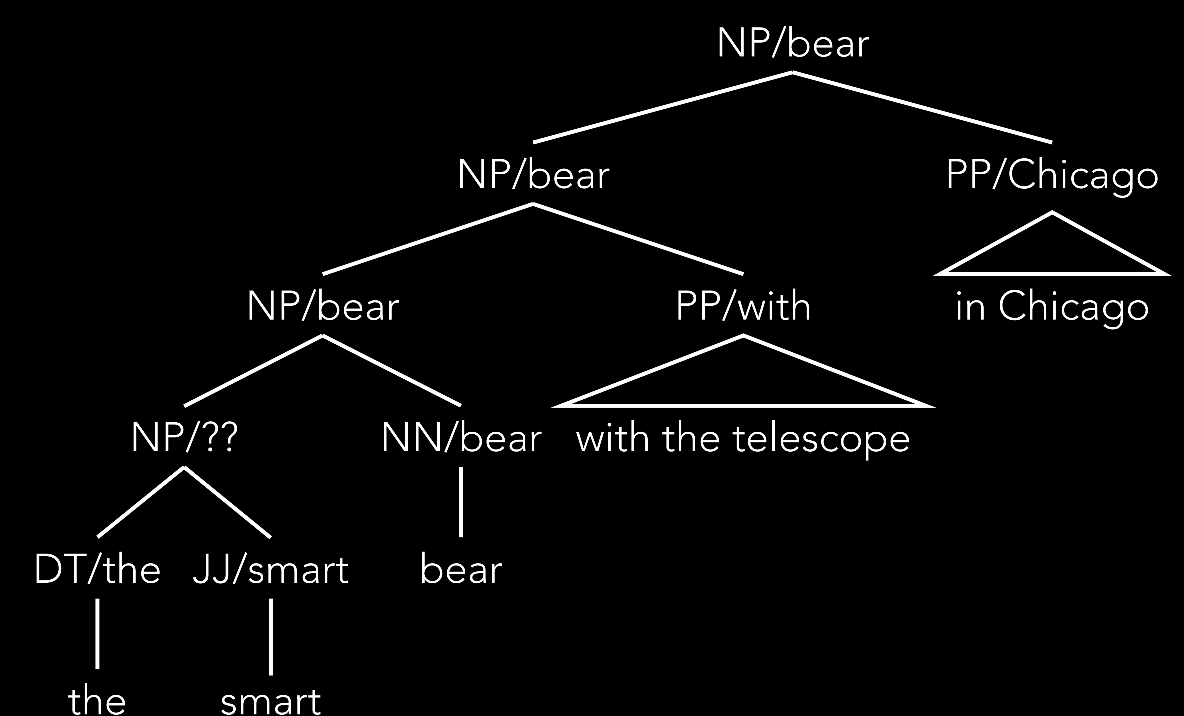

Left binarization

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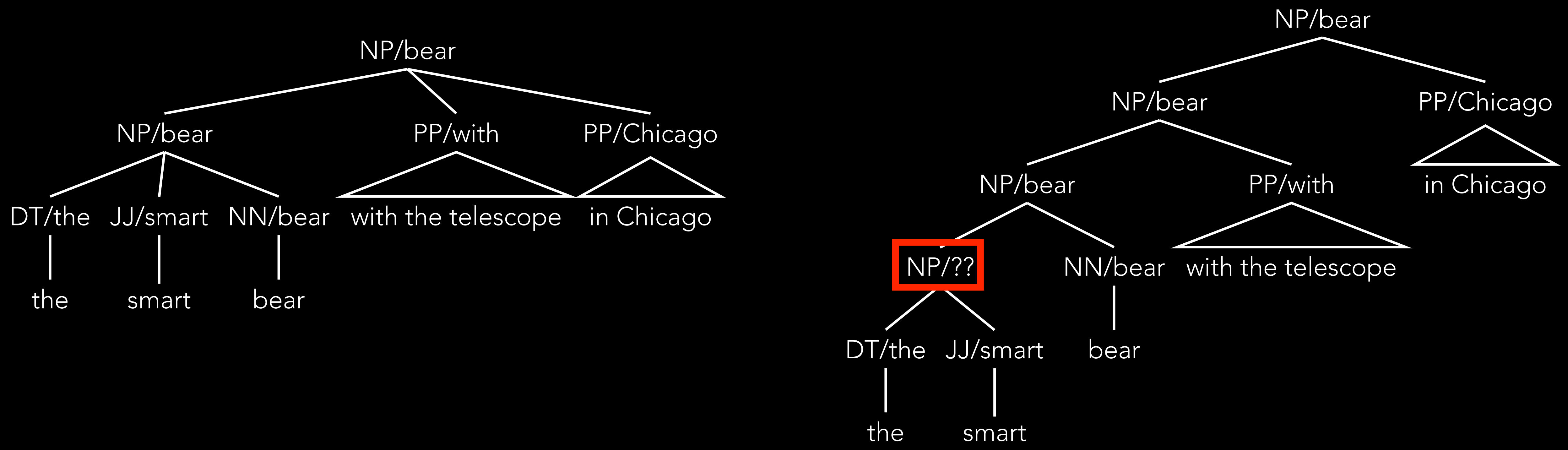

Left binarization

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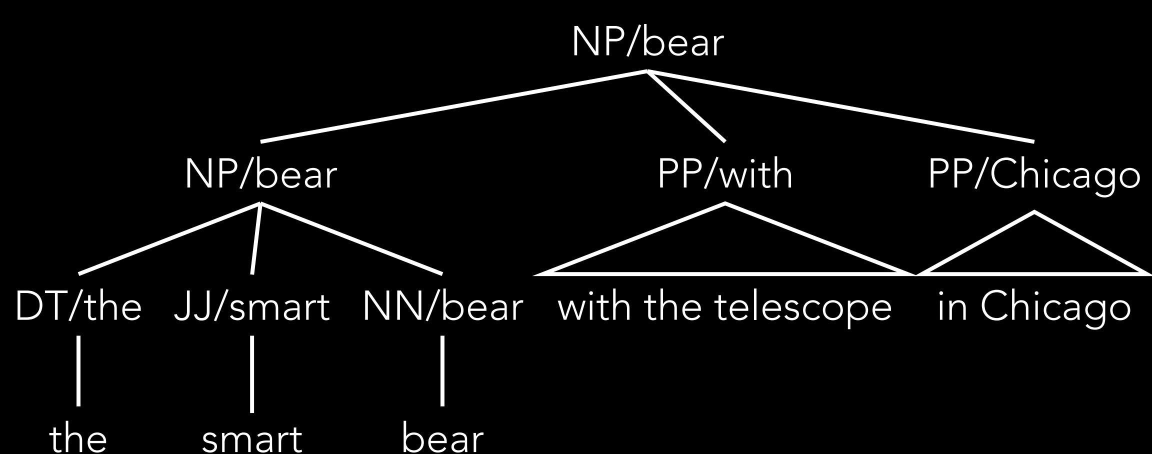

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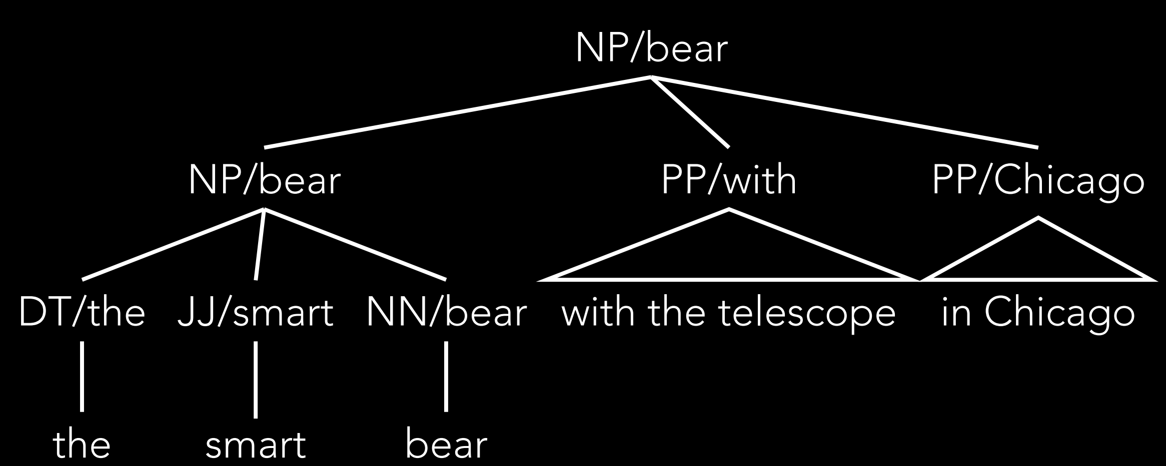

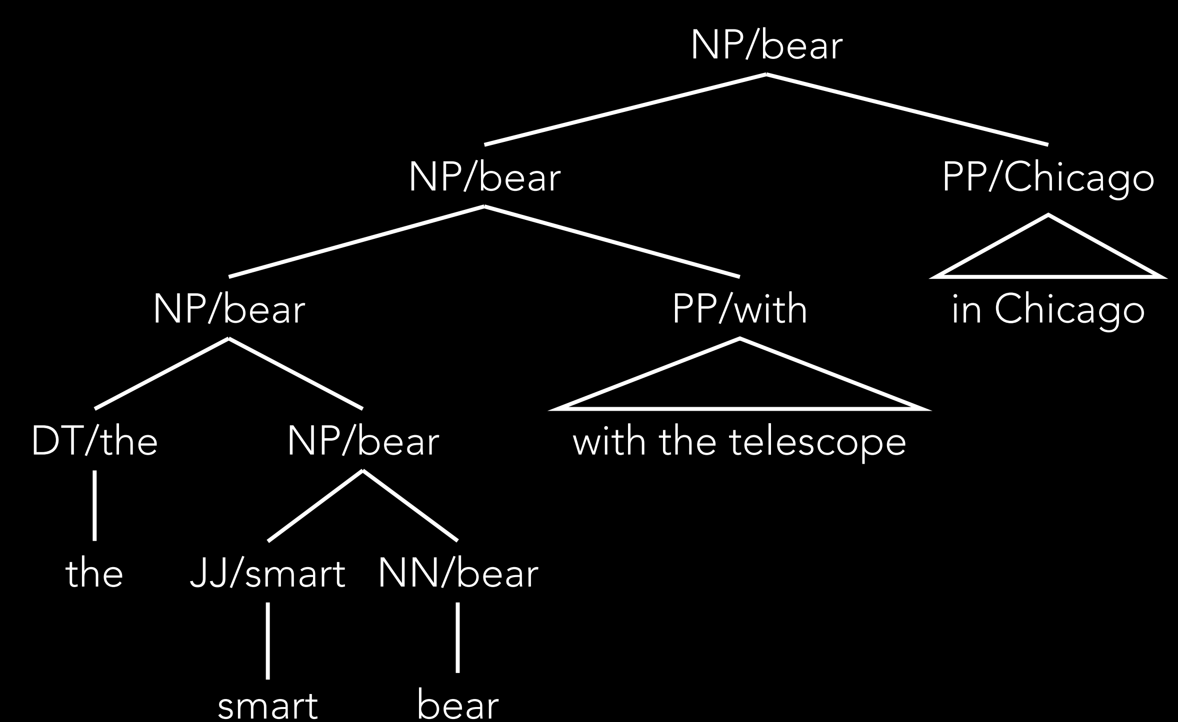

Head binarization!

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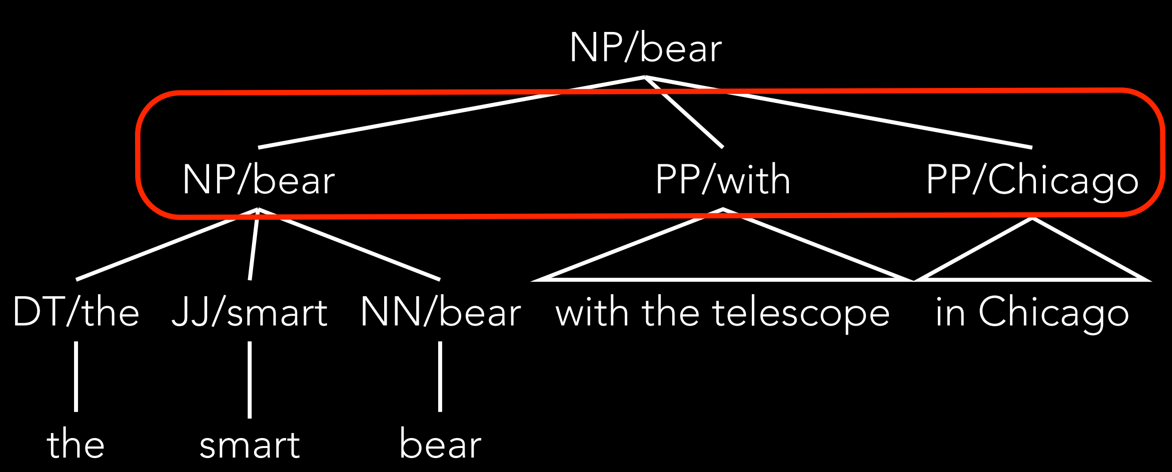
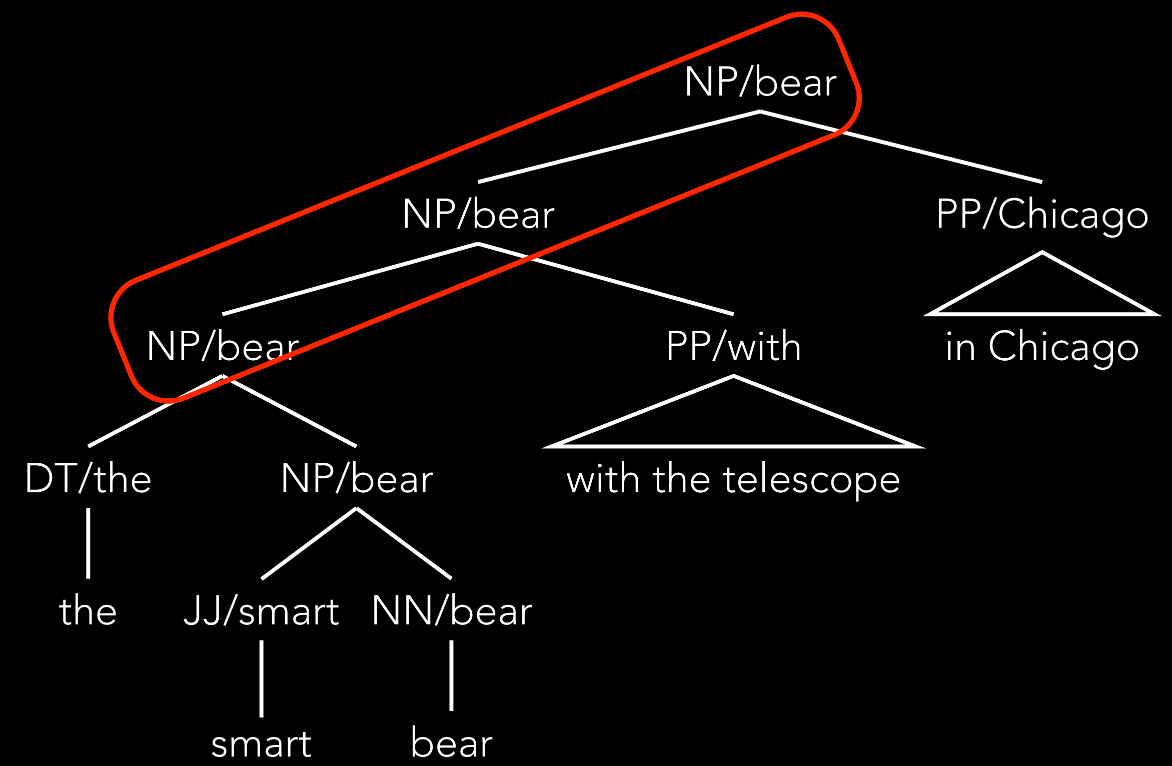


Left (for NP PP PP)



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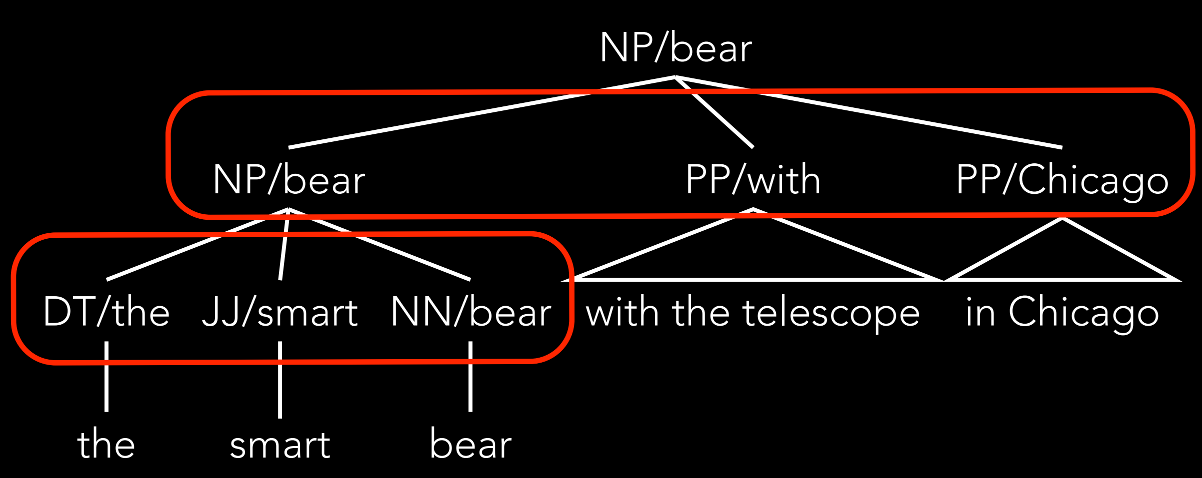
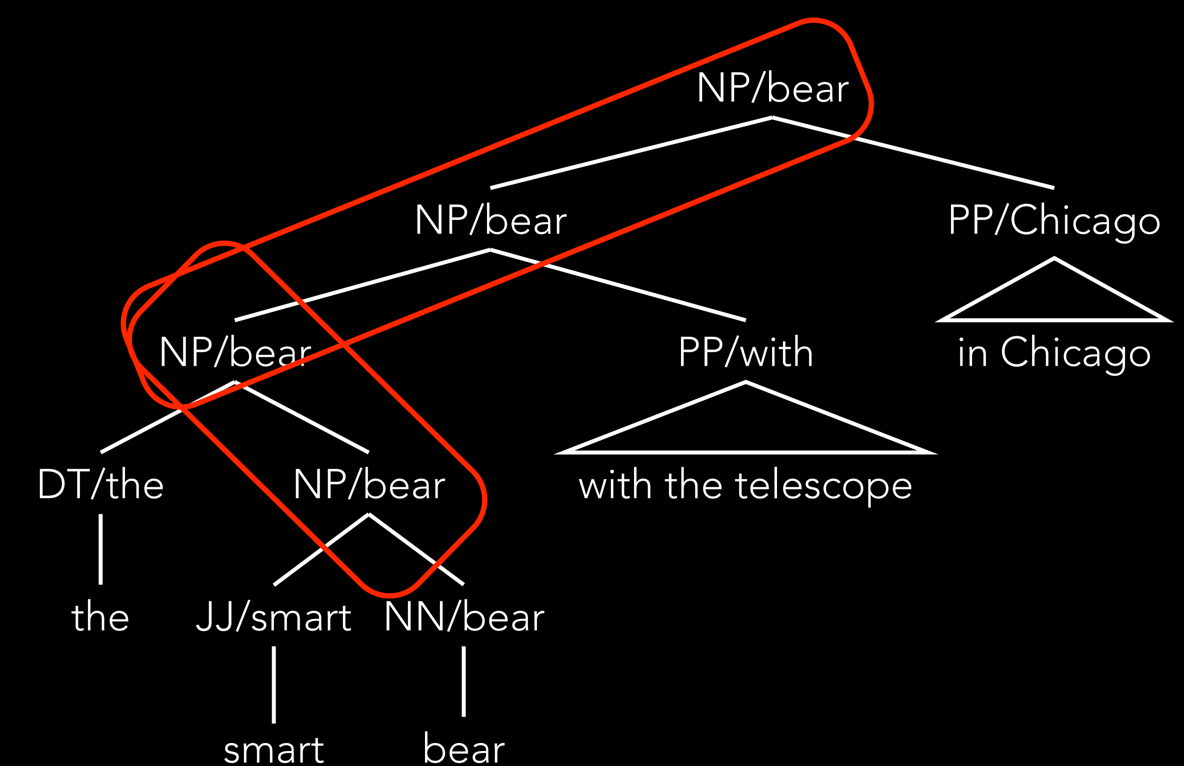


Left (for NP PP PP)

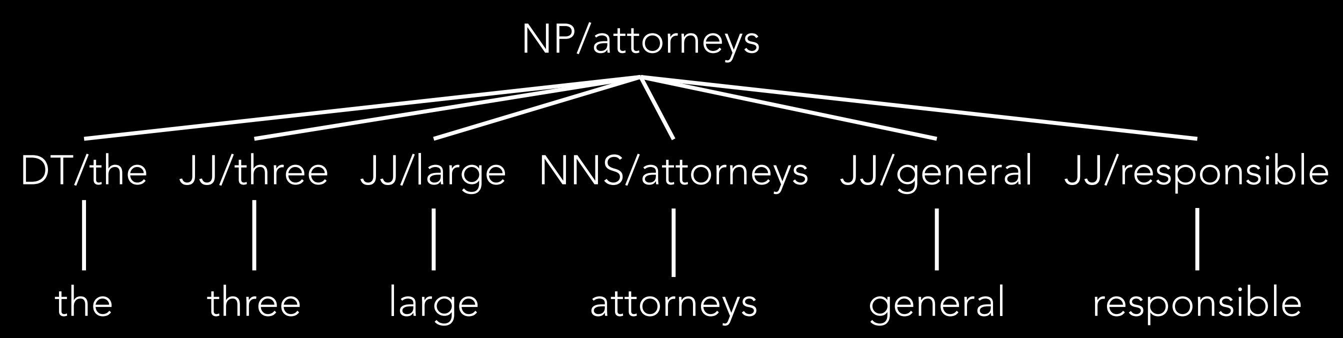
Right (for DT JJ NN)



Head binarization!

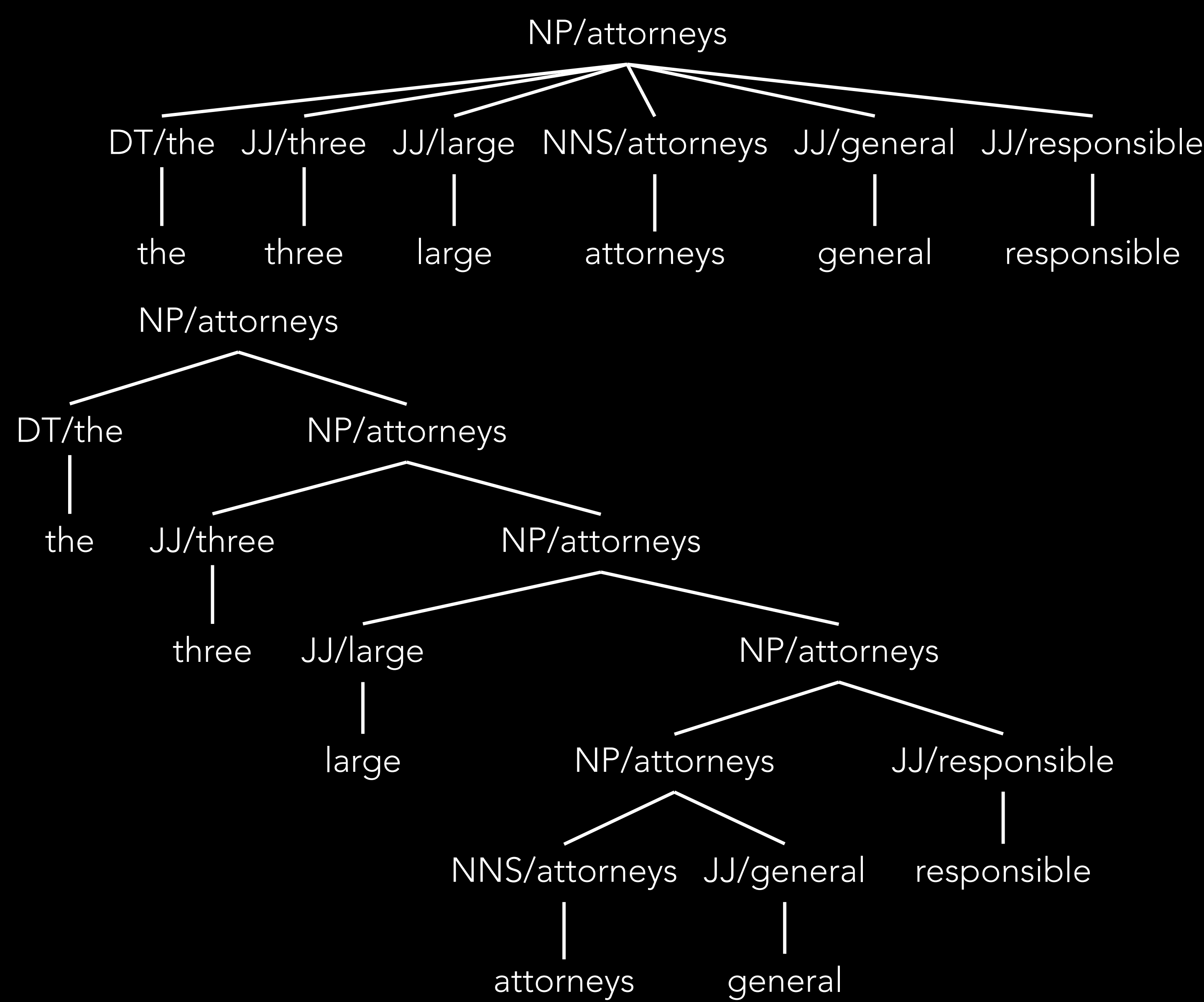
Lexicalization and Binarization

More complicated example



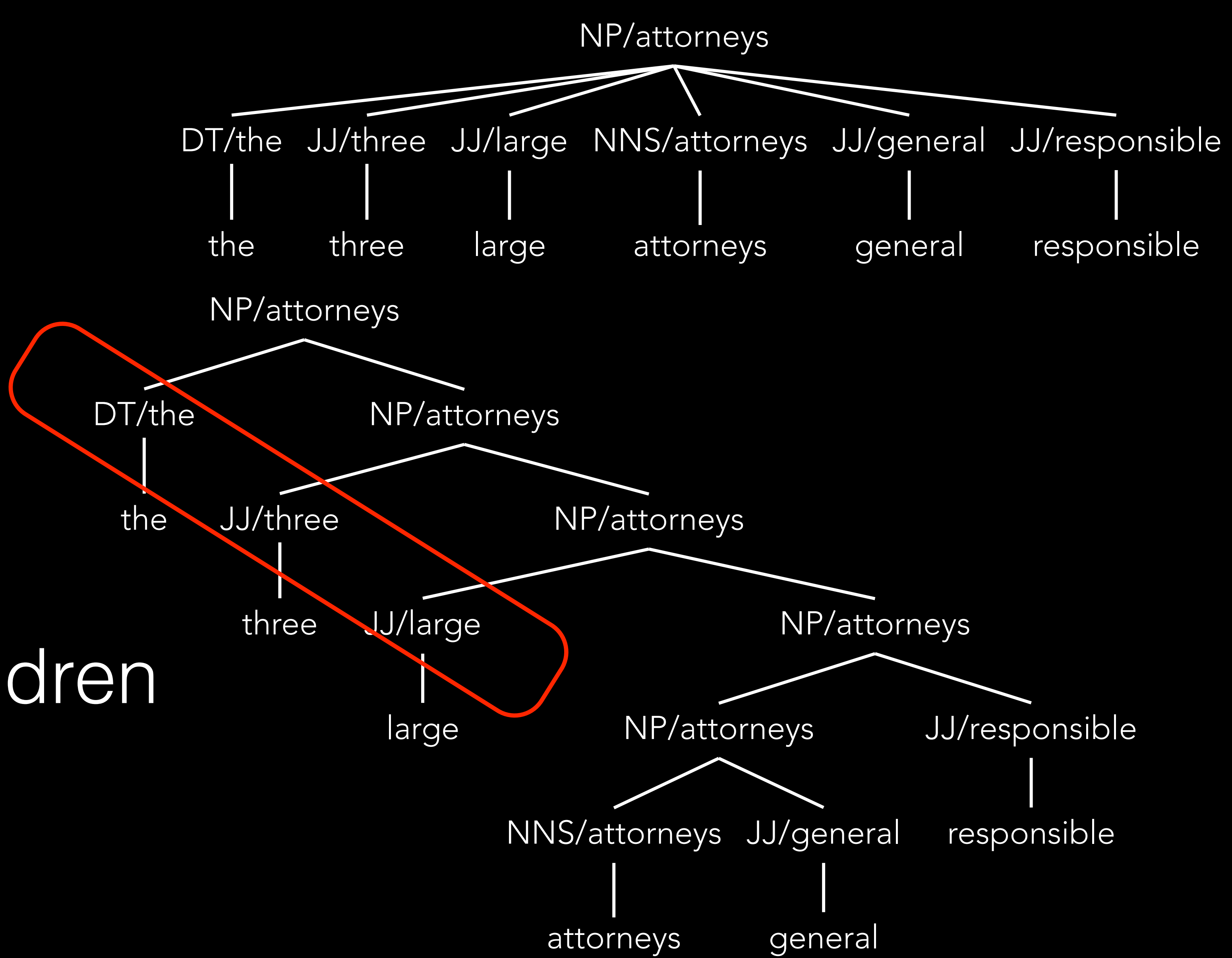
Lexicalization and Binarization

More complicated example



Lexicalization and Binarization

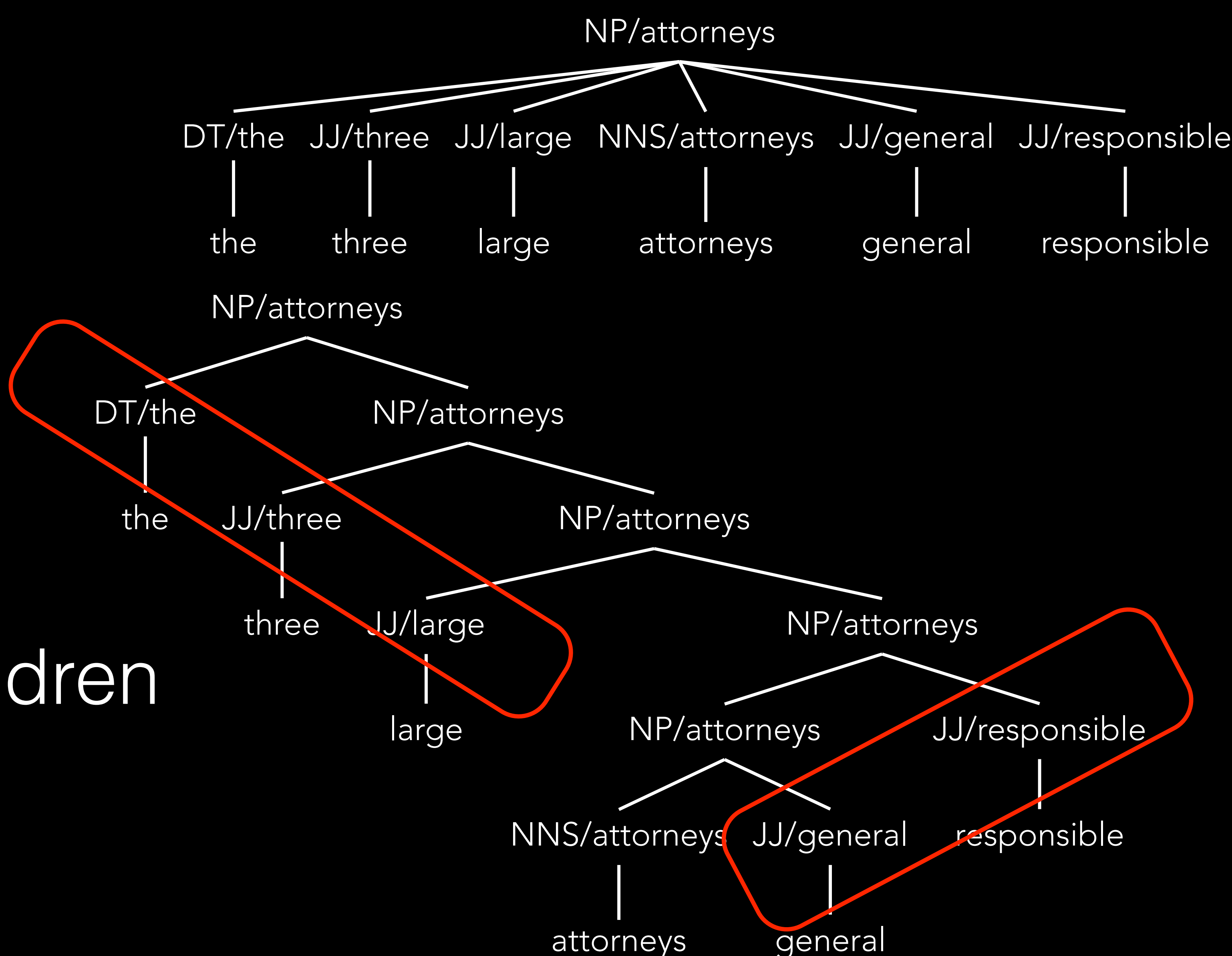
More complicated example



Left children

Lexicalization and Binarization

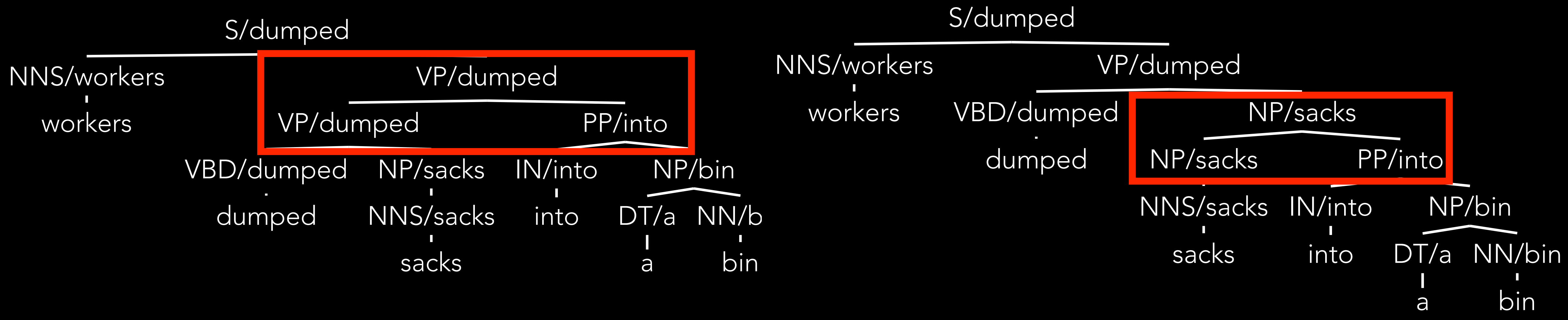
More complicated example



Left children

Right children

Head lexicalization

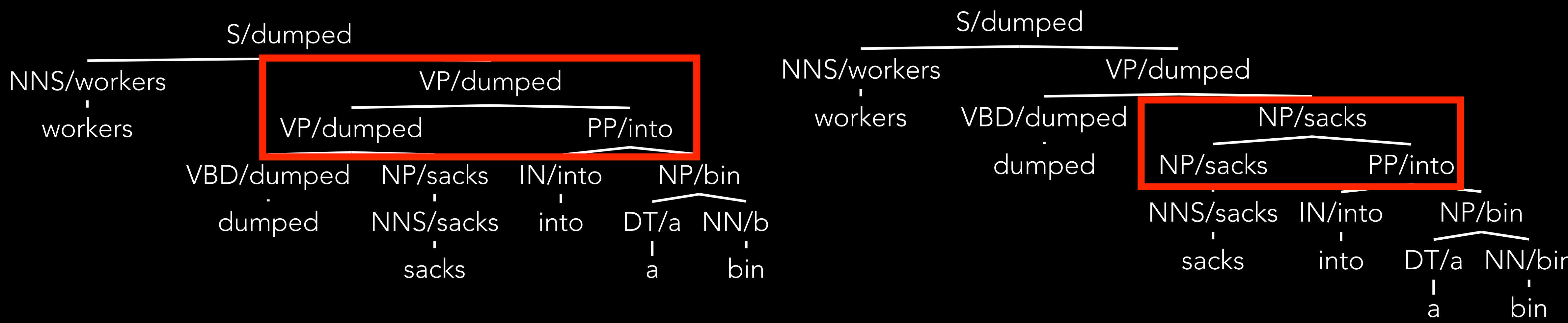


VP/dumped -> VP/dumped PP/into

more likely than

NP/sacks-> NP/sacks PP/into

Head lexicalization



VP/dumped -> VP/dumped PP/into

more likely than

NP/sacks-> NP/sacks PP/into

But now our parameter space is getting very large and our estimates are going to be very poor!

Head lexicalization

Head lexicalization

If your training data is

Head lexicalization

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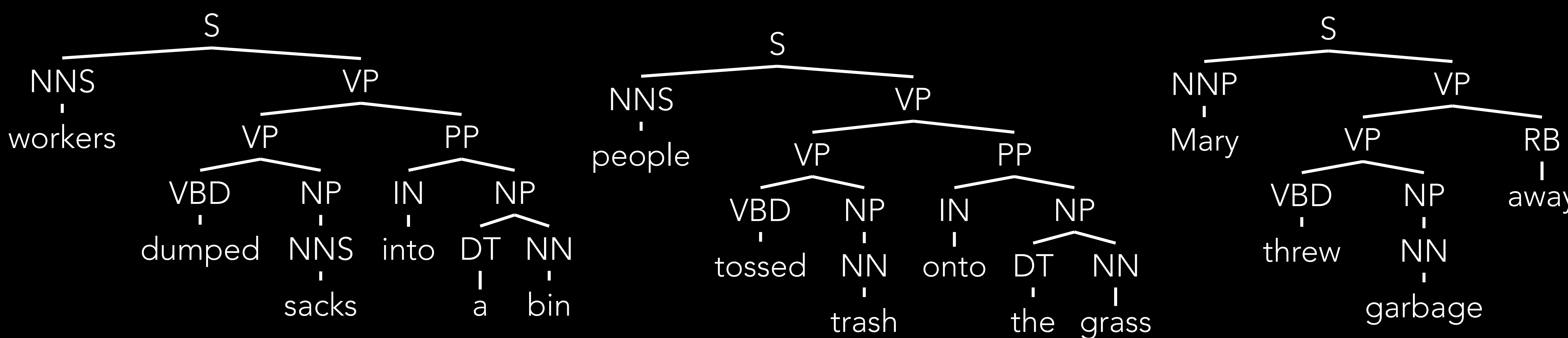

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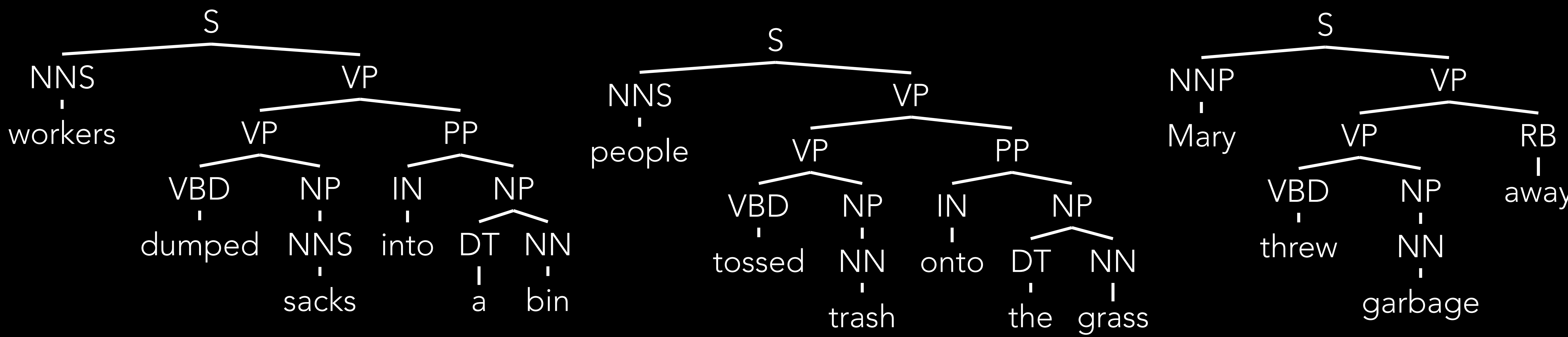

And you want to parse

Head lexicalization

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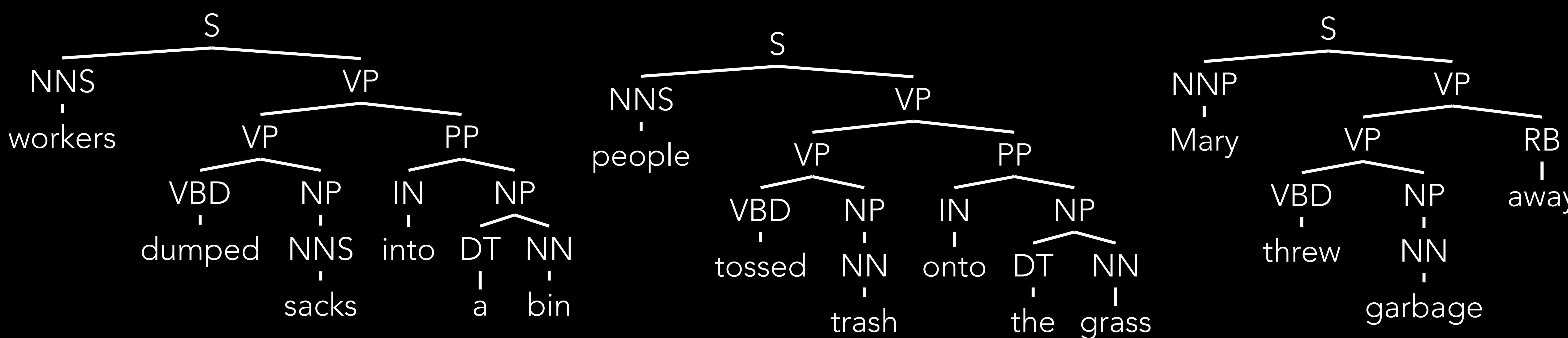

And you want to parse

workers threw trash
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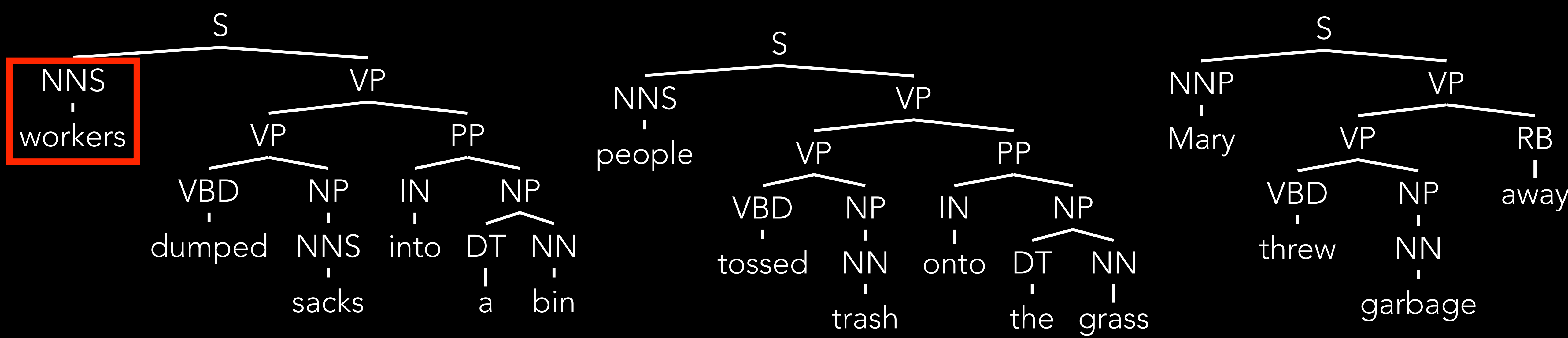

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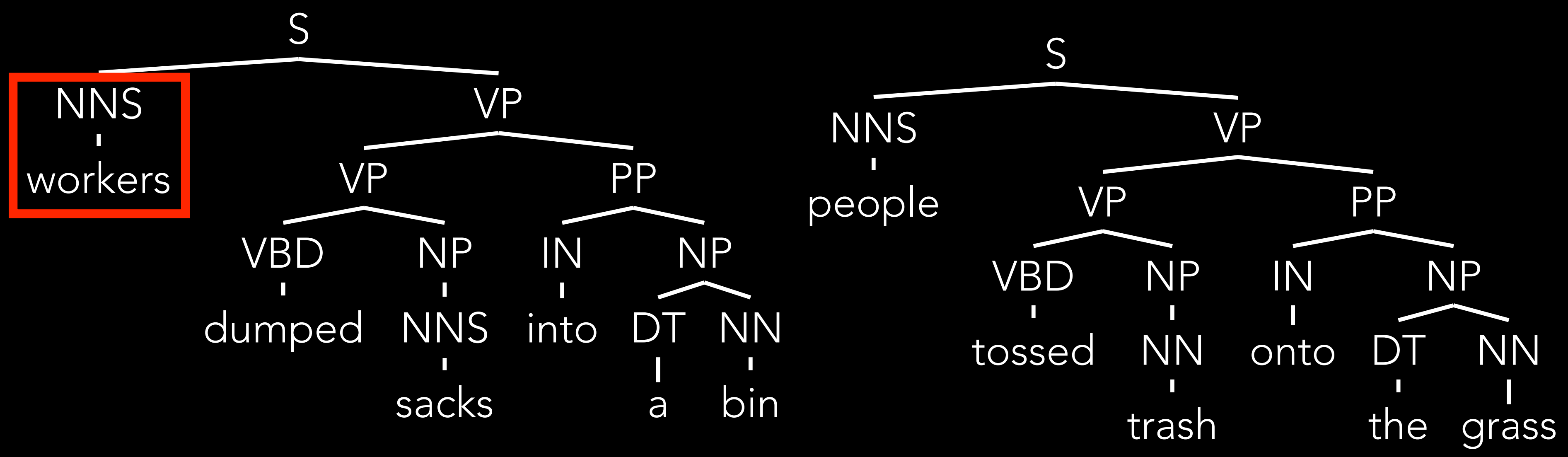

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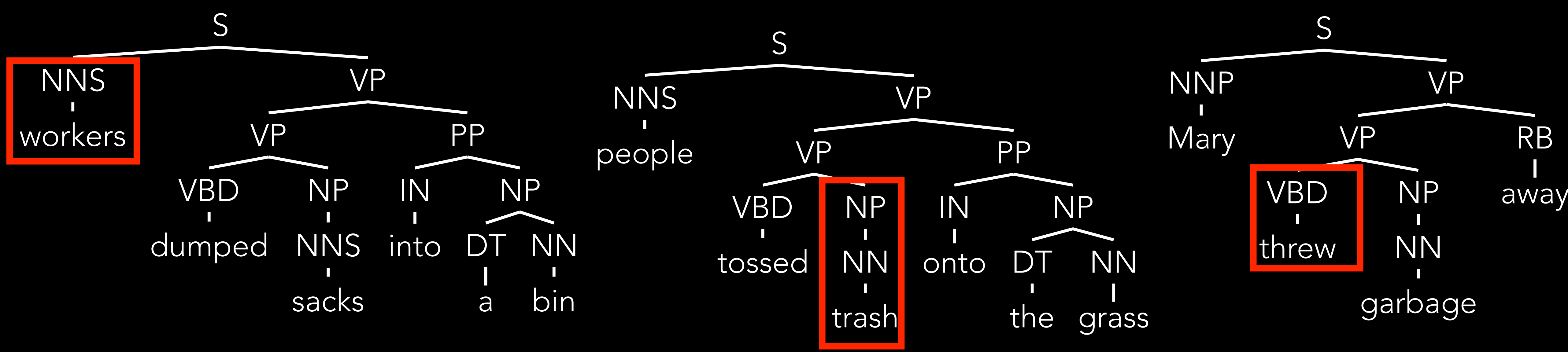

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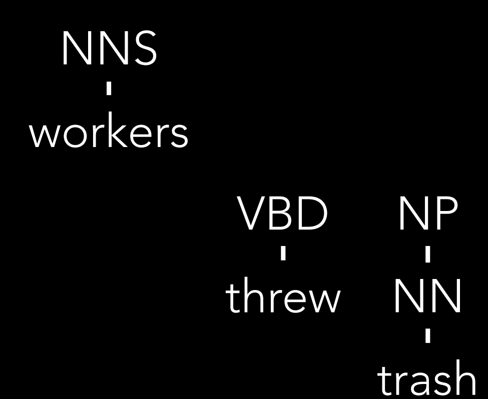

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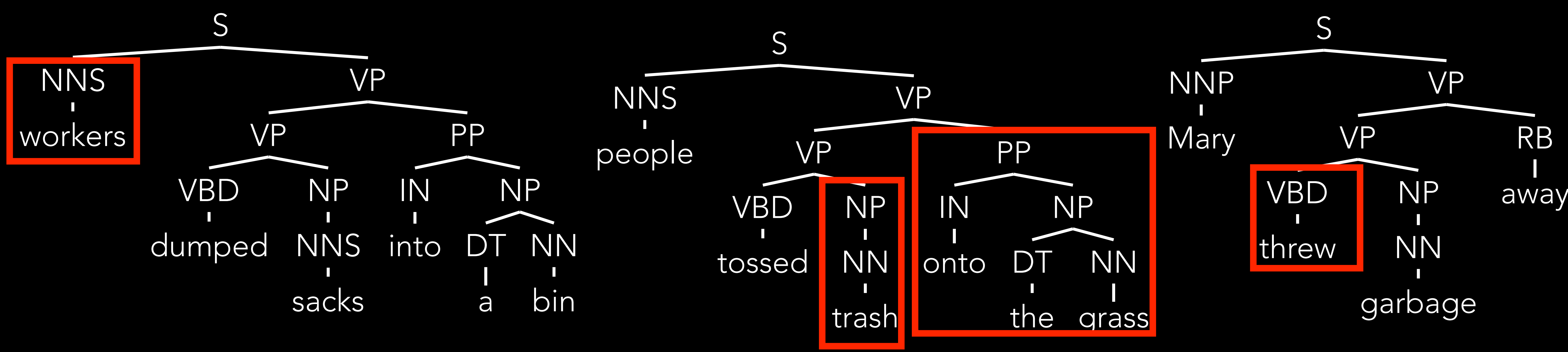

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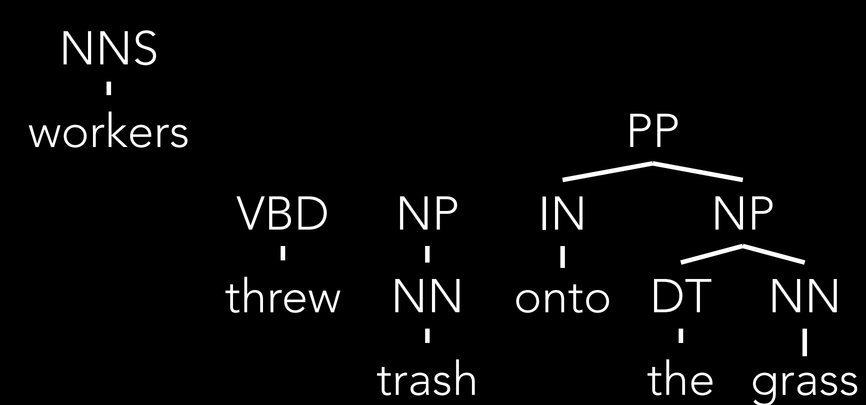

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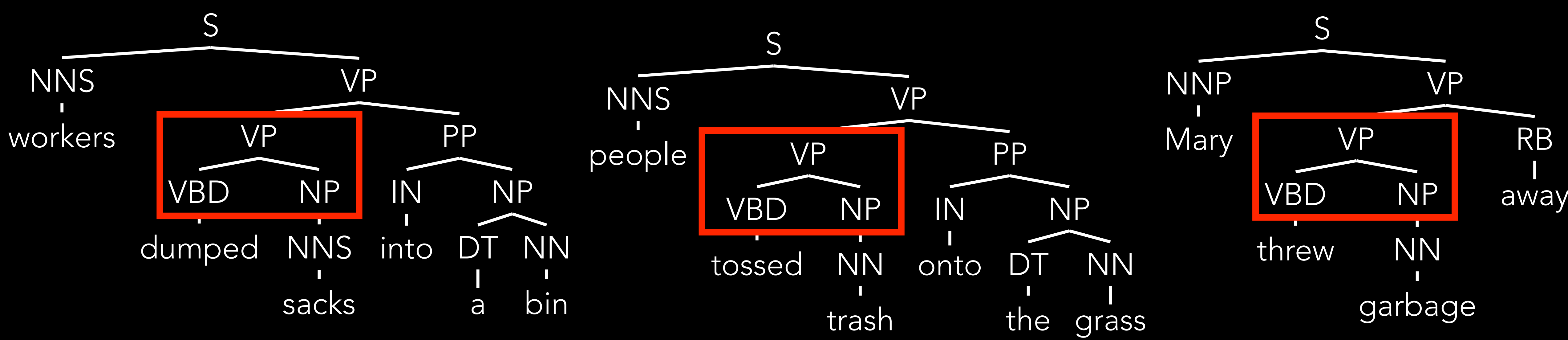

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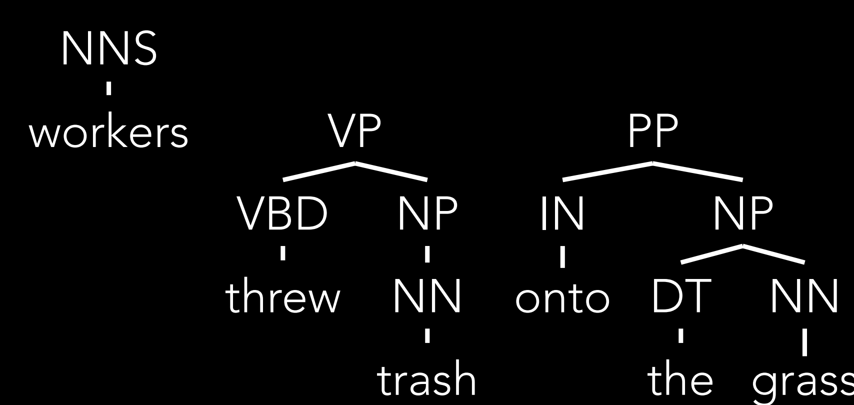

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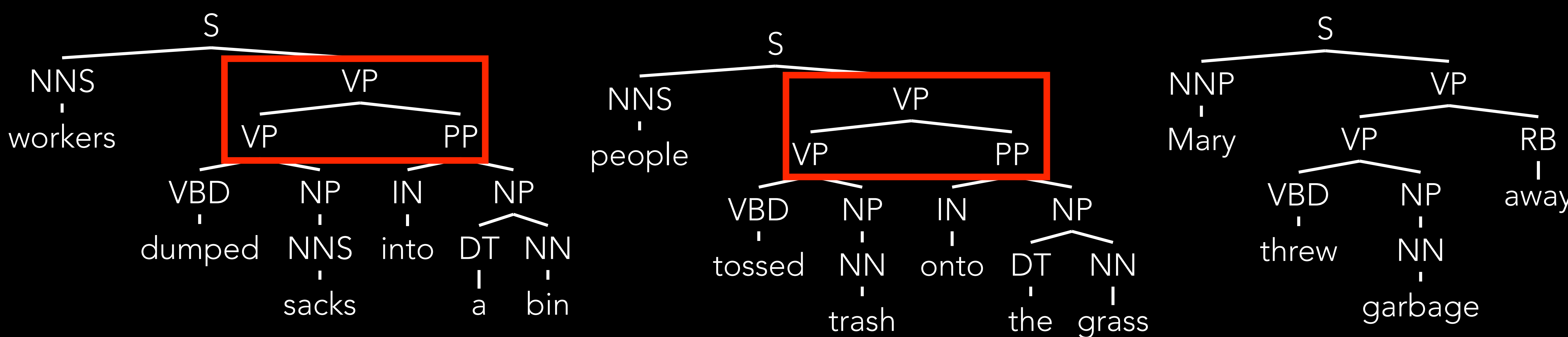

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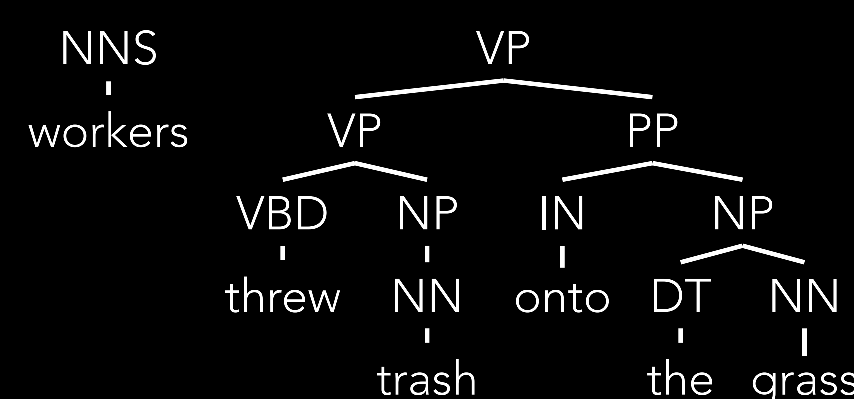

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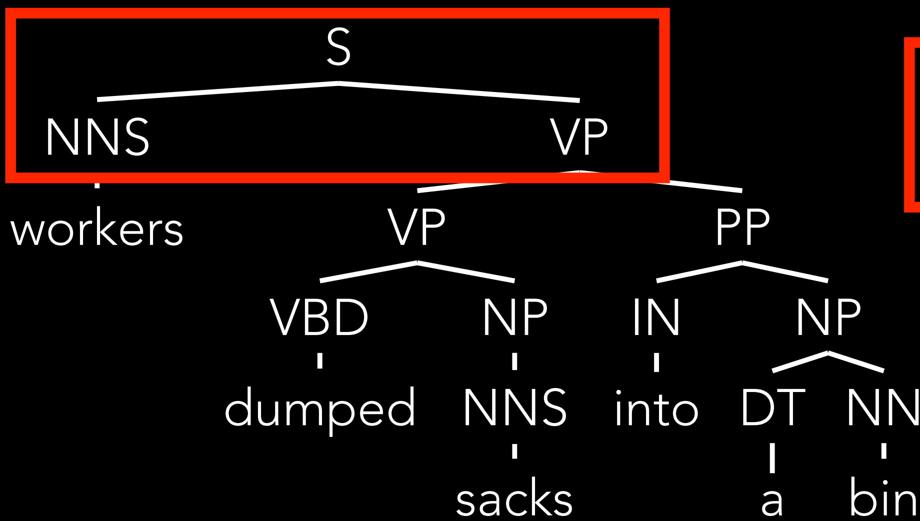

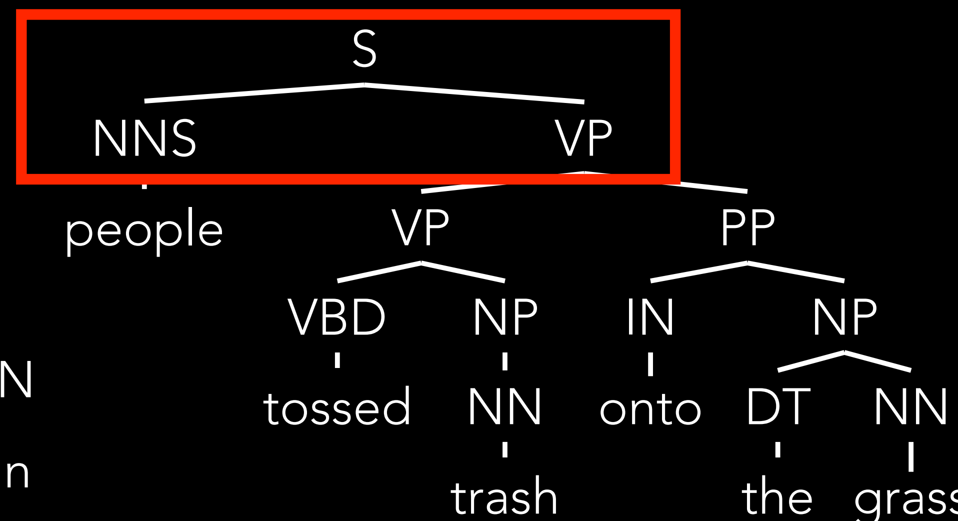

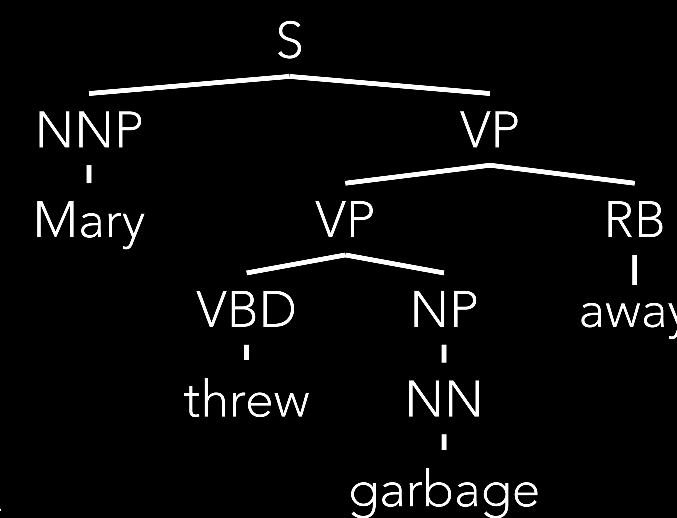

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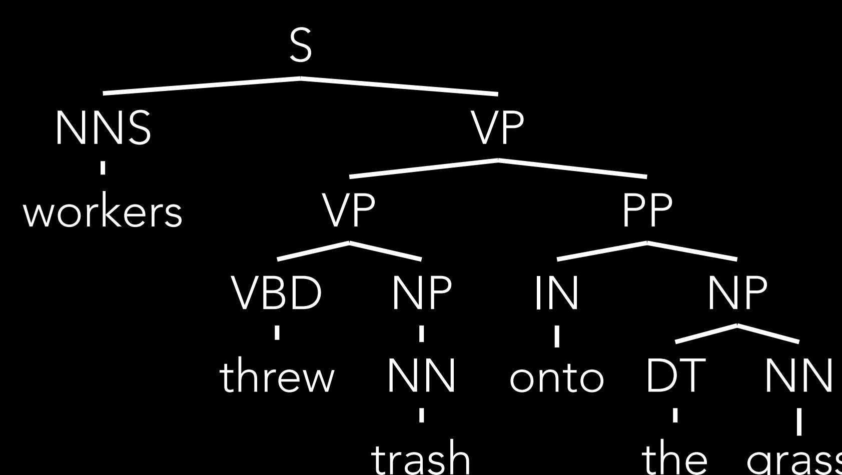
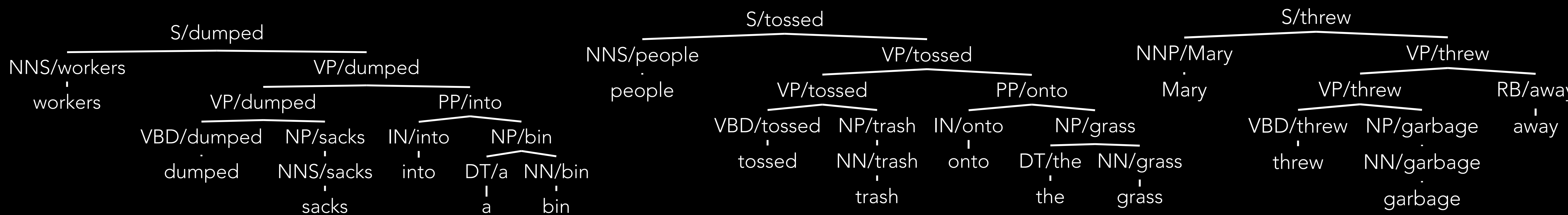


You can!

Head lexicalization

But if we lexicalize



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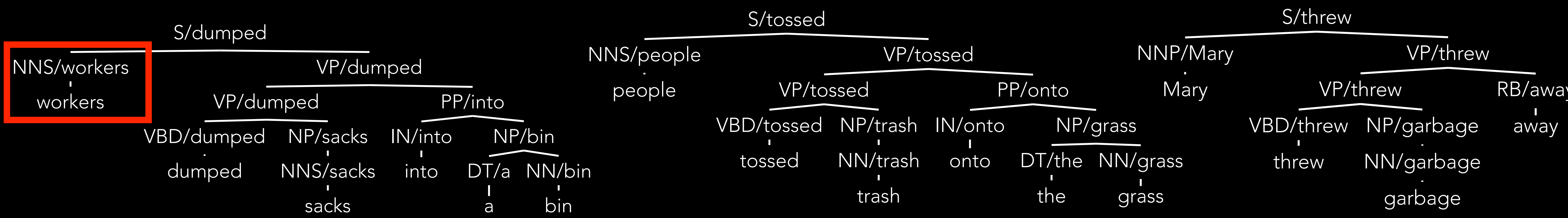
Head lexicalization

But if we lexicalize



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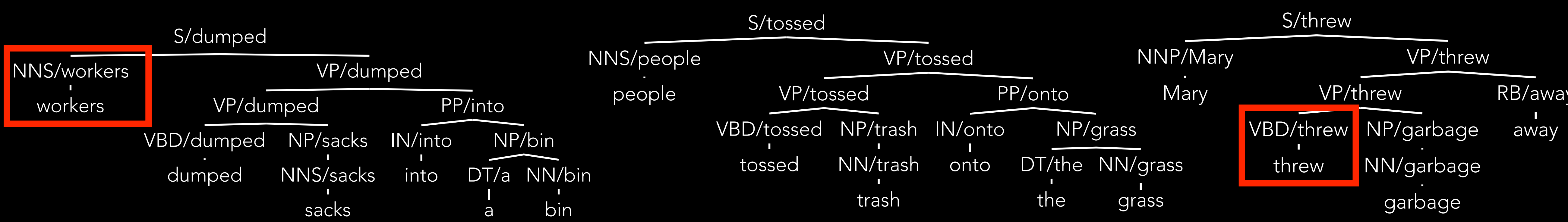

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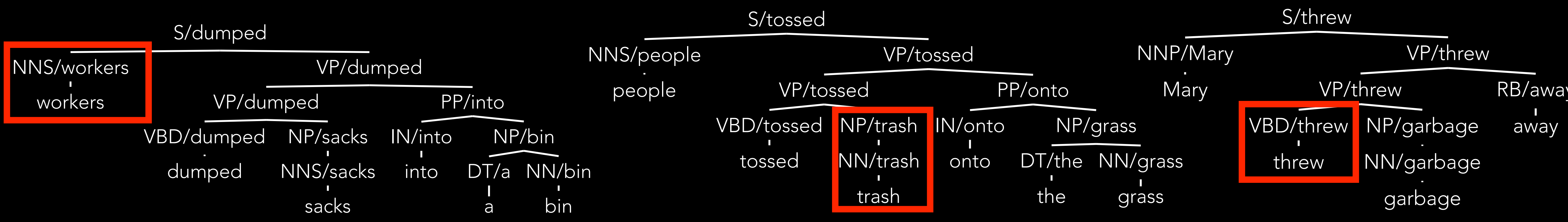

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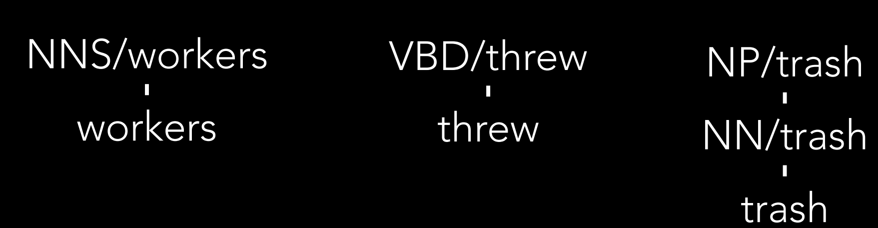

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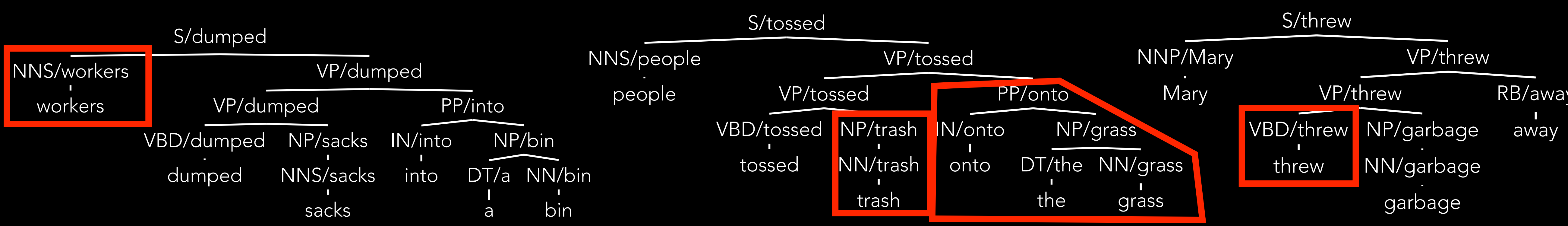

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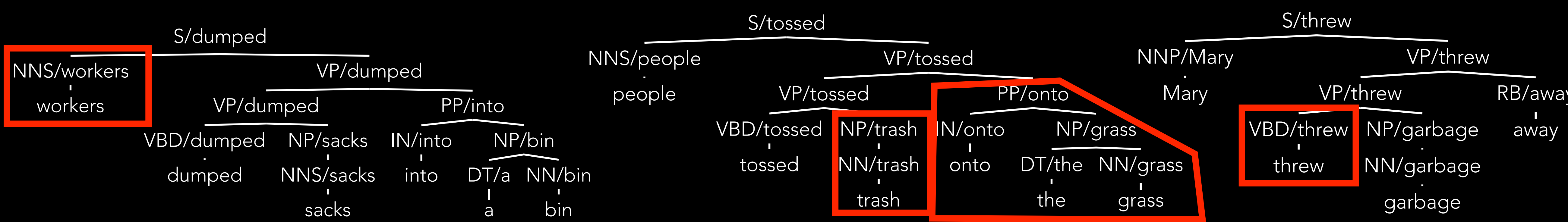

workers threw trash
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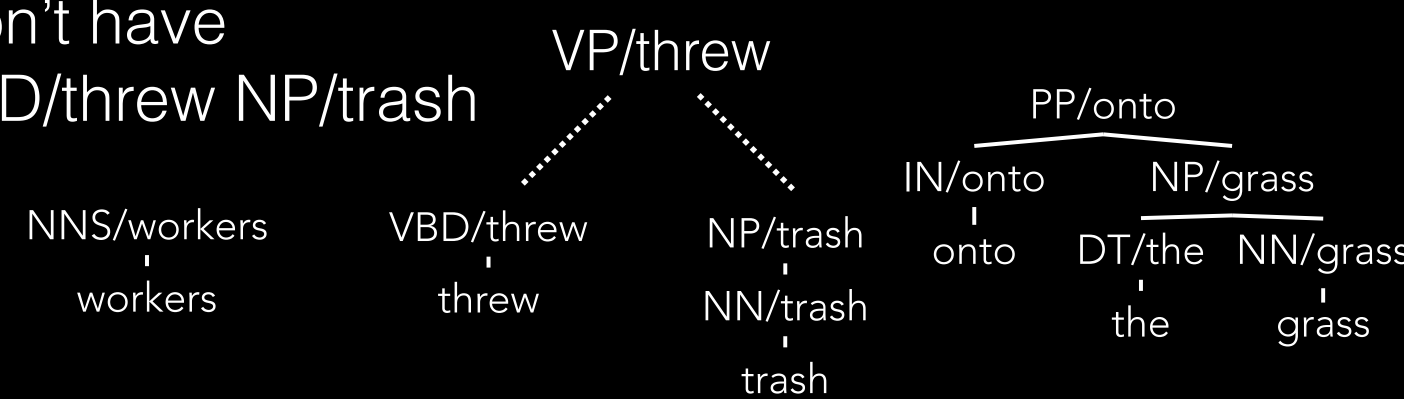
We don’t have
VP/threw -> VBD/threw NP/trash



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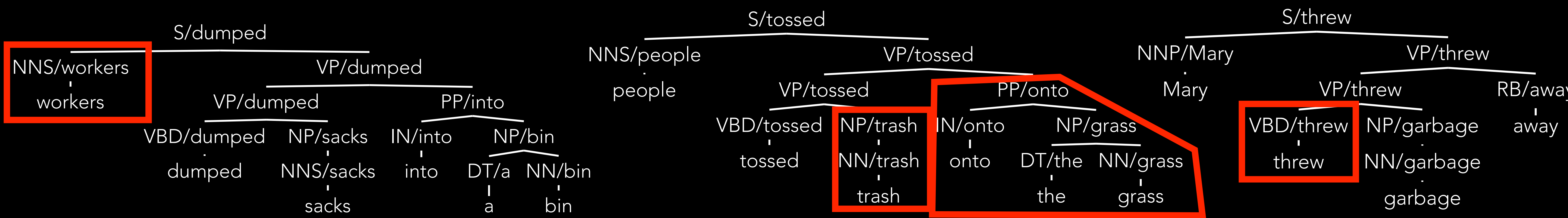

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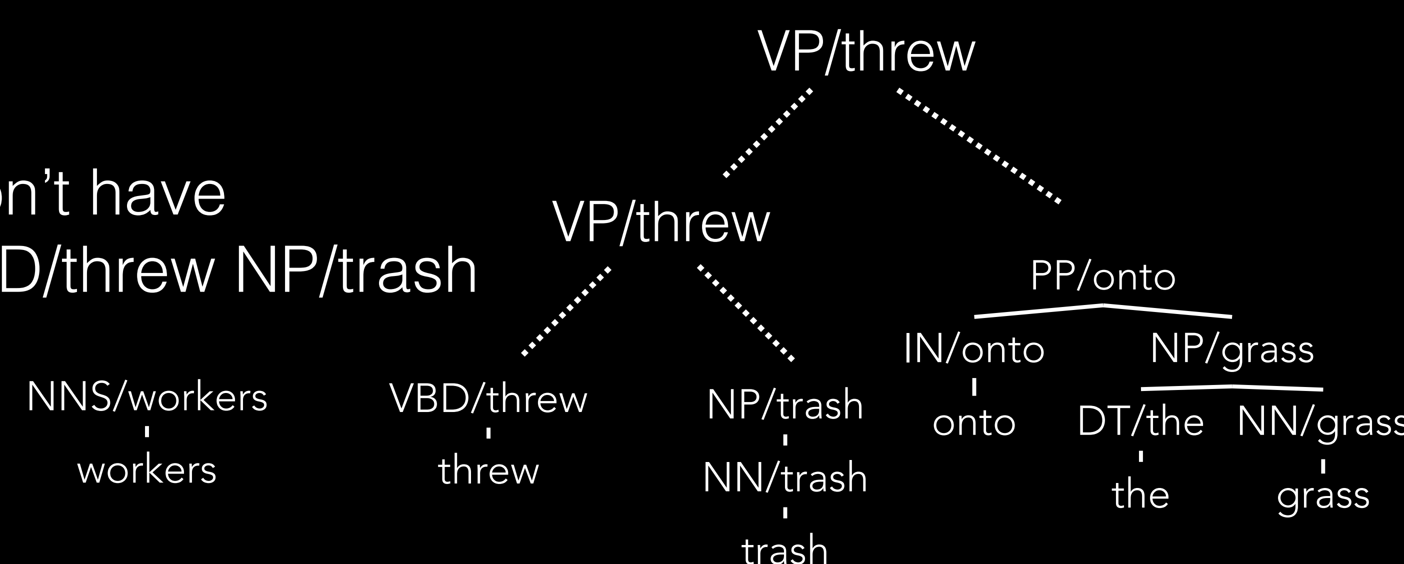

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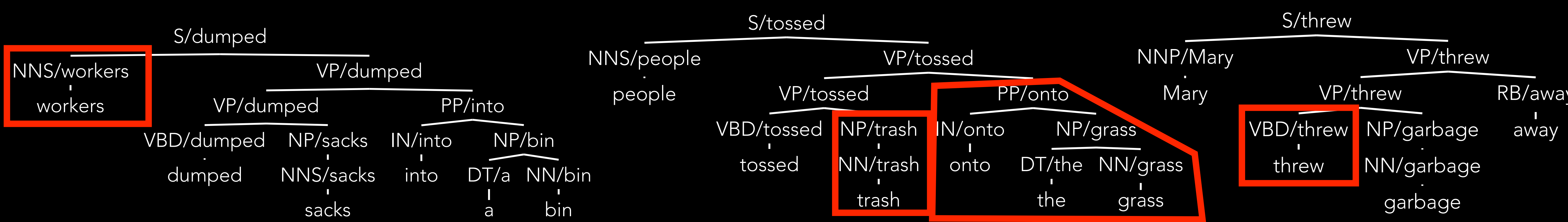

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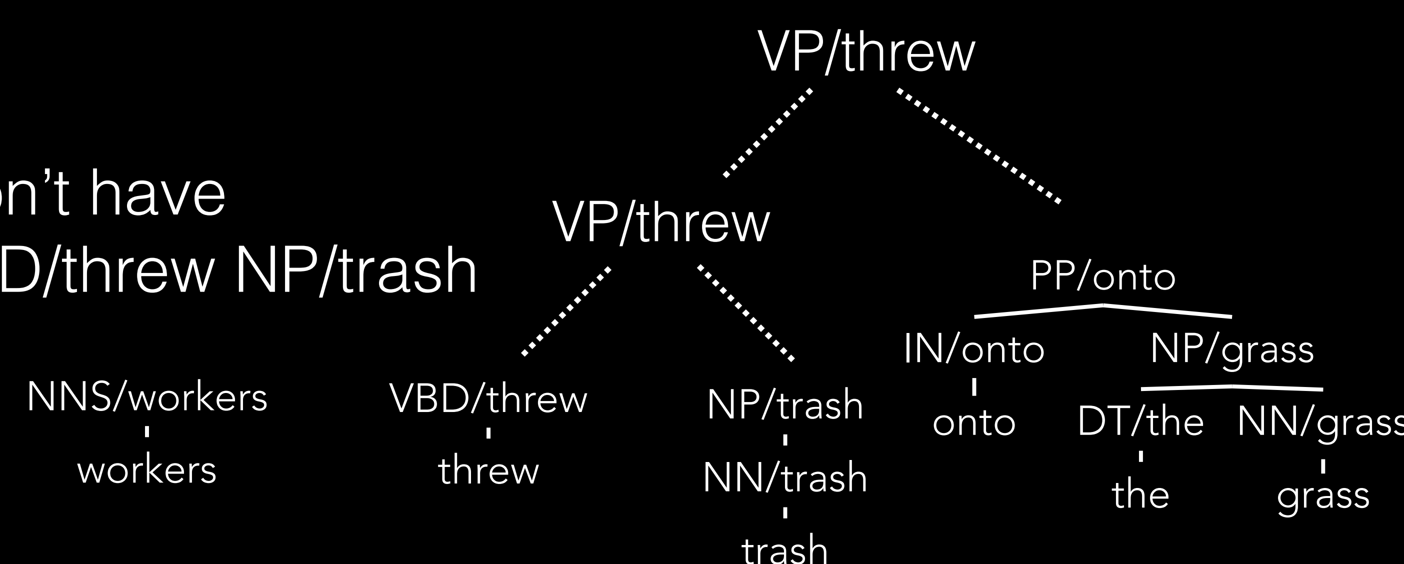

We don't have
VP/threw -> VBD/threw NP/trash

Now we have a problem!

Smoothing Lexicalized PCFGs

We want to estimate

P(VP/threw -> VP/threw PP/onto | VP/threw)

Smoothing Lexicalized PCFGs

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= P(VP -> <u>VP</u> PP, onto | VP, threw)

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P(VP/threw -> VP/threw PP/onto | VP/threw)

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or more generally

P(X -> YZ, m | X, h)

Smoothing Lexicalized PCFGs

We want to estimate

P(VP/threw -> VP/threw PP/onto | VP/threw)

= P(VP -> <u>VP</u> PP, onto | VP, threw)

or more generally

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since X and h were already chosen, leaving the rule and the lexicalization of the non-head path to choose.

Smoothing Lexicalized PCFGs

First apply the chain rule

Smoothing Lexicalized PCFGs

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$$P(X \rightarrow YZ, m \mid X, h) = P(X \rightarrow YZ \mid X, h)\, P(m \mid X \rightarrow YZ, X, h)$$

Smoothing Lexicalized PCFGs

First apply the chain rule

$$P(X \text{ -> } YZ, m \mid X, h) = \underbrace{P(X \text{ -> } YZ \mid X, h)}_{\text{rule model}} P(m \mid X \text{ -> } YZ, X, h)$$

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Smoothing Lexicalized PCFGs

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Now we consider a means for smoothing each of these components

Smoothing Lexicalized PCFGs

First apply the chain rule

$$\text{P(X -> YZ, m | X, h)} = \underbrace{\text{P(X -> YZ | X, h)}}_{\text{rule model}} \ \underbrace{\text{P(m | X -> YZ, X, h)}}_{\text{modifier model}}$$

Now we consider a means for smoothing each of these components

Interpolate P(X -> YZ | X, h) with P(X -> YZ | X)

Smoothing Lexicalized PCFGs

First apply the chain rule

$$P(X \text{ -> } YZ, m \mid X, h) = \underbrace{P(X \text{ -> } YZ \mid X, h)}_{\text{rule model}} \underbrace{P(m \mid X \text{ -> } YZ, X, h)}_{\text{modifier model}}$$

Now we consider a means for smoothing each of these components

Interpolate $P(X \text{ -> } YZ \mid X, h)$ with $P(X \text{ -> } YZ \mid X)$

Interpolate $P(m \mid X \text{ -> } YZ, X, h)$ with $P(m \mid X \text{ -> } YZ)$

Smoothing Lexicalized PCFGs

Let r be a vanilla rule (e.g. X -> YZ), X be its root symbol, h be its head, and m be its modifier

Smoothing Lexicalized PCFGs

Let r be a vanilla rule (e.g. X -> YZ), X be its root symbol, h be its head, and m be its modifier

$$P(r, m \mid X, h) = P(r \mid X, h)\, P(m \mid r, X, h)$$

Smoothing Lexicalized PCFGs

Let r be a vanilla rule (e.g. X -> YZ), X be its root symbol, h be its head, and m be its modifier

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$$P(r, m \mid X, h) = \underbrace{P(r \mid X, h)}_{\text{rule model}} \underbrace{P(m \mid r, X, h)}_{\text{modifier model}}$$

Rule Model

Smoothing Lexicalized PCFGs

Let r be a vanilla rule (e.g. X -> YZ), X be its root symbol, h be its head, and m be its modifier

$$P(r, m \mid X, h) = \underbrace{P(r \mid X, h)}_{\text{rule model}} \underbrace{P(m \mid r, X, h)}_{\text{modifier model}}$$

Rule Model

$$P(r \mid X, h) = \lambda_1 P_{ML}(r \mid X, h) + (1-\lambda_1) P_{ML}(r \mid X)$$

Smoothing Lexicalized PCFGs

Let r be a vanilla rule (e.g. X -> YZ), X be its root symbol, h be its head, and m be its modifier

$$P(r, m \mid X, h) = \underbrace{P(r \mid X, h)}_{\text{rule model}} \underbrace{P(m \mid r, X, h)}_{\text{modifier model}}$$

Rule Model

$$P(r \mid X, h) = \lambda_1 P_{ML}(r \mid X, h) + (1-\lambda_1) P_{ML}(r \mid X)$$

$$P_{ML}(r \mid X, h) = \frac{\text{count}(r, h)}{\text{count}(X, h)}$$

Smoothing Lexicalized PCFGs

Let r be a vanilla rule (e.g. X -> YZ), X be its root symbol, h be its head, and m be its modifier

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Rule Model

$$P(r \mid X, h) = \lambda_1 P_{ML}(r \mid X, h) + (1-\lambda_1) P_{ML}(r \mid X)$$

$$P_{ML}(r \mid X, h) = \frac{\text{count}(r, h)}{\text{count}(X, h)}$$

X/h ->Y/h Z/*

X/h

Smoothing Lexicalized PCFGs

Let r be a vanilla rule (e.g. X -> YZ), X be its root symbol, h be its head, and m be its modifier

$$P(r, m \mid X, h) = \underbrace{P(r \mid X, h)}_{\text{rule model}} \underbrace{P(m \mid r, X, h)}_{\text{modifier model}}$$

Rule Model

$$P(r \mid X, h) = \lambda_1 P_{ML}(r \mid X, h) + (1-\lambda_1) P_{ML}(r \mid X)$$

$$P_{ML}(r \mid X, h) = \frac{\text{count}(r, h)}{\text{count}(X, h)}$$

X/h ->Y/h Z/*

X/h

$$P_{ML}(r \mid X) = \frac{\text{count}(r)}{\text{count}(X)}$$

Smoothing Lexicalized PCFGs

Let r be a vanilla rule (e.g. X -> YZ), X be its root symbol, h be its head, and m be its modifier

$$P(r, m \mid X, h) = \underbrace{P(r \mid X, h)}_{\text{rule model}} \underbrace{P(m \mid r, X, h)}_{\text{modifier model}}$$

Rule Model

$$P(r \mid X, h) = \lambda_1 P_{ML}(r \mid X, h) + (1-\lambda_1) P_{ML}(r \mid X)$$

$$P_{ML}(r \mid X, h) = \frac{\text{count}(r, h)}{\text{count}(X, h)} \qquad \frac{X/h \to Y/h\ Z/*}{X/h}$$

$$P_{ML}(r \mid X) = \frac{\text{count}(r)}{\text{count}(X)} \qquad \frac{X/* \to Y/*\ Z/*}{X/*}$$

Smoothing Lexicalized PCFGs

Let r be a vanilla rule (e.g. X -> YZ), X be its root symbol, h be its head, and m be its modifier

$$P(r, m \mid X, h) = \underbrace{P(r \mid X, h)}_{\text{rule model}}\ \underbrace{P(m \mid r, X, h)}_{\text{modifier model}}$$

Rule Model

$$P(r \mid X, h) = \lambda_1 P_{ML}(r \mid X, h) + (1-\lambda_1) P_{ML}(r \mid X)$$

$$P_{ML}(r \mid X, h) = \frac{\text{count}(r, h)}{\text{count}(X, h)} \qquad \frac{X/h \rightarrow Y/h\ Z/*}{X/h}$$

$$P_{ML}(r \mid X) = \frac{\text{count}(r)}{\text{count}(X)} \qquad \frac{X/* \rightarrow Y/*\ Z/*}{X/*}$$

Vanilla PCFG!

Smoothing Lexicalized PCFGs

Let r be a vanilla rule (e.g. X -> YZ), X be its root symbol, h be its head, and m be its modifier

$$P(r, m \mid X, h) = \underbrace{P(r \mid X, h)}_{\text{rule model}} \underbrace{P(m \mid r, X, h)}_{\text{modifier model}}$$

Modifier Model

Smoothing Lexicalized PCFGs

Let r be a vanilla rule (e.g. X -> YZ), X be its root symbol, h be its head, and m be its modifier

$$P(r, m \mid X, h) = \underbrace{P(r \mid X, h)}_{\text{rule model}} \underbrace{P(m \mid r, X, h)}_{\text{modifier model}}$$

Modifier Model

$$P(m \mid r, X, h) = \lambda_2 P_{ML}(m \mid r, X, h) + (1-\lambda_2) P_{ML}(m \mid r)$$

Smoothing Lexicalized PCFGs

Let r be a vanilla rule (e.g. X -> YZ), X be its root symbol, h be its head, and m be its modifier

$$P(r, m \mid X, h) = \underbrace{P(r \mid X, h)}_{\text{rule model}} \underbrace{P(m \mid r, X, h)}_{\text{modifier model}}$$

Modifier Model

$$P(m \mid r, X, h) = \lambda_2 P_{ML}(m \mid r, X, h) + (1-\lambda_2) P_{ML}(m \mid r)$$

$$P_{ML}(m \mid r, X, h) = \frac{\text{count}(m, r, X, h)}{\text{count}(r, X, h)}$$

Smoothing Lexicalized PCFGs

Let r be a vanilla rule (e.g. X -> YZ), X be its root symbol, h be its head, and m be its modifier

$$P(r, m \mid X, h) = \underbrace{P(r \mid X, h)}_{\text{rule model}} \underbrace{P(m \mid r, X, h)}_{\text{modifier model}}$$

Modifier Model

$$P(m \mid r, X, h) = \lambda_2 P_{ML}(m \mid r, X, h) + (1-\lambda_2) P_{ML}(m \mid r)$$

$$P_{ML}(m \mid r, X, h) = \frac{\text{count}(m, r, X, h)}{\text{count}(r, X, h)}$$

X/h ->Y/h Z/m

X/h ->Y/h Z/*

Smoothing Lexicalized PCFGs

Let r be a vanilla rule (e.g. X -> YZ), X be its root symbol, h be its head, and m be its modifier

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X/h ->Y/h Z/m

X/h ->Y/h Z/*

$$P_{ML}(m \mid r) = \frac{\text{count}(m, r)}{\text{count}(r)}$$

Smoothing Lexicalized PCFGs

Let r be a vanilla rule (e.g. X -> YZ), X be its root symbol, h be its head, and m be its modifier

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$$P_{ML}(m \mid r, X, h) = \frac{\text{count}(m, r, X, h)}{\text{count}(r, X, h)}$$

X/h ->Y/h Z/m

X/h ->Y/h Z/*

$$P_{ML}(m \mid r) = \frac{\text{count}(m, r)}{\text{count}(r)}$$

X/* ->Y/* Z/m

X/* ->Y/* Z/*

Head lexicalization

Head lexicalization

By decomposing we can estimate unseen lexicalized rules

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Assume we saw each training tree 20 times

Head lexicalization

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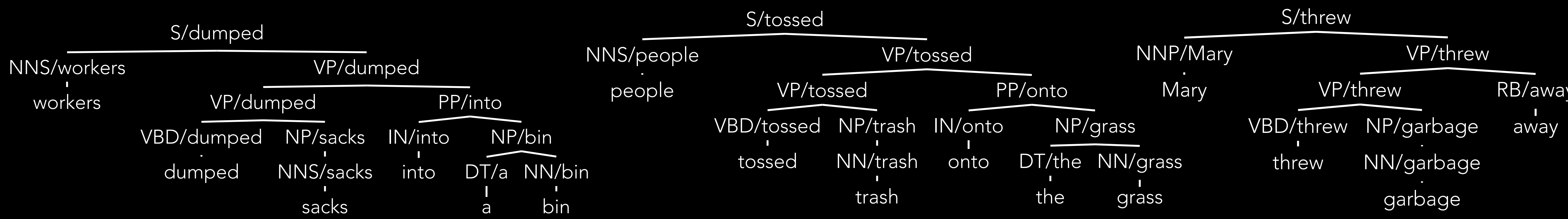
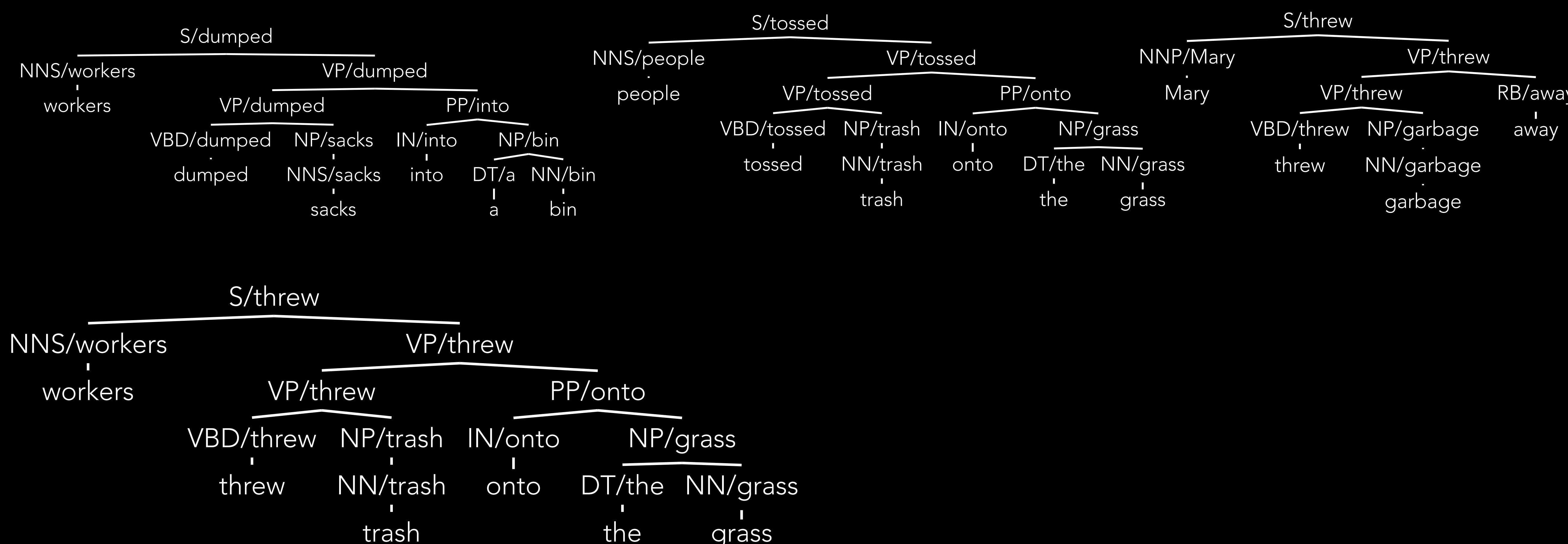


Head lexicalization

By decomposing we can estimate unseen lexicalized rules

Assume we saw each training tree 20 times



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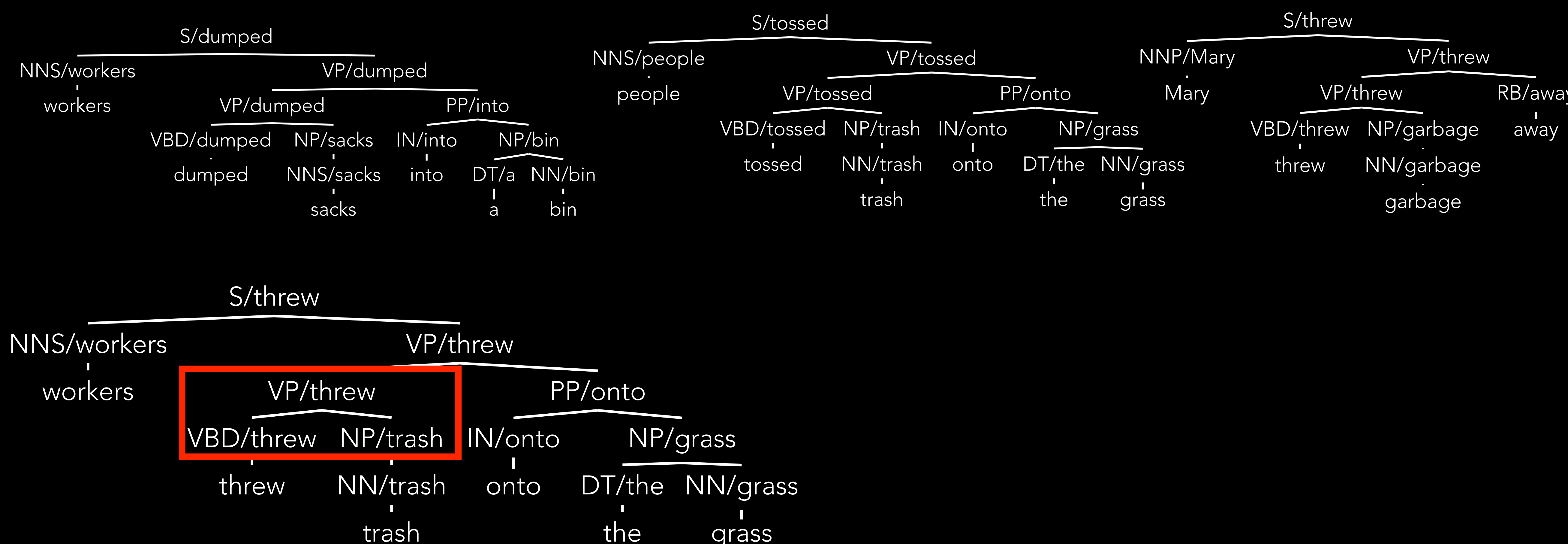

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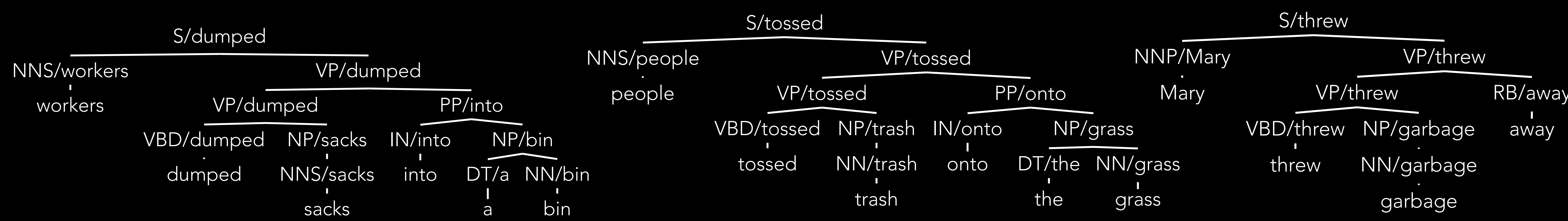
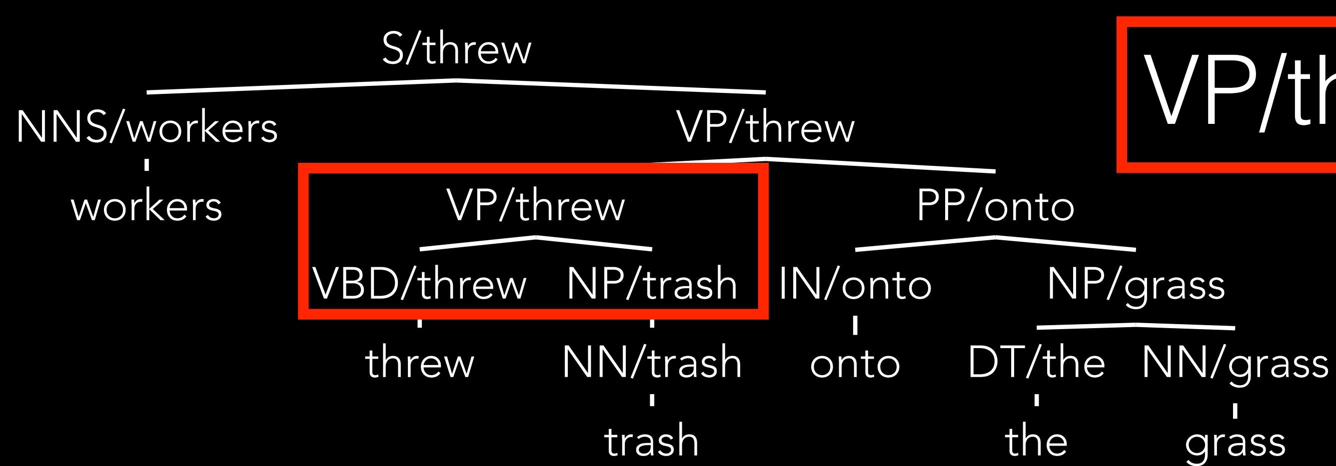


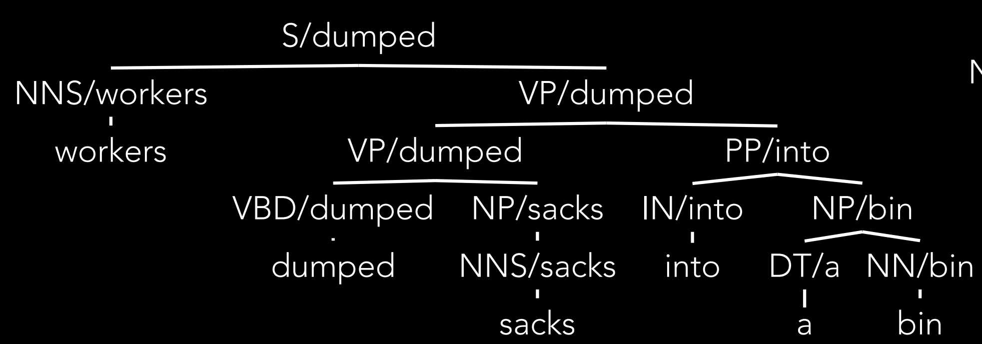


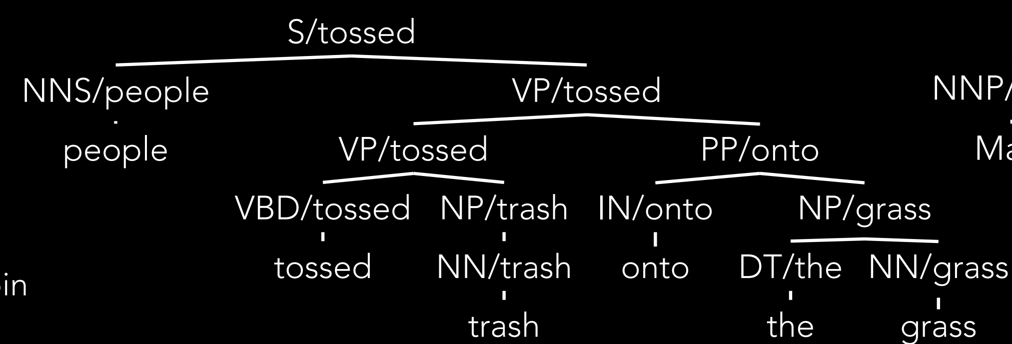
VP/threw -> VBD/threw NP/trash

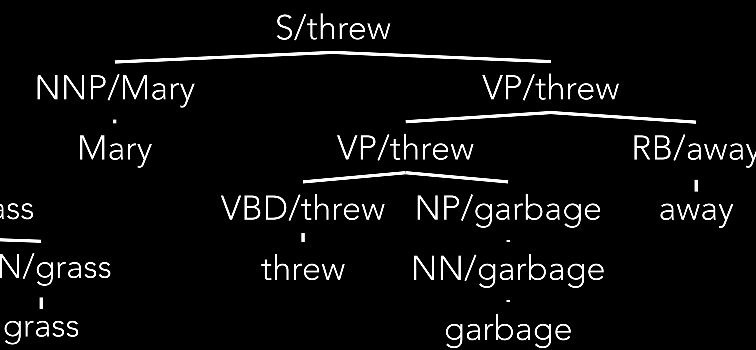
Head lexicalization

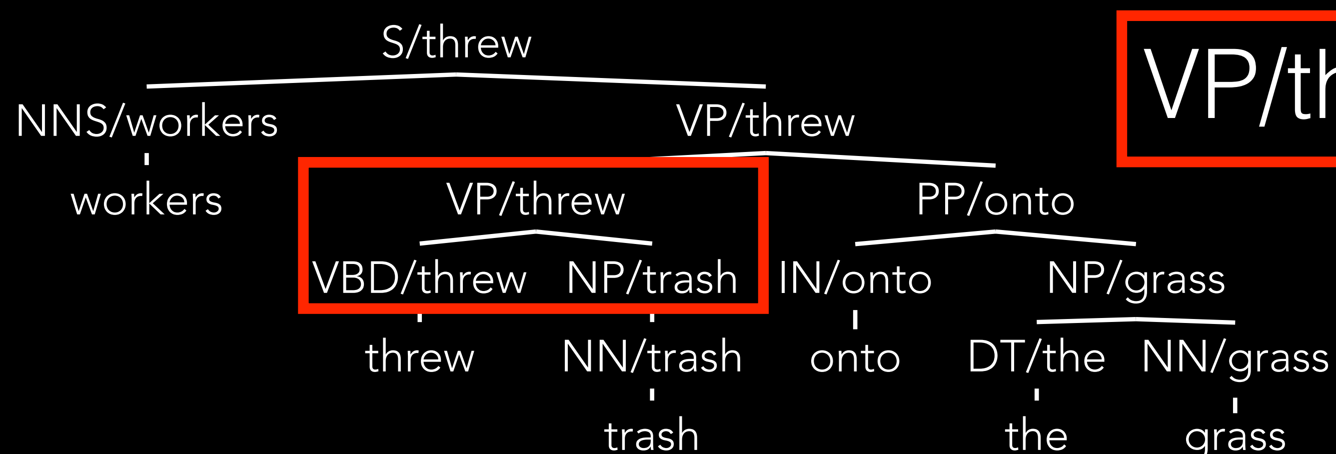
By decomposing we can estimate unseen lexicalized rules

Assume we saw each training tree 20 times









VP/threw -> VBD/threw NP/trash

$$P(r \mid X, h) = \lambda_1 P_{ML}(r \mid X, h) + (1-\lambda_1) P_{ML}(r \mid X)$$

Head lexicalization

By decomposing we can estimate unseen lexicalized rules

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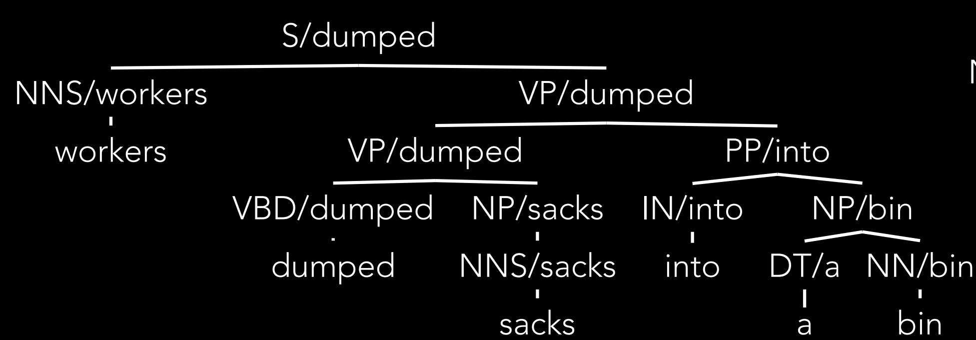

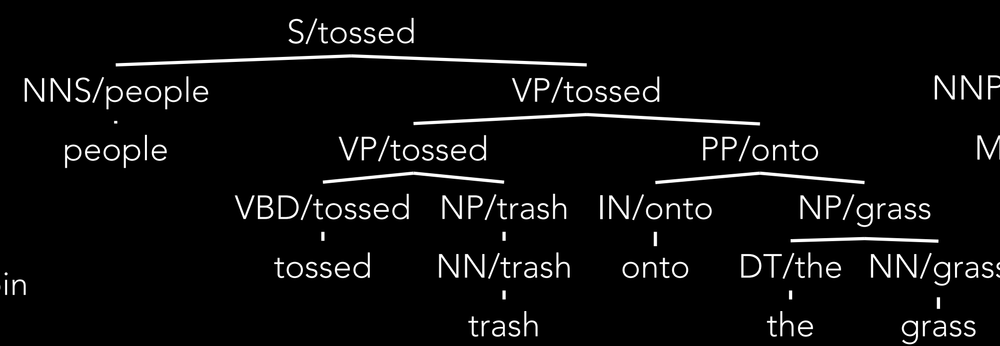

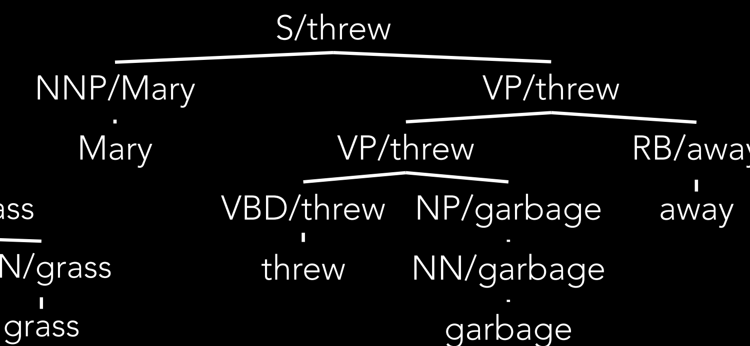

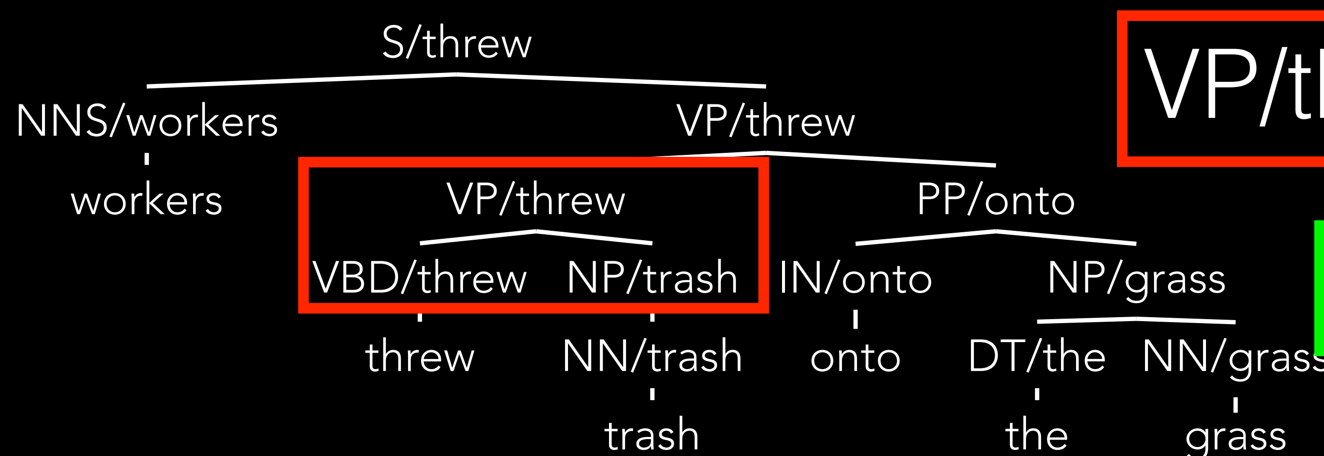

VP/threw -> VBD/threw NP/trash

VP/threw -> VBD/threw NP

$$P(r \mid X, h) = \lambda_1 P_{ML}(r \mid X, h) + (1-\lambda_1) P_{ML}(r \mid X)$$

Head lexicalization

By decomposing we can estimate unseen lexicalized rules

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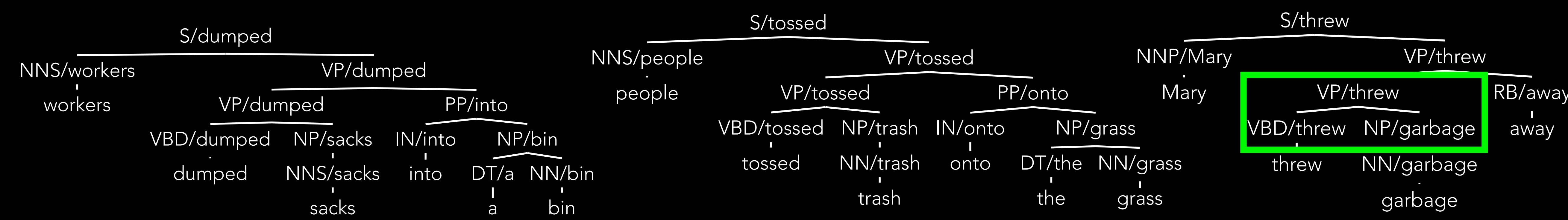

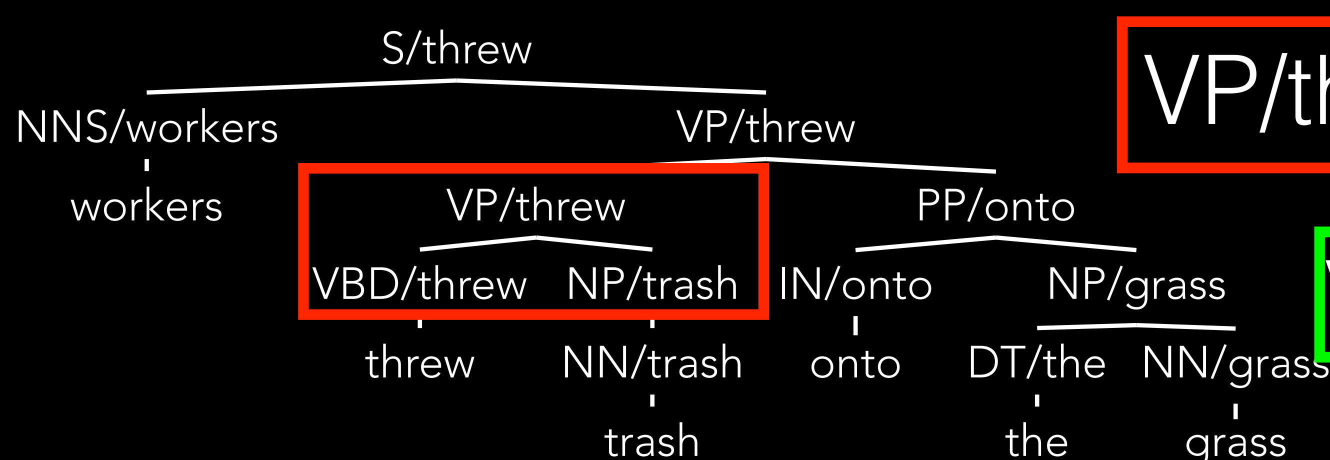

VP/threw -> VBD/threw NP/trash

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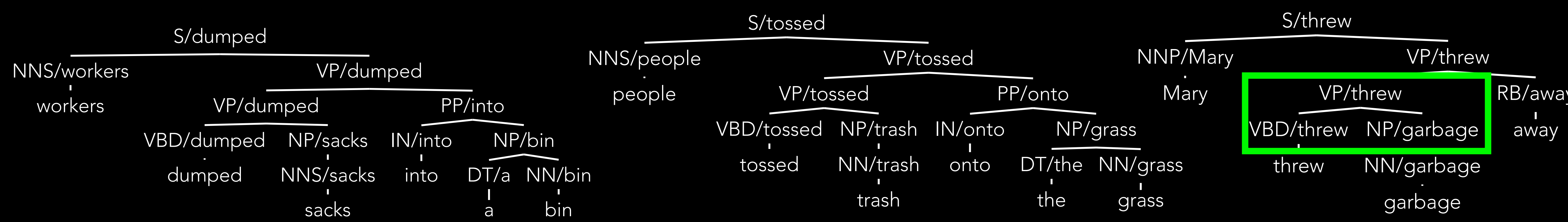

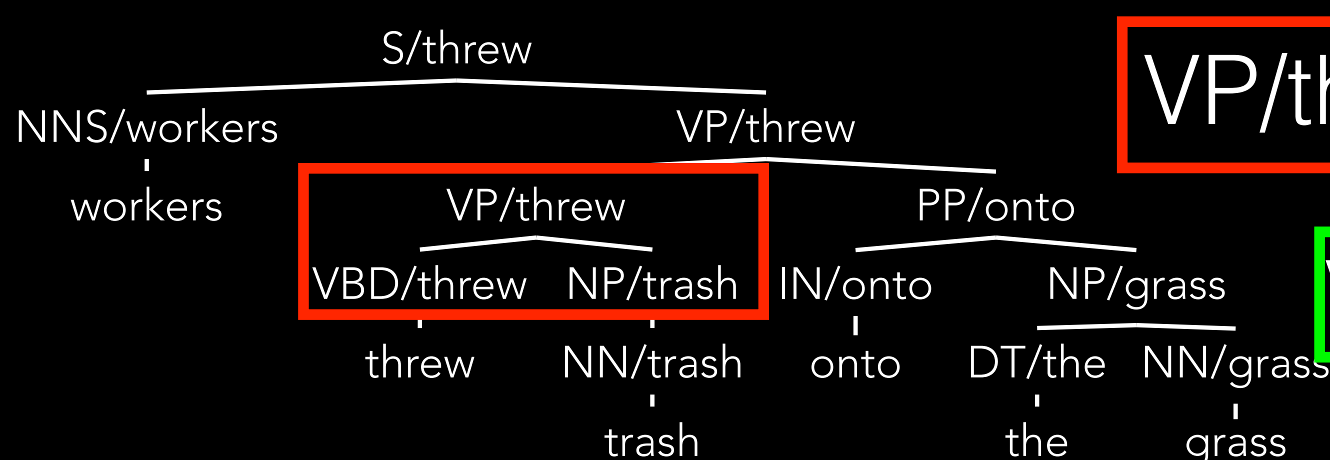

VP/threw -> VBD/threw NP/trash

VP/threw -> VBD/threw NP

VP/threw -> …

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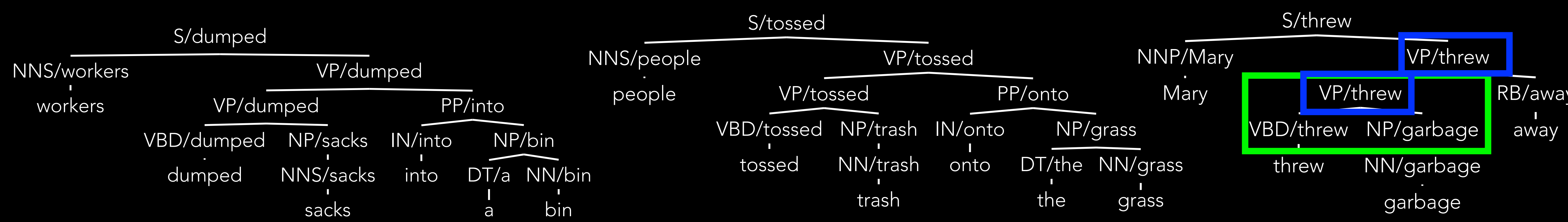

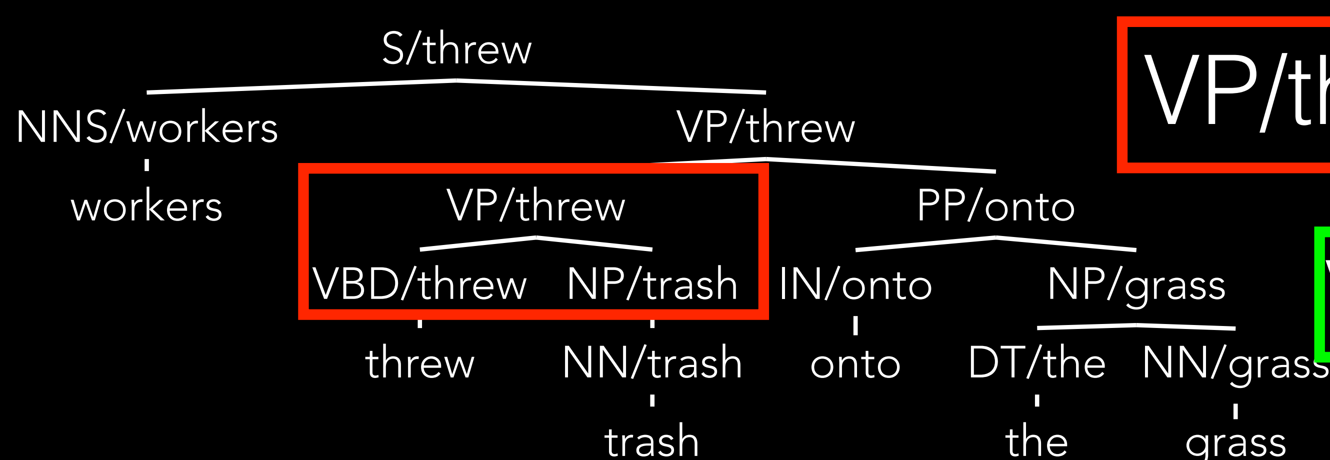

VP/threw -> VBD/threw NP/trash

VP/threw -> VBD/threw NP

VP/threw -> …

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By decomposing we can estimate unseen lexicalized rules

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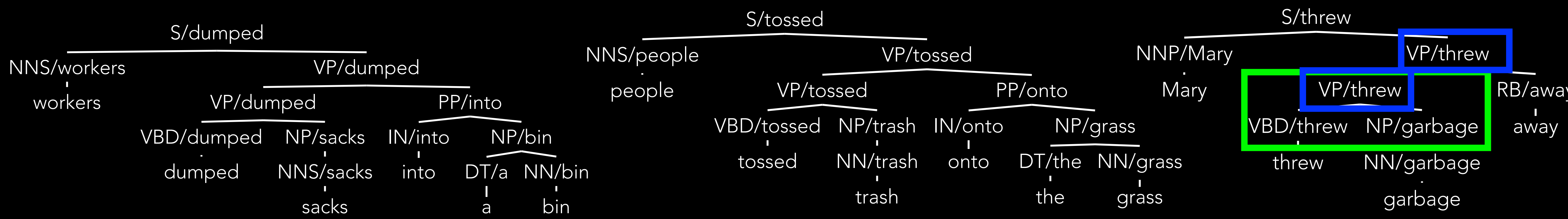
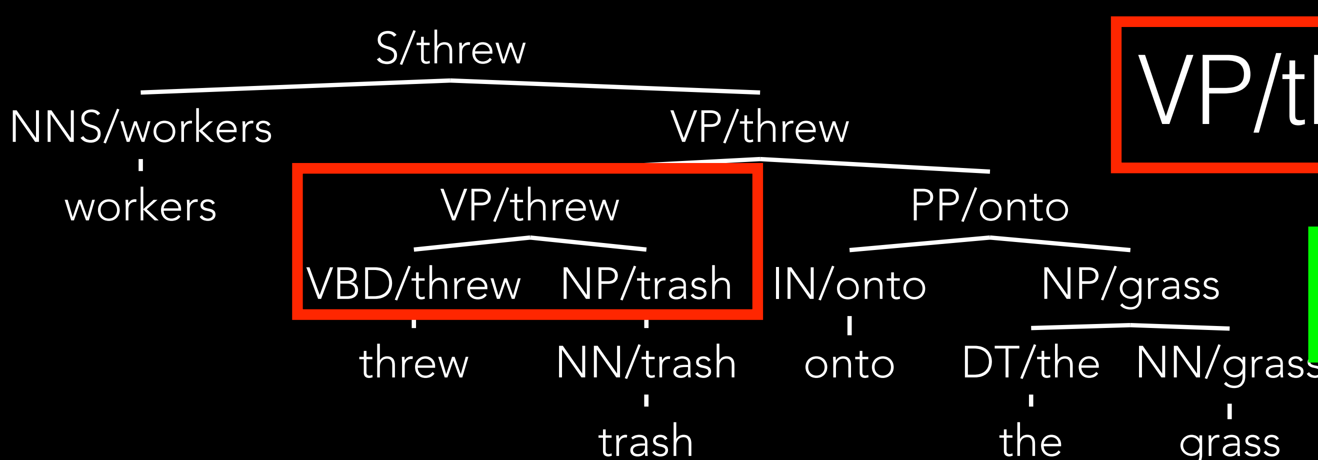




VP/threw -> VBD/threw NP/trash

VP/threw -> VBD/threw NP

VP/threw -> …

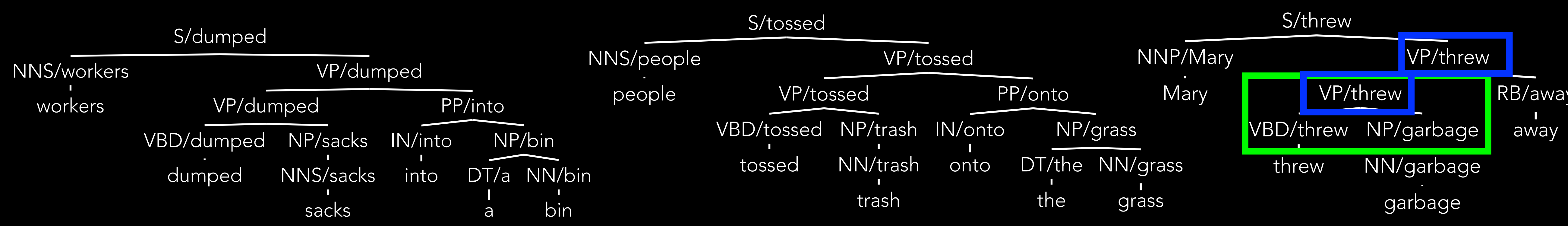
$$P(r \mid X, h) = \lambda_1 P_{ML}(r \mid X, h) + (1-\lambda_1) P_{ML}(r \mid X)$$

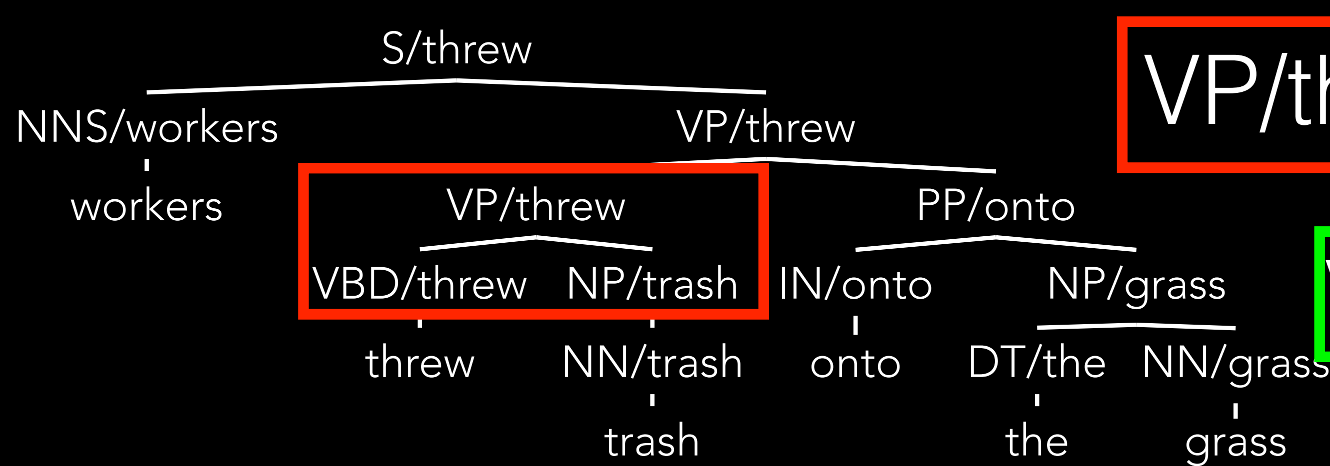
20/40

Head lexicalization

By decomposing we can estimate unseen lexicalized rules

Assume we saw each training tree 20 times





VP/threw -> VBD/threw NP/trash

VP/threw -> VBD/threw NP

VP/threw -> …

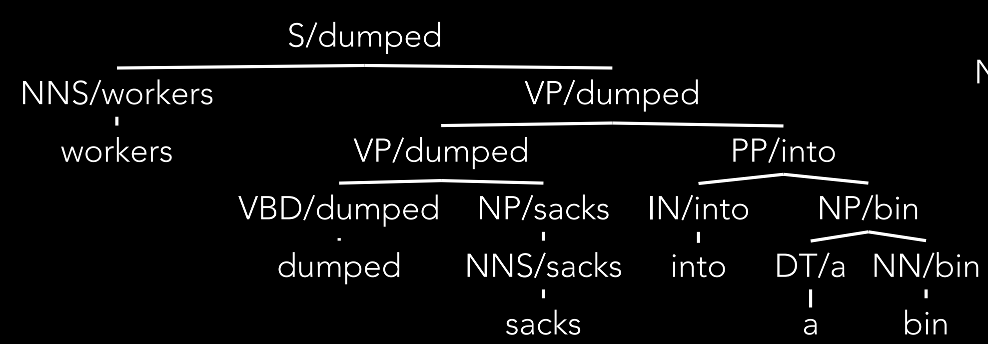
$$P(r \mid X, h) = \lambda_1 P_{ML}(r \mid X, h) + (1-\lambda_1) P_{ML}(r \mid X)$$

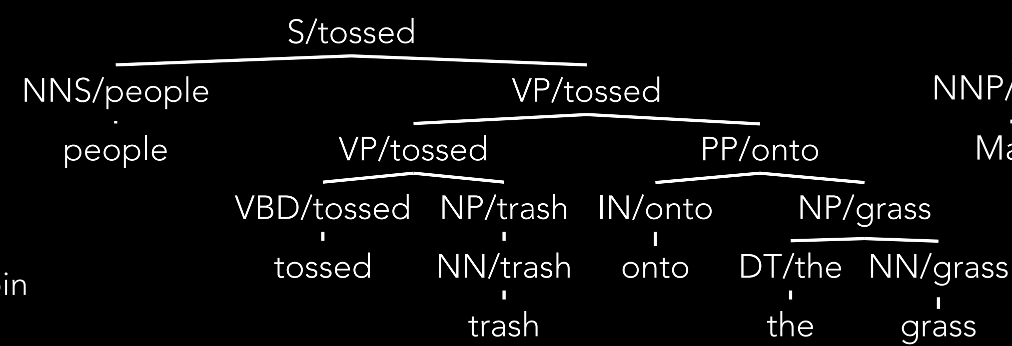
$$\boxed{20}/40$$

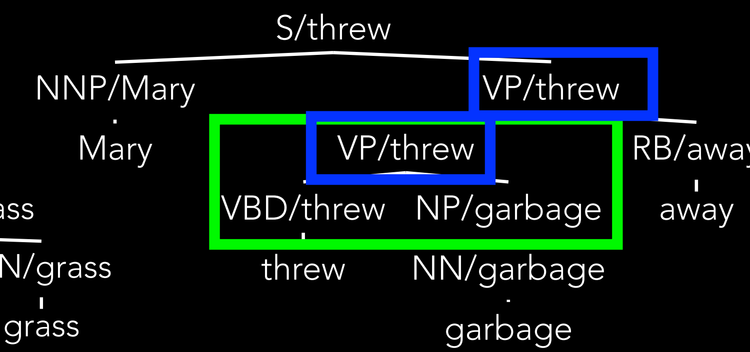
Head lexicalization

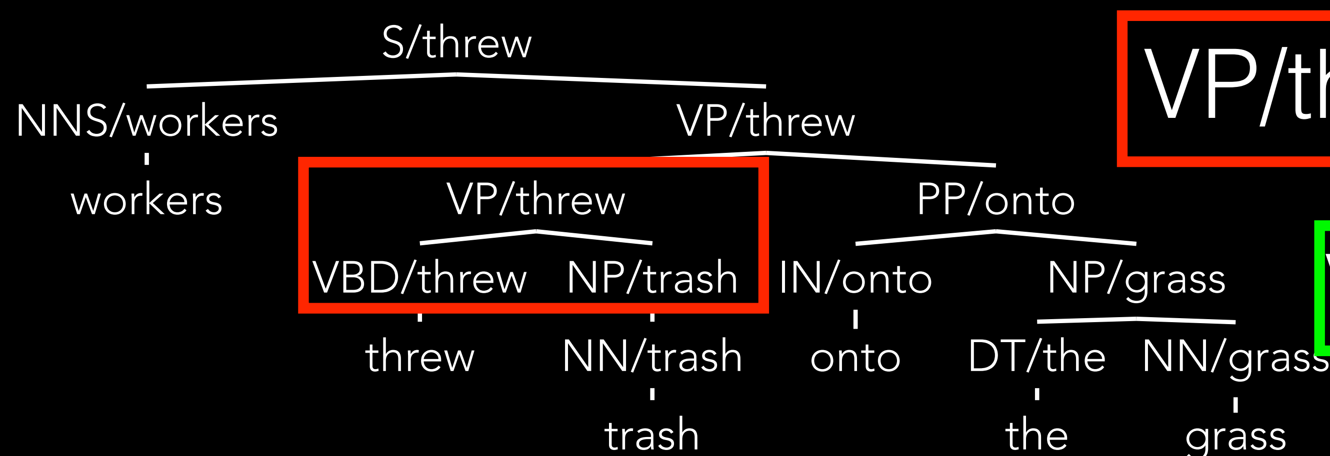
By decomposing we can estimate unseen lexicalized rules

Assume we saw each training tree 20 times









VP/threw -> VBD/threw NP/trash

VP/threw -> VBD/threw NP

VP/threw -> …

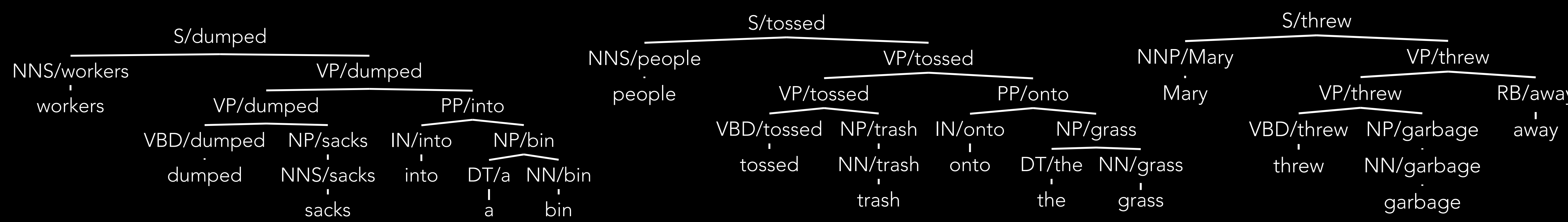
$$P(r \mid X, h) = \lambda_1 P_{ML}(r \mid X, h) + (1-\lambda_1) P_{ML}(r \mid X)$$

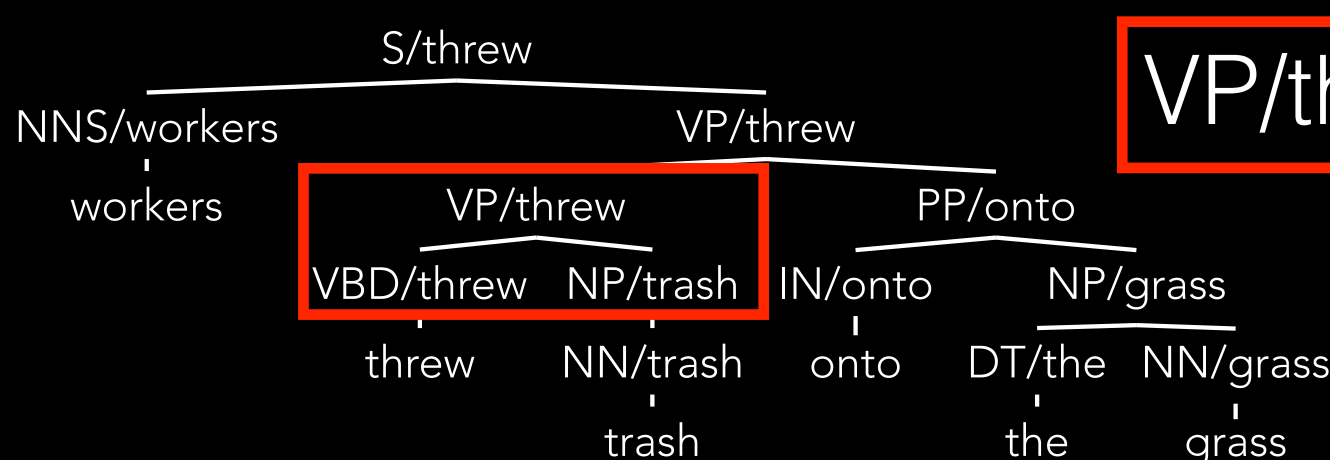
$$\frac{20}{40}$$

Head lexicalization

By decomposing we can estimate unseen lexicalized rules

Assume we saw each training tree 20 times





$\boxed{\text{VP/threw -> VBD/threw NP/trash}}$

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20/40

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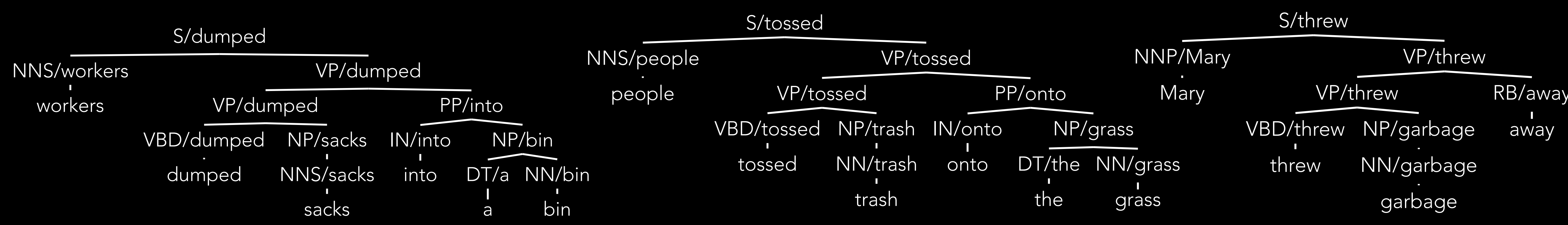

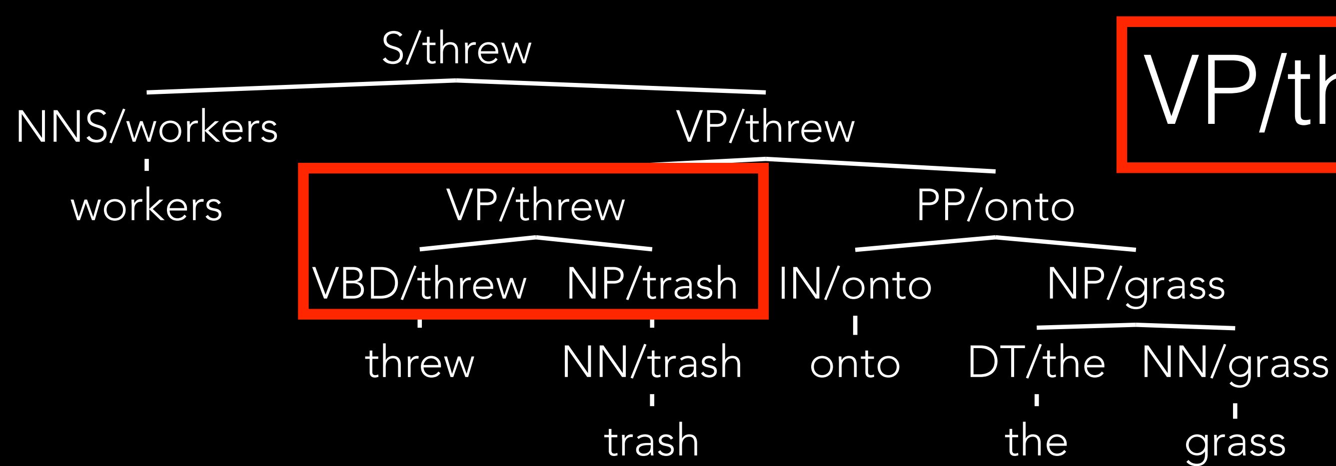

VP/threw -> VBD/threw NP/trash

VP -> VBD NP

$$P(r \mid X, h) = \lambda_1 P_{ML}(r \mid X, h) + (1-\lambda_1) P_{ML}(r \mid X)$$

20/40

Head lexicalization

By decomposing we can estimate unseen lexicalized rules

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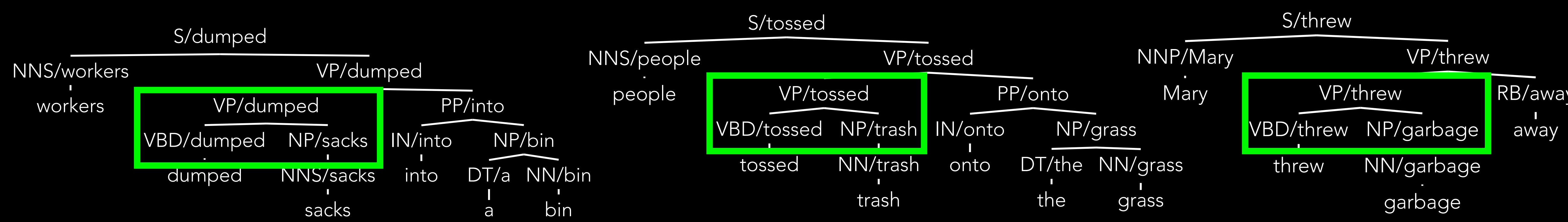

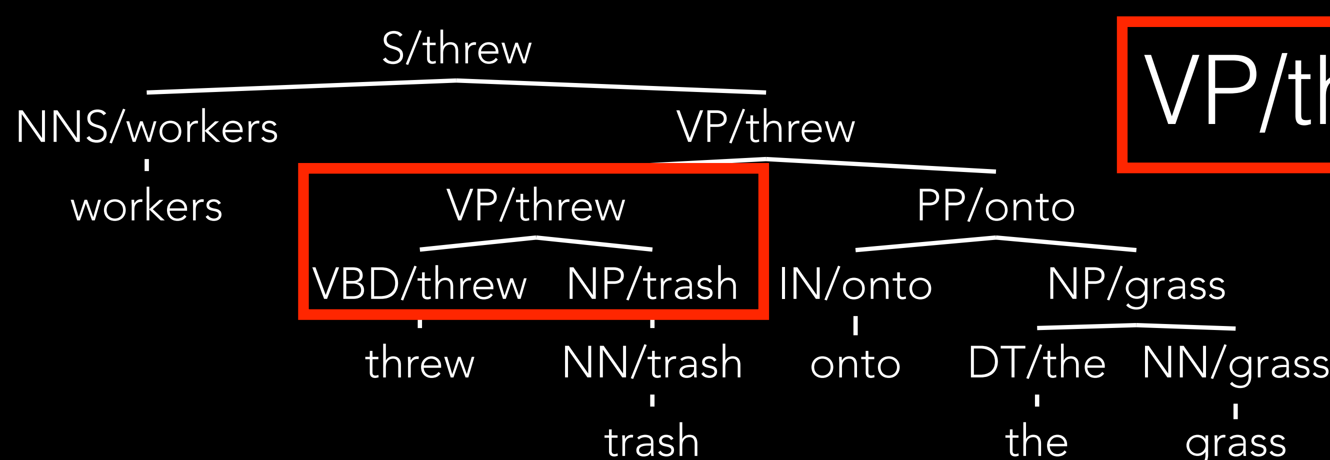

VP/threw -> VBD/threw NP/trash

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20/40

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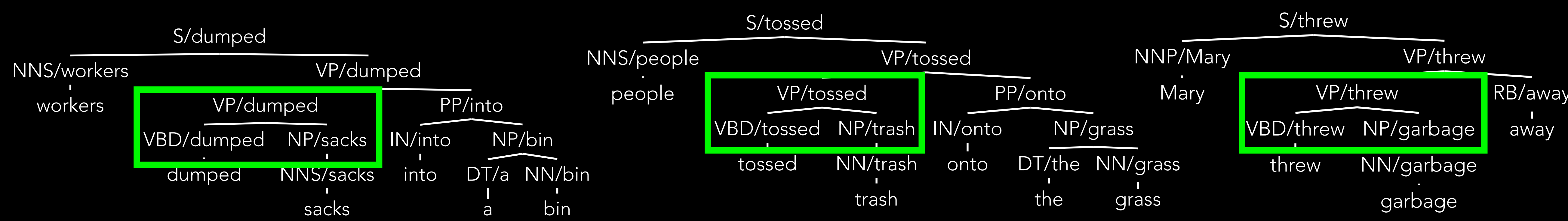

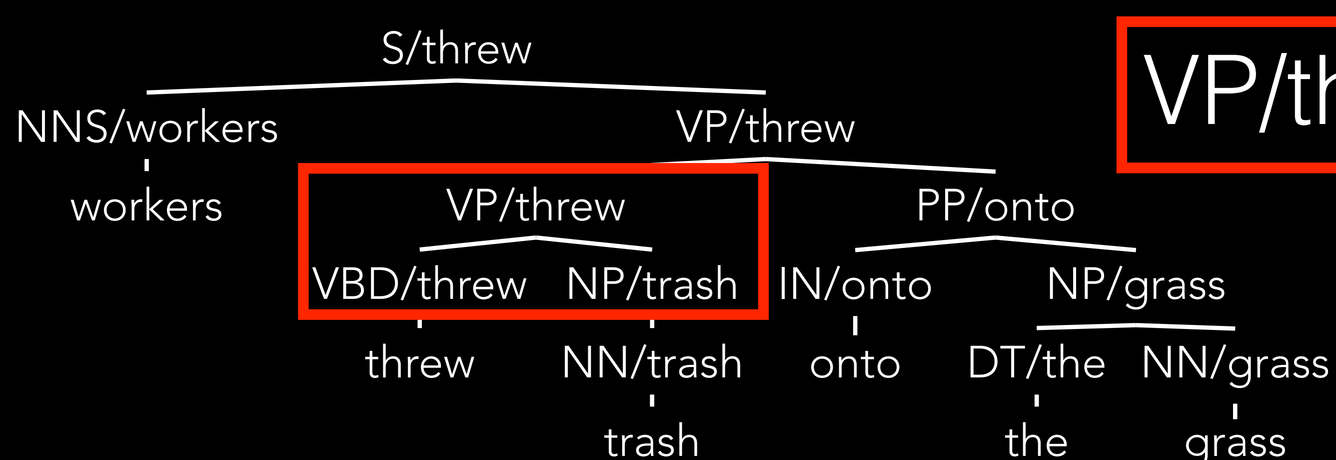

VP/threw -> VBD/threw NP/trash

VP -> VBD NP

VP -> ...

$$P(r \mid X, h) = \lambda_1 P_{ML}(r \mid X, h) + (1-\lambda_1) P_{ML}(r \mid X)$$

20/40

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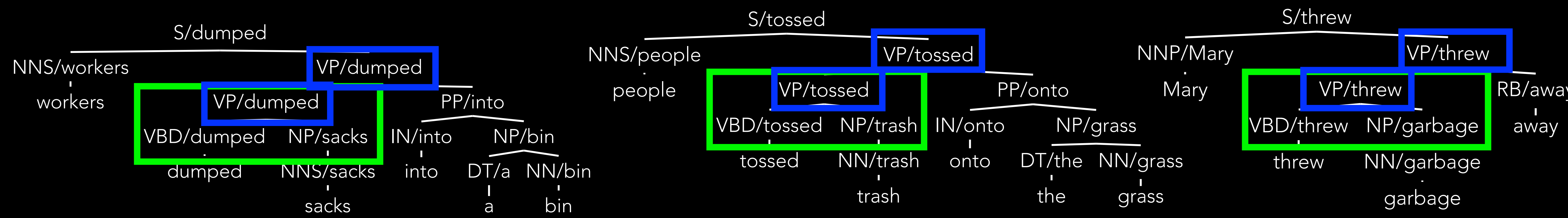

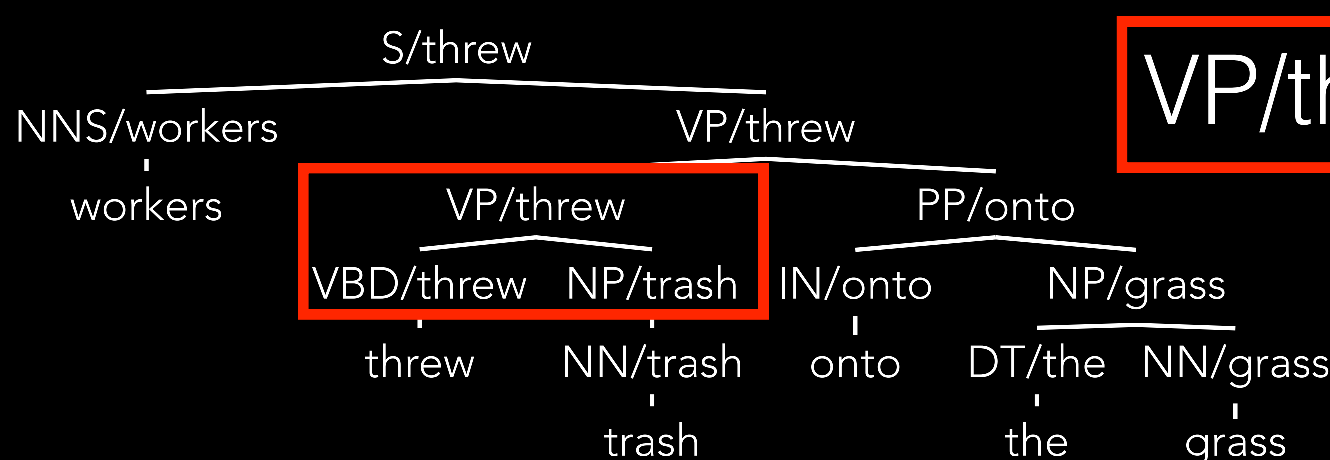

VP/threw -> VBD/threw NP/trash

VP -> VBD NP

VP -> …

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20/40

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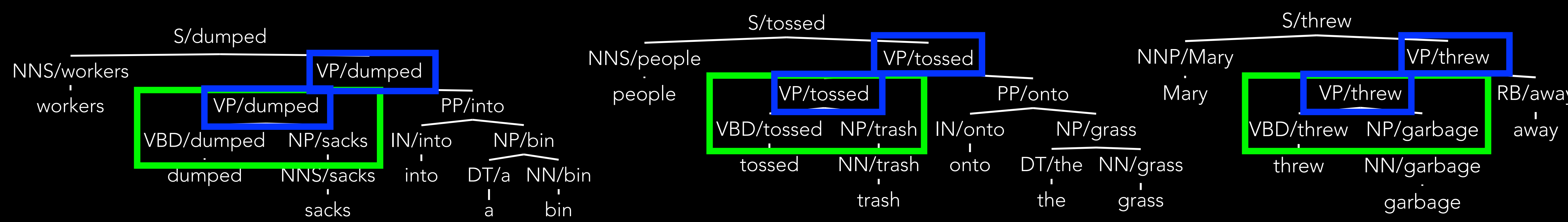
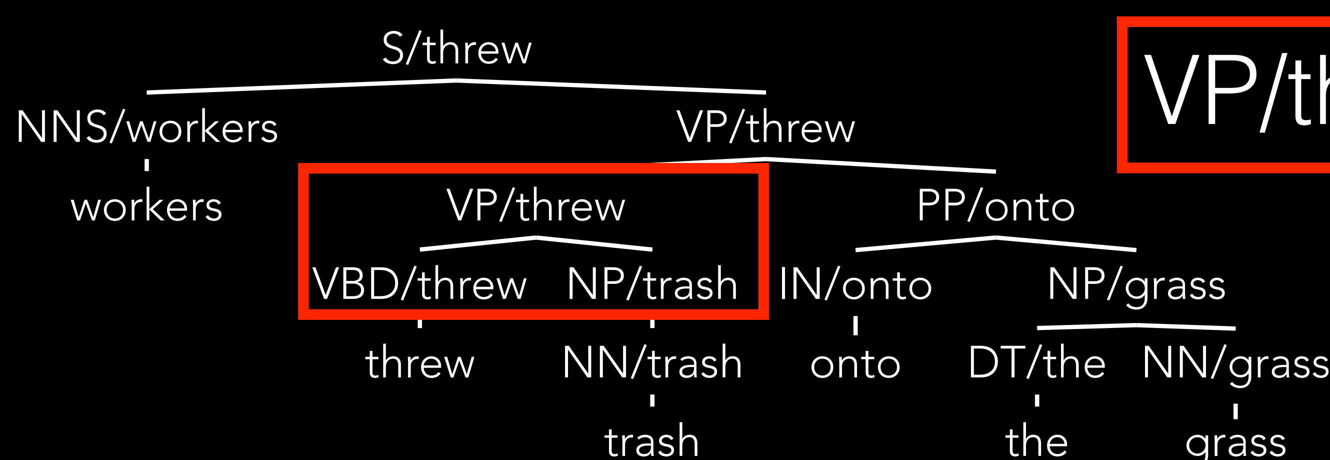




VP/threw -> VBD/threw NP/trash

VP -> VBD NP

VP -> ...

$$P(r \mid X, h) = \lambda_1 P_{ML}(r \mid X, h) + (1-\lambda_1) P_{ML}(r \mid X)$$

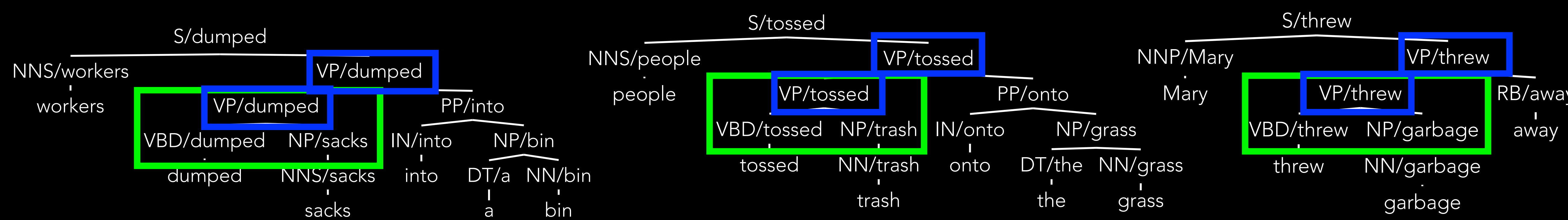
20/40

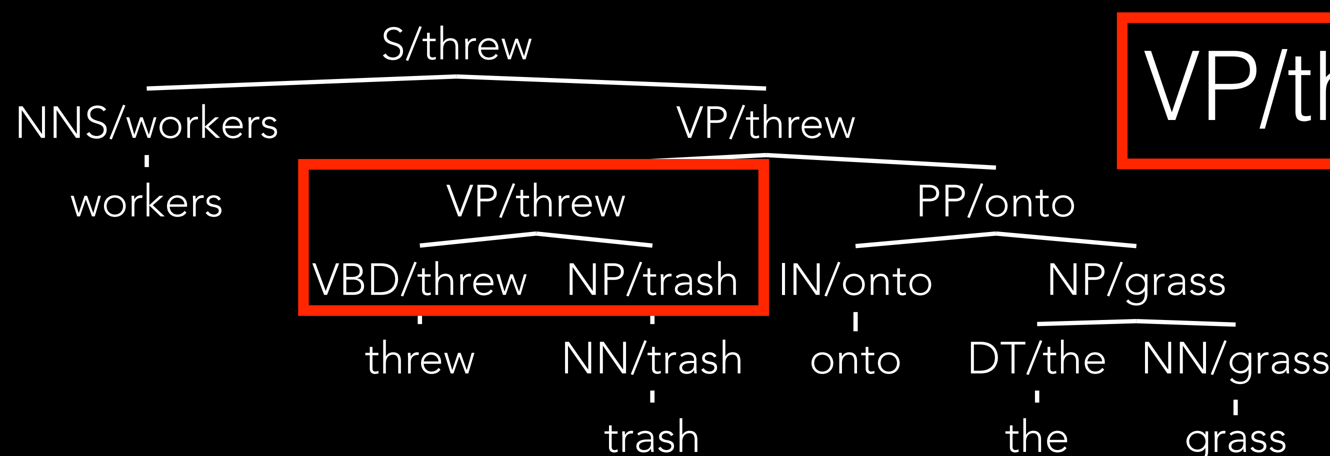
60/120

Head lexicalization

By decomposing we can estimate unseen lexicalized rules

Assume we saw each training tree 20 times





VP/threw -> VBD/threw NP/trash

VP -> VBD NP

VP -> ...

$$P(r \mid X, h) = \lambda_1 P_{ML}(r \mid X, h) + (1-\lambda_1) P_{ML}(r \mid X)$$

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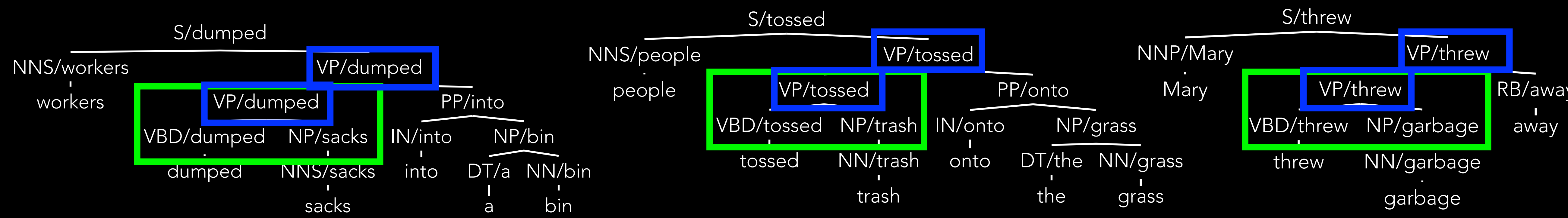

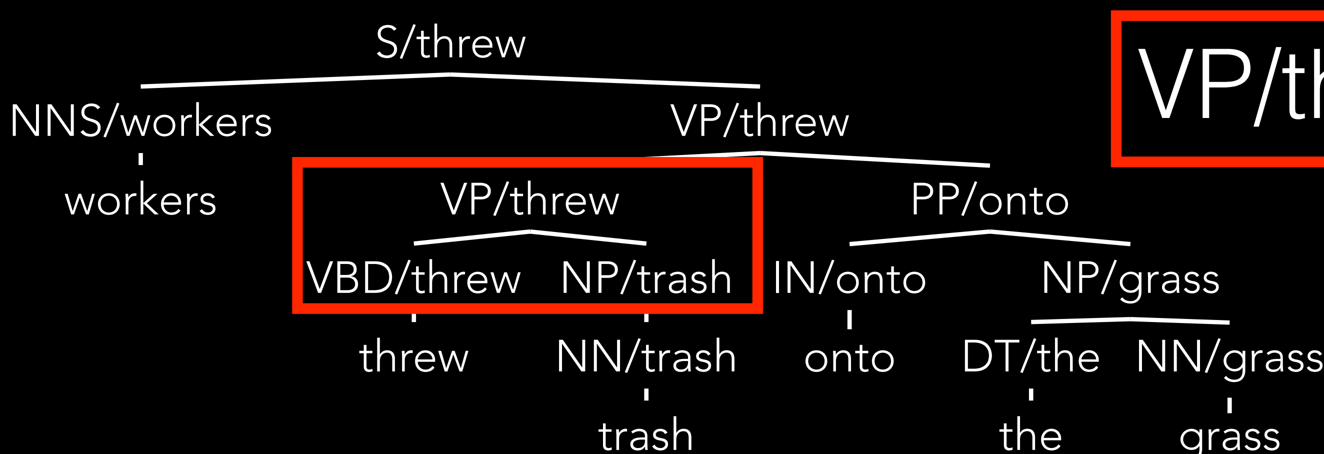

$\boxed{\text{VP/threw -> VBD/threw NP/trash}}$

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20/40

$\boxed{60}/\boxed{120}$

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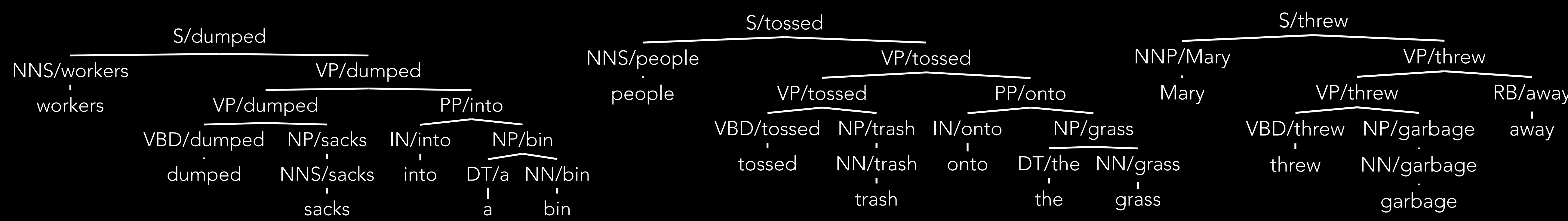

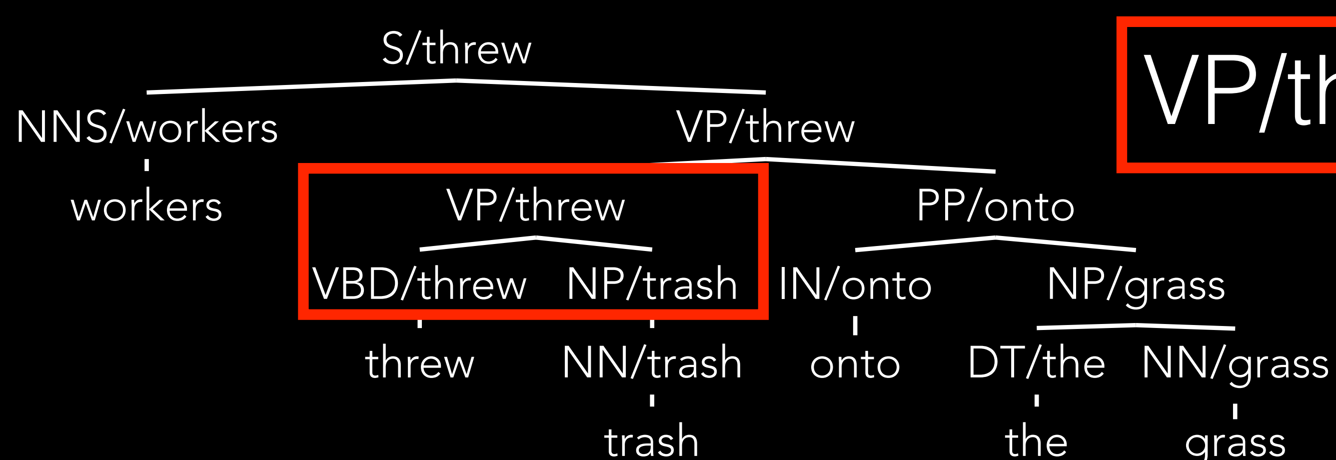

VP/threw -> VBD/threw NP/trash

$$P(m \mid r, X, h) = \lambda_2 P_{ML}(m \mid r, X, h) + (1-\lambda_2) P_{ML}(m \mid r)$$

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By decomposing we can estimate unseen lexicalized rules

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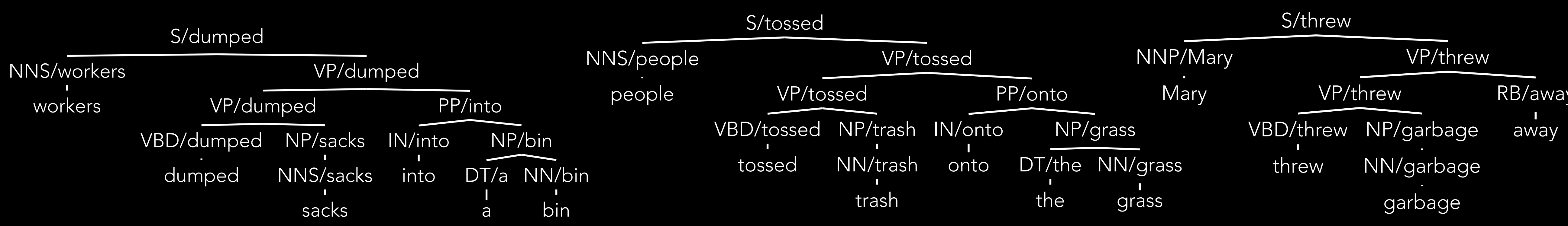

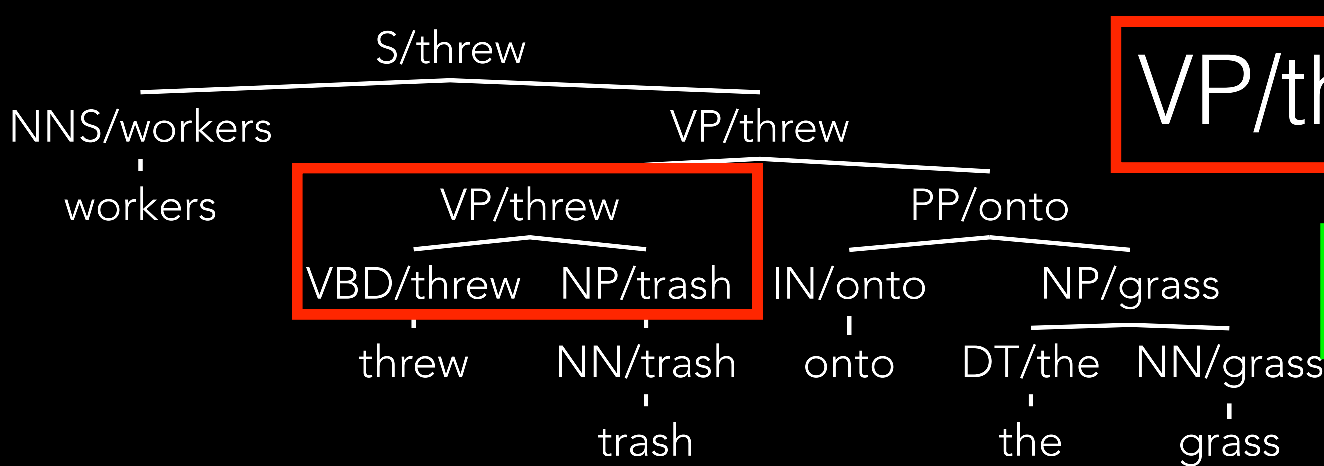

VP/threw -> VBD/threw NP/trash

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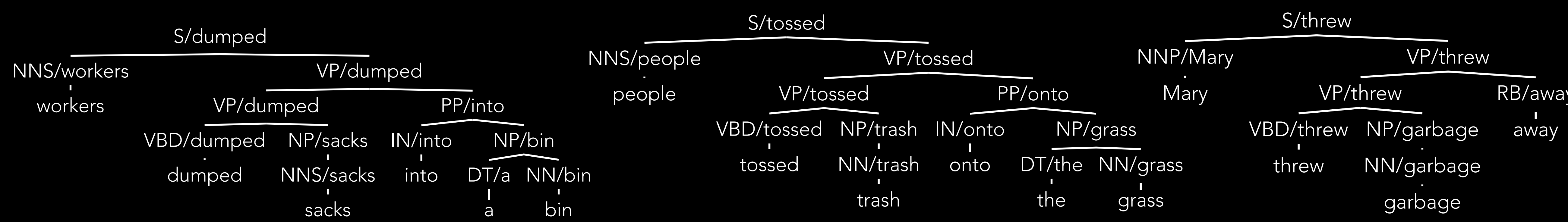

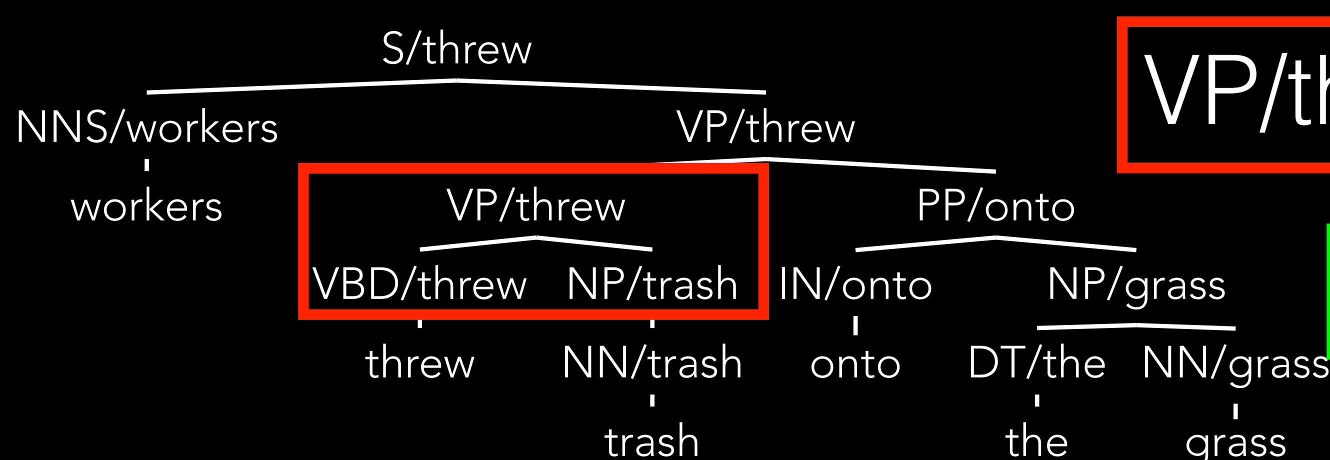

VP/threw -> VBD/threw NP/trash

VP/threw -> VBD/threw NP/trash

VP/threw -> VBD/threw NP

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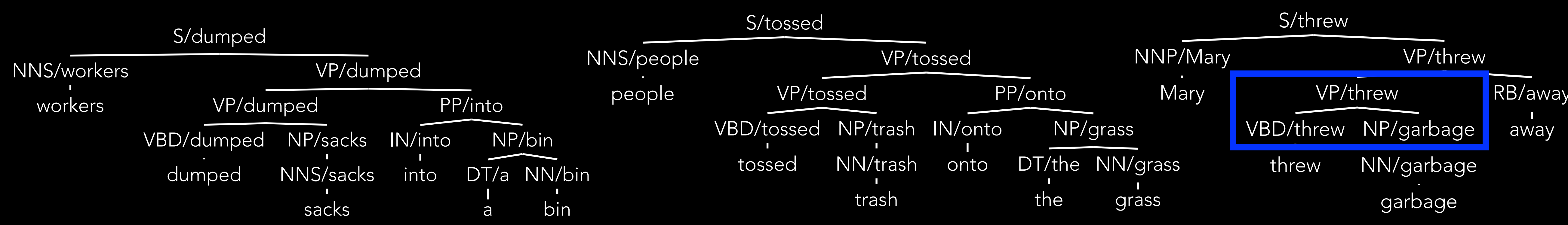

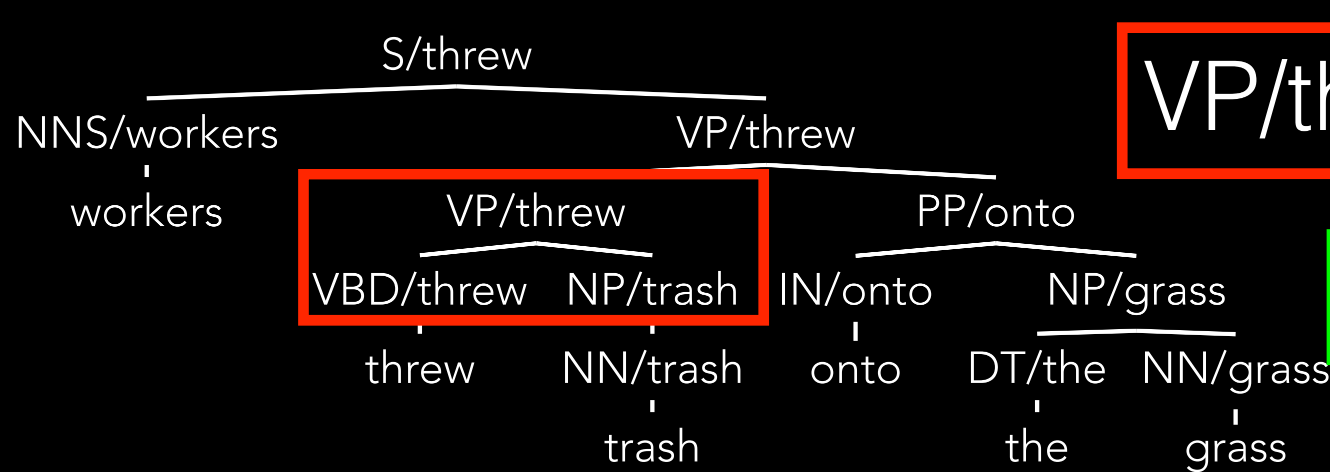

VP/threw -> VBD/threw NP/trash

VP/threw -> VBD/threw NP/trash

VP/threw -> VBD/threw NP

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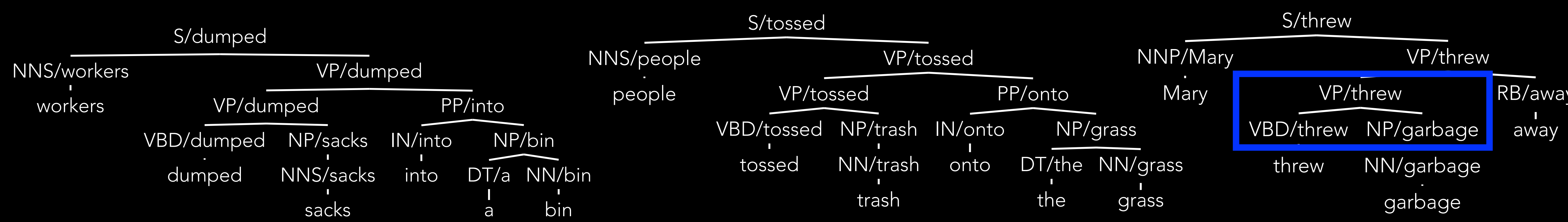

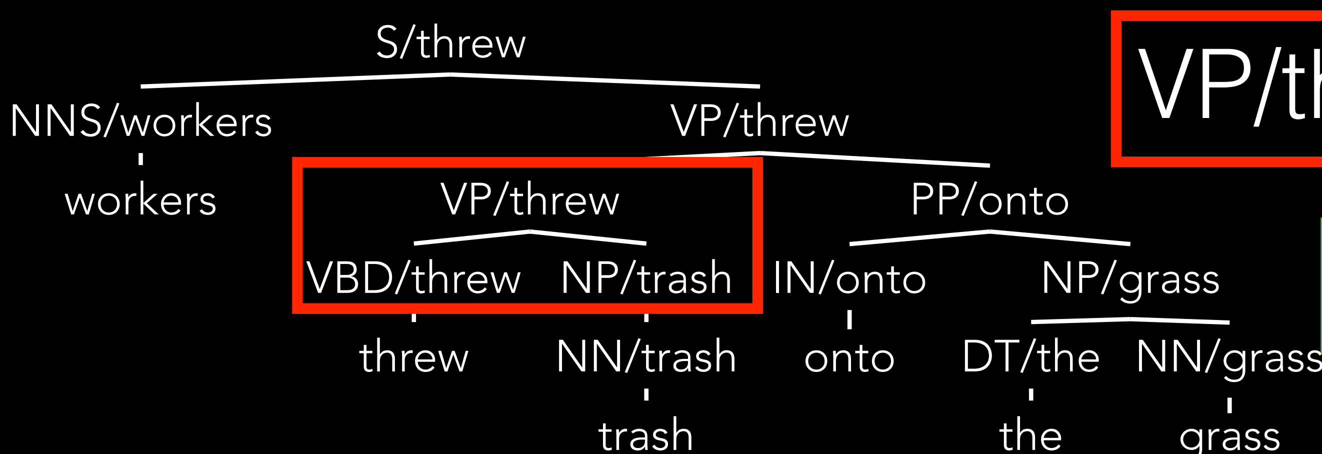

VP/threw -> VBD/threw NP/trash

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VP/threw -> VBD/threw NP

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0/20

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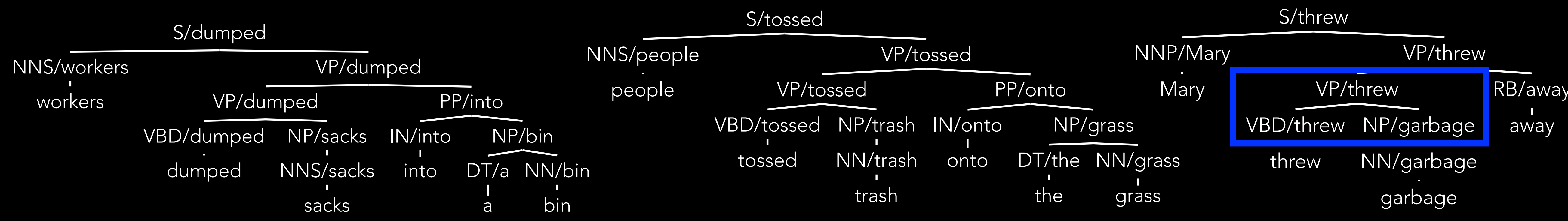

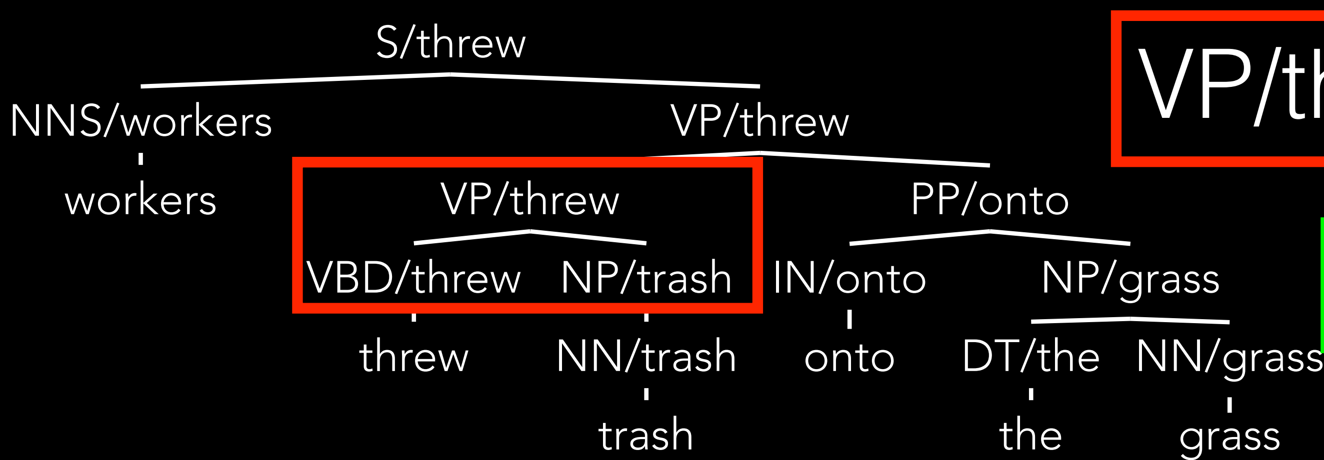

VP/threw -> VBD/threw NP/trash

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VP/threw -> VBD/threw NP

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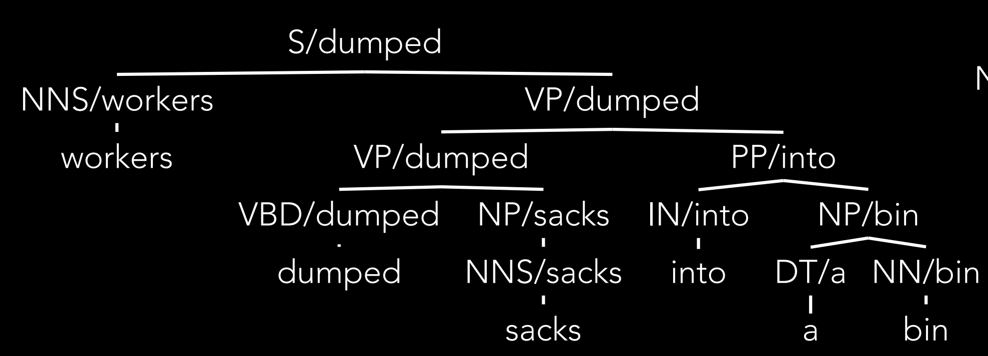

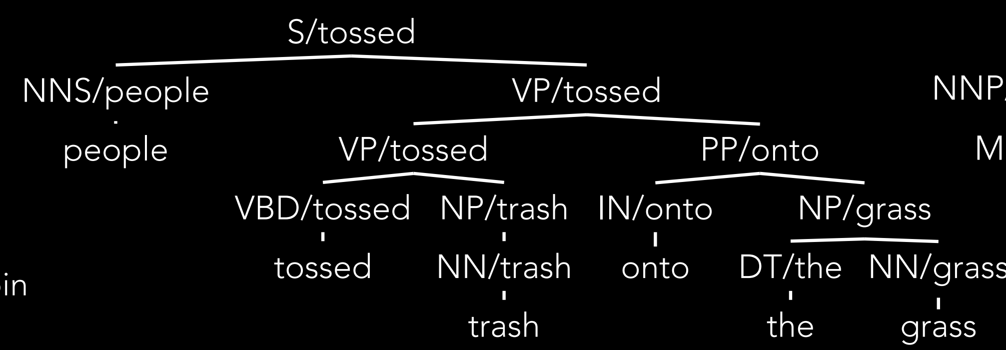

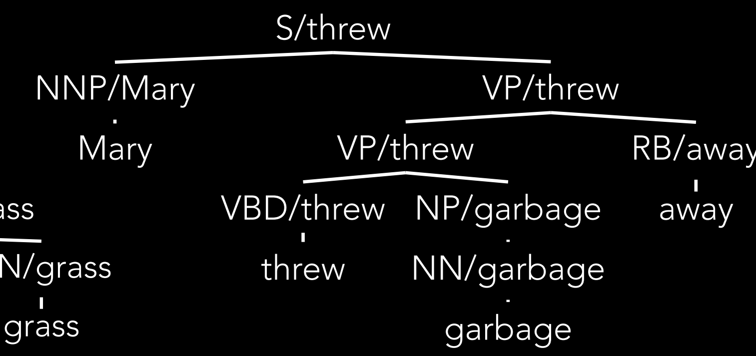

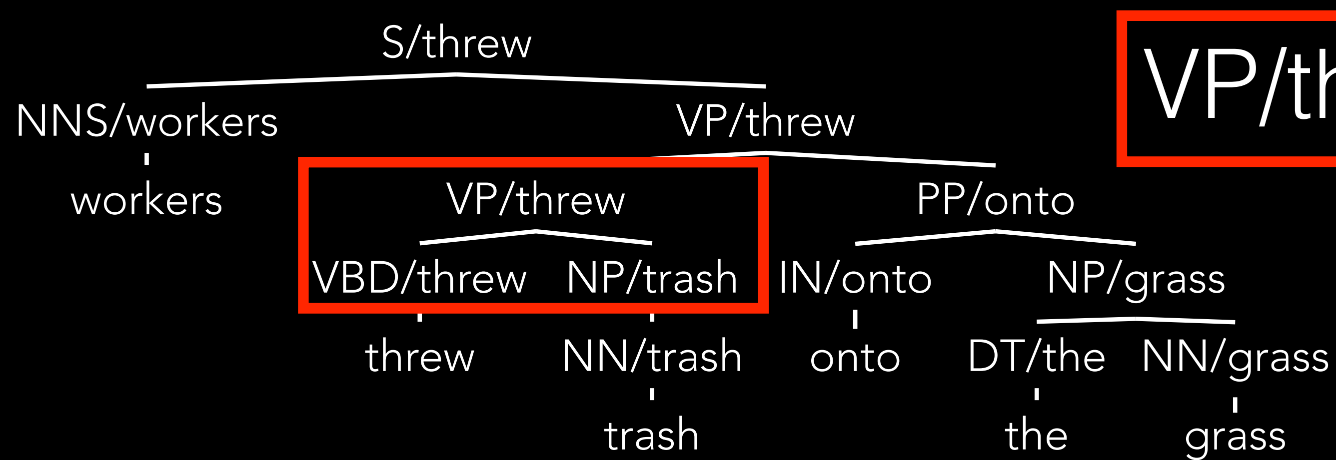

VP/threw -> VBD/threw NP/trash

$$P(m \mid r, X, h) = \lambda_2 P_{ML}(m \mid r, X, h) + (1-\lambda_2) P_{ML}(m \mid r)$$

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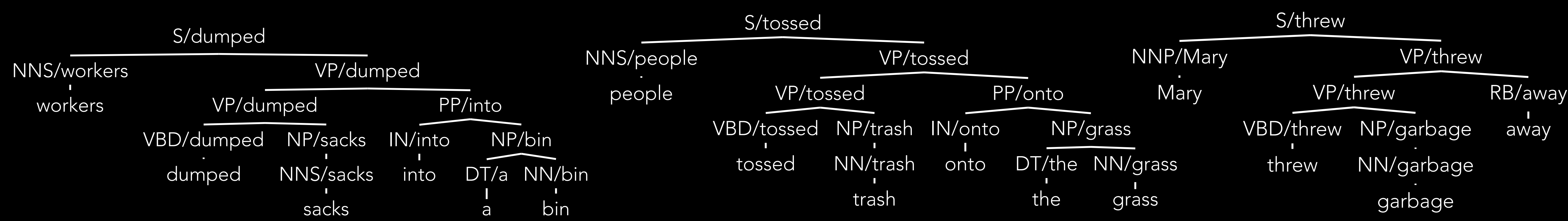

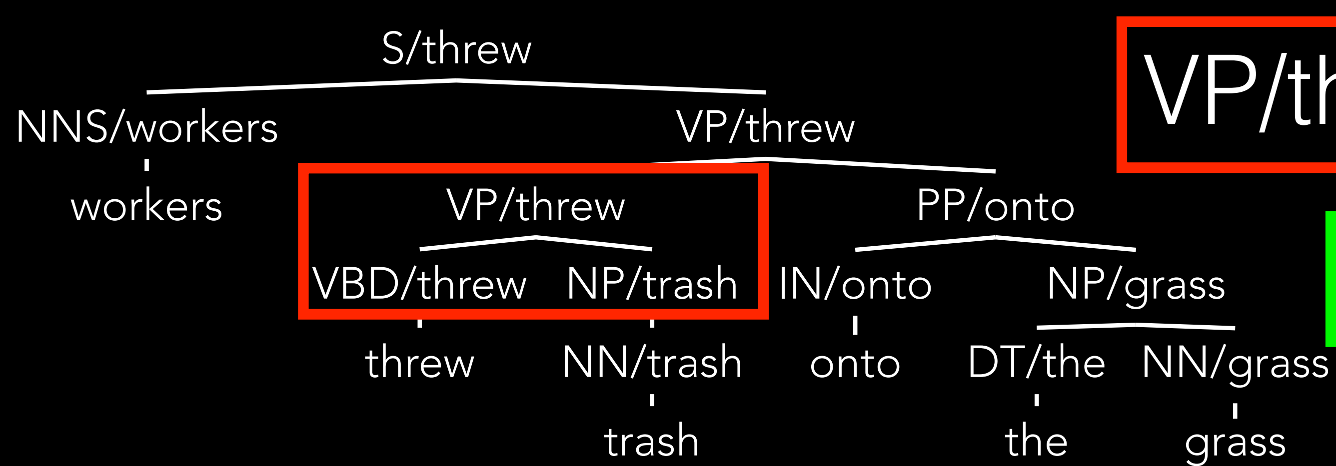

VP/threw -> VBD/threw NP/trash

VP -> VBD NP/trash

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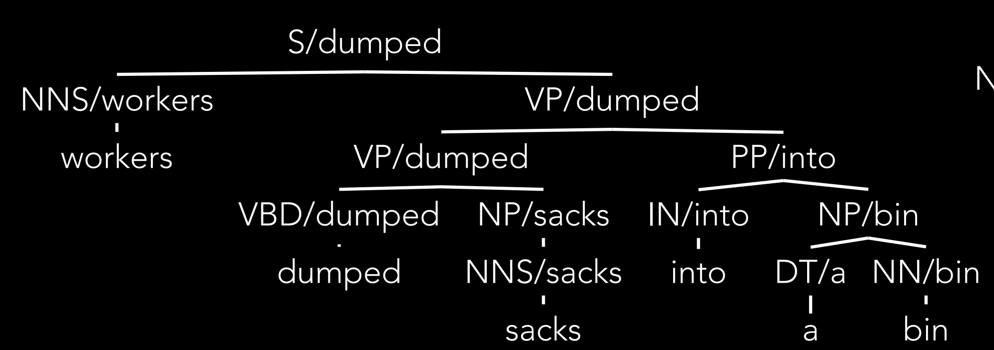

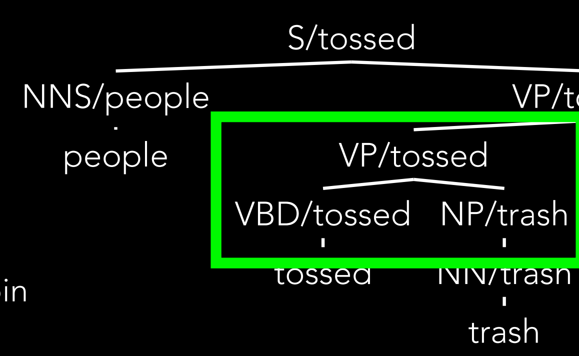

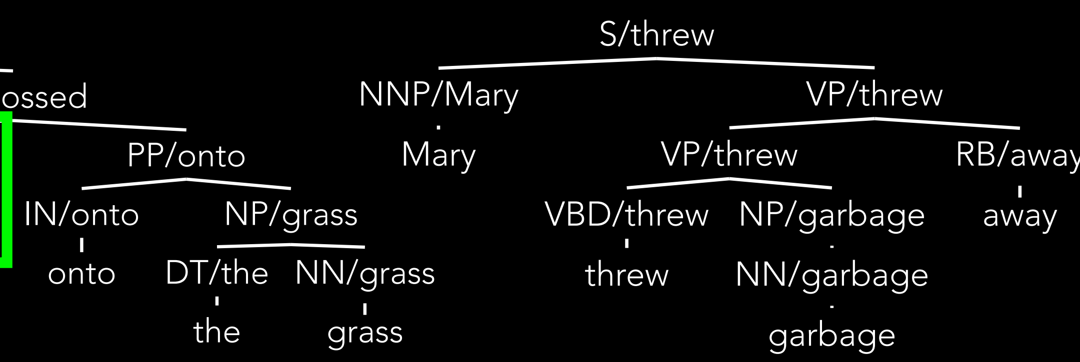

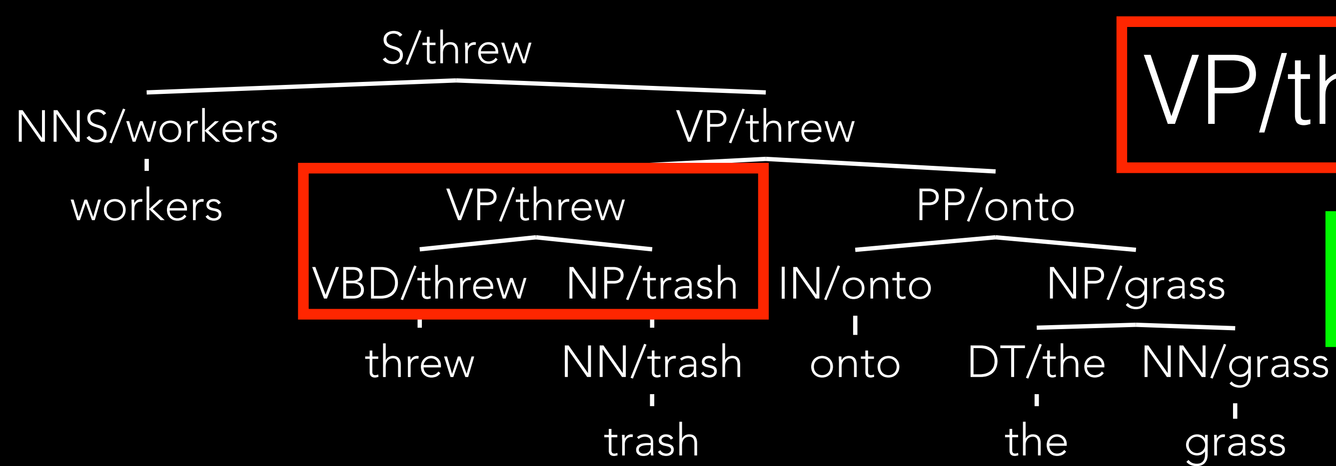

VP/threw -> VBD/threw NP/trash

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0/20

Head lexicalization

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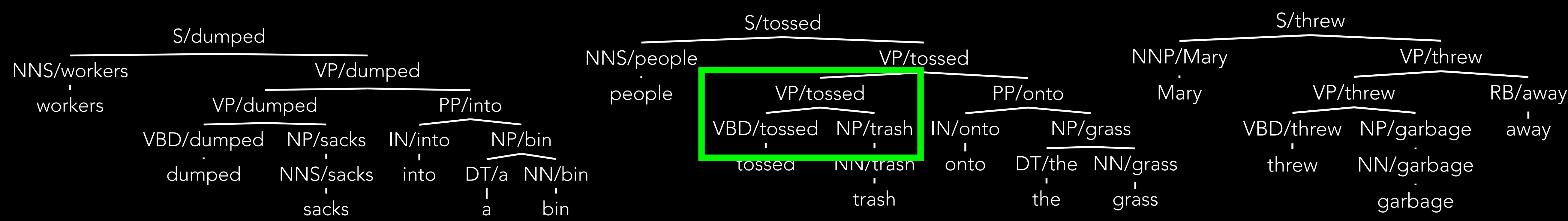

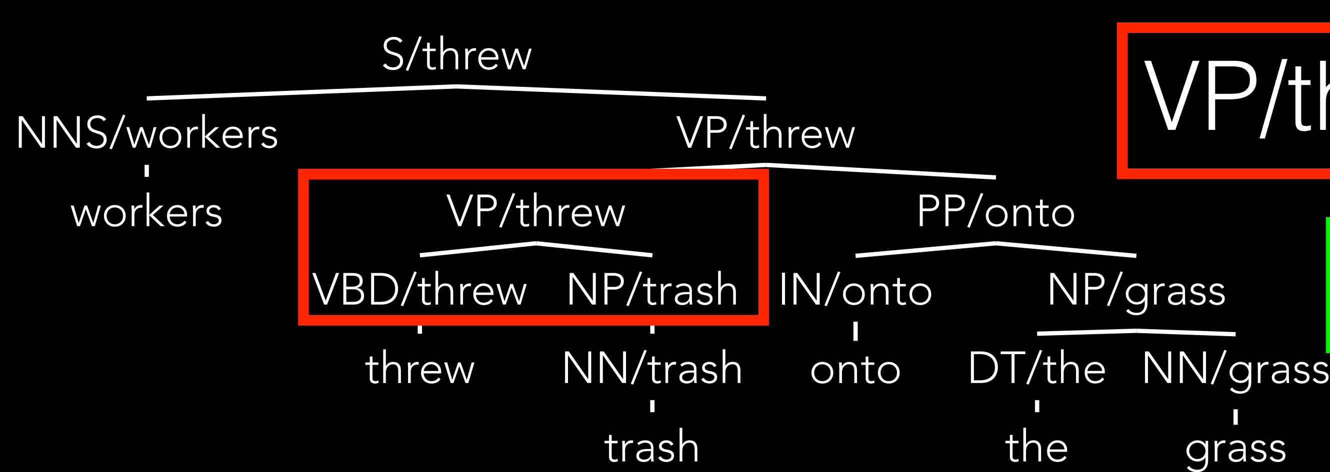

VP/threw -> VBD/threw NP/trash

VP -> VBD NP/trash

VP -> VBD NP

$$P(m \mid r, X, h) = \lambda_2 P_{ML}(m \mid r, X, h) + (1-\lambda_2) P_{ML}(m \mid r)$$

0/20

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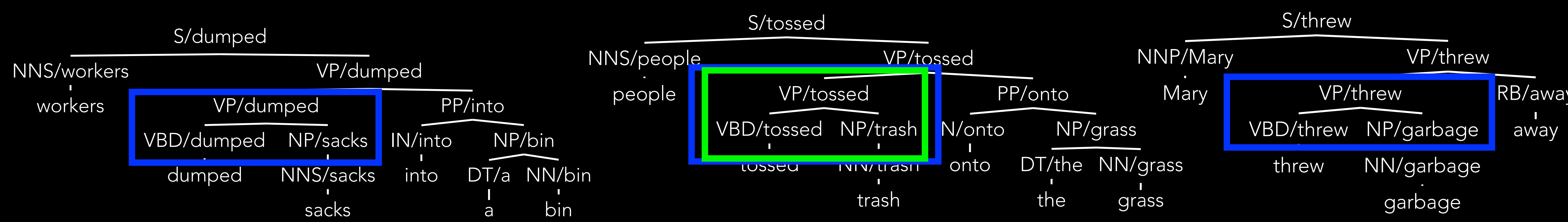

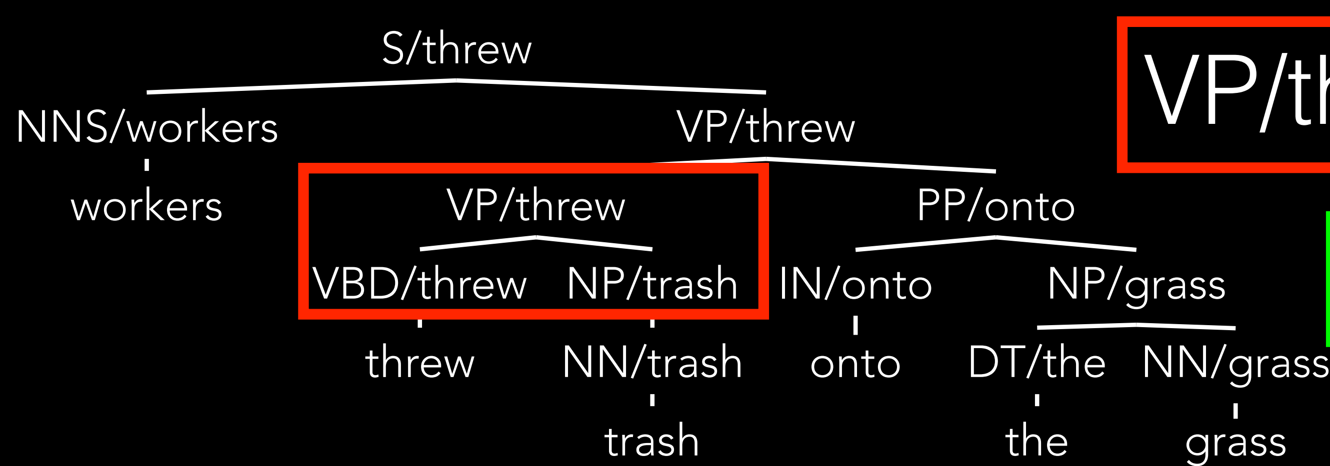

VP/threw -> VBD/threw NP/trash

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0/20

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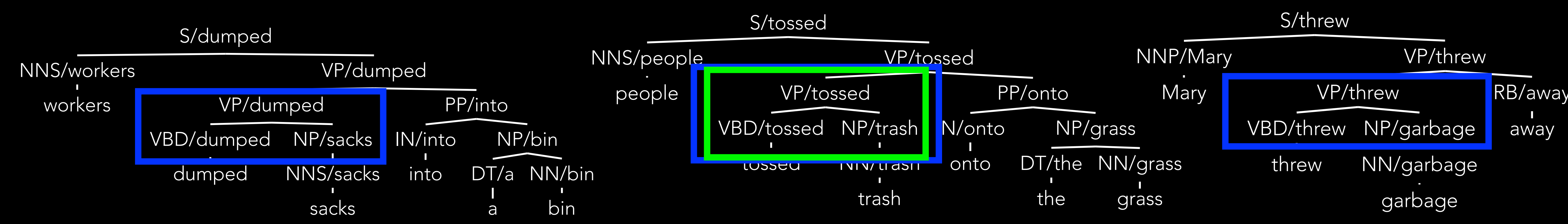

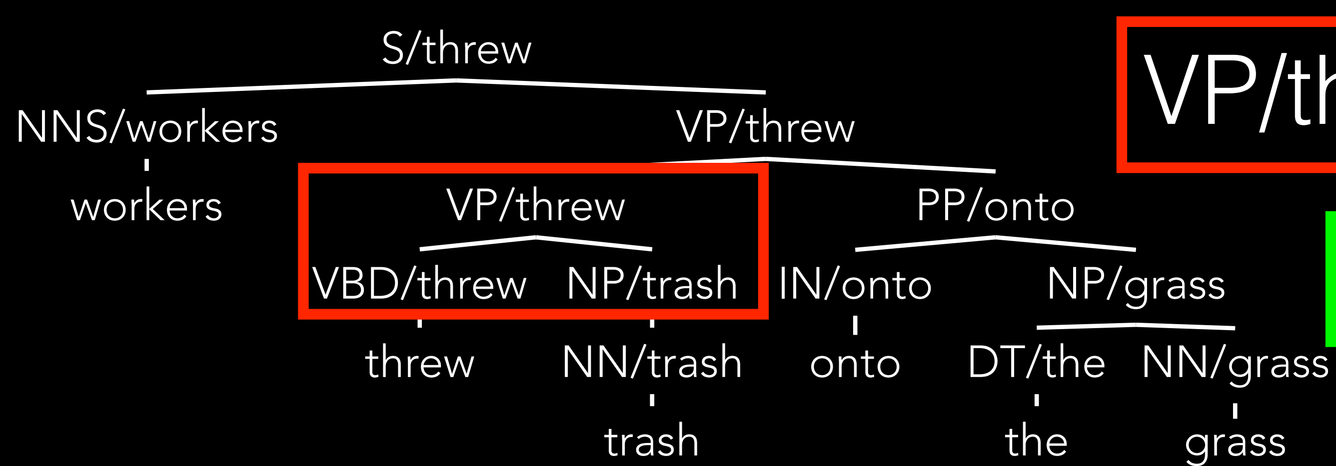

VP/threw -> VBD/threw NP/trash

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0/20 20/60

Head lexicalization

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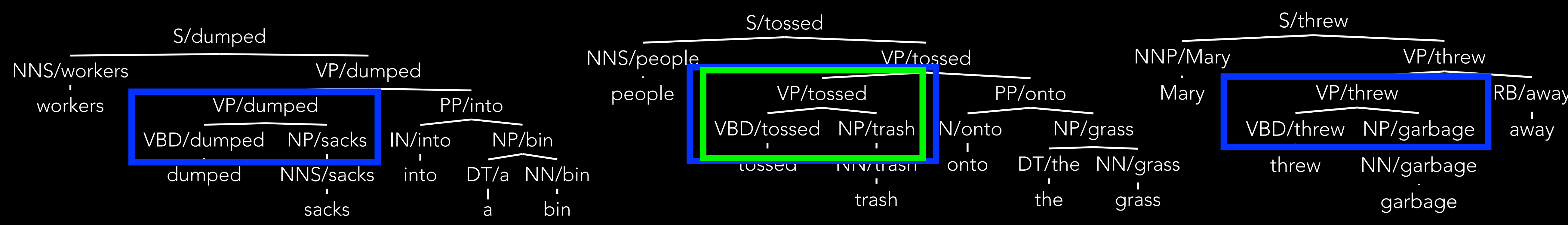

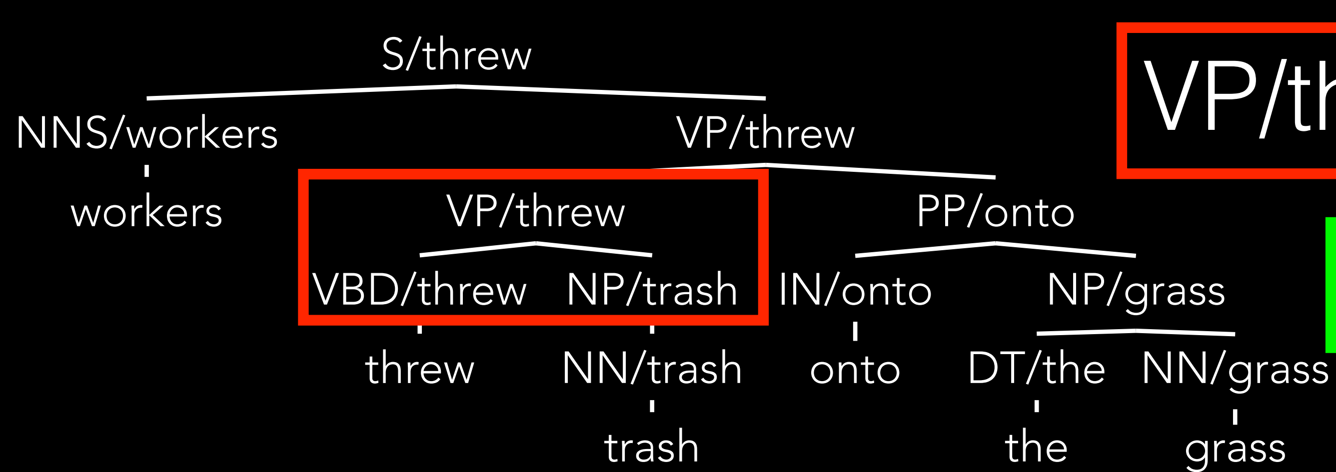

VP/threw -> VBD/threw NP/trash

VP -> VBD NP/trash

VP -> VBD NP

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0/20 $\qquad$ $\boxed{20}$/60

Head lexicalization

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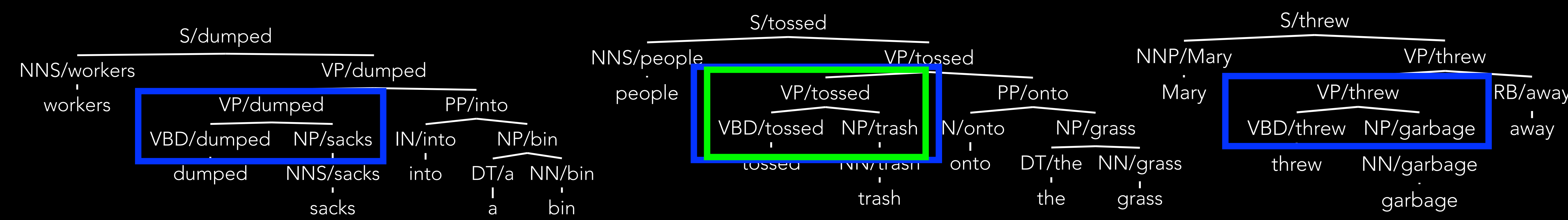

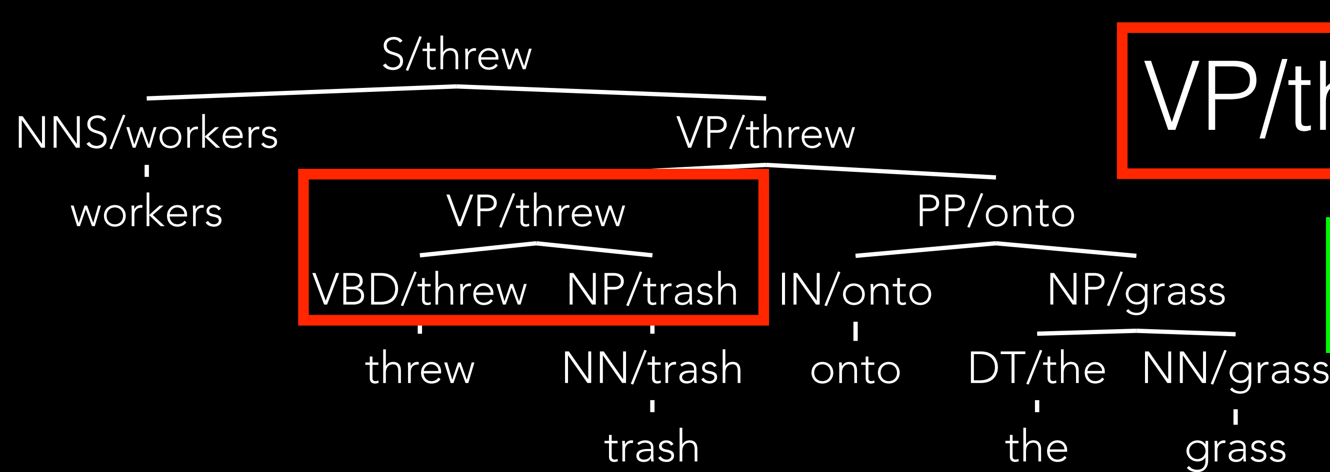

VP/threw -> VBD/threw NP/trash

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0/20

$\boxed{20}/\boxed{60}$

Head lexicalization

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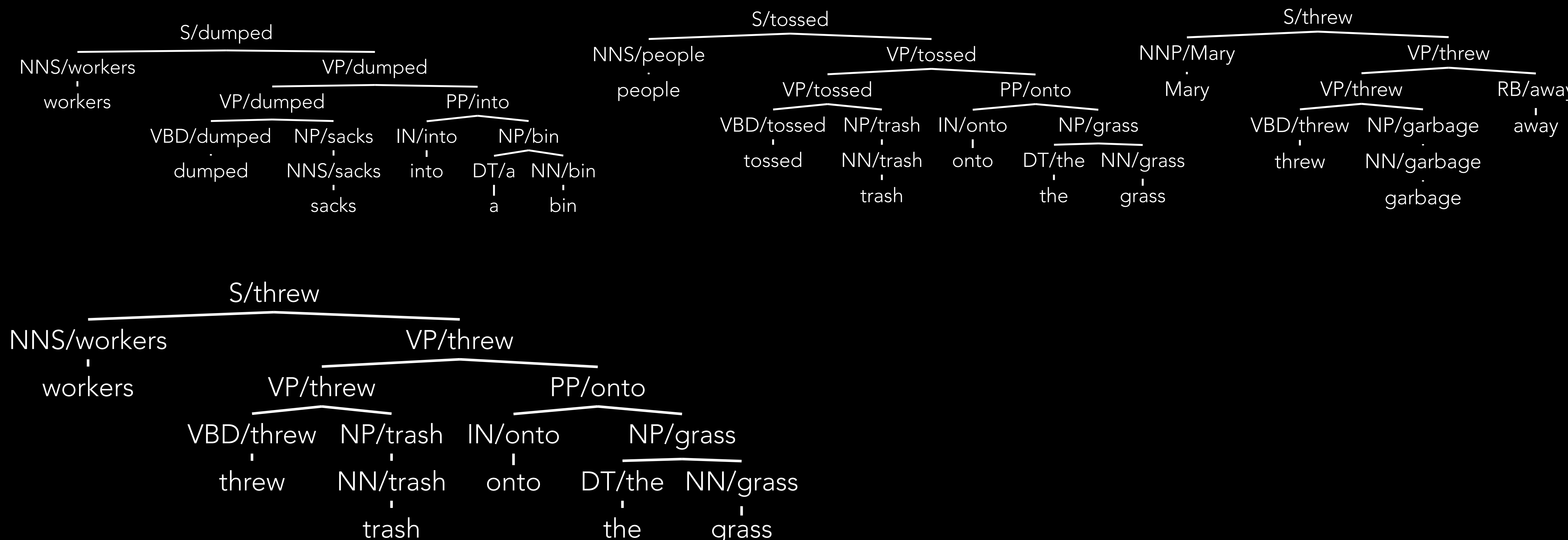

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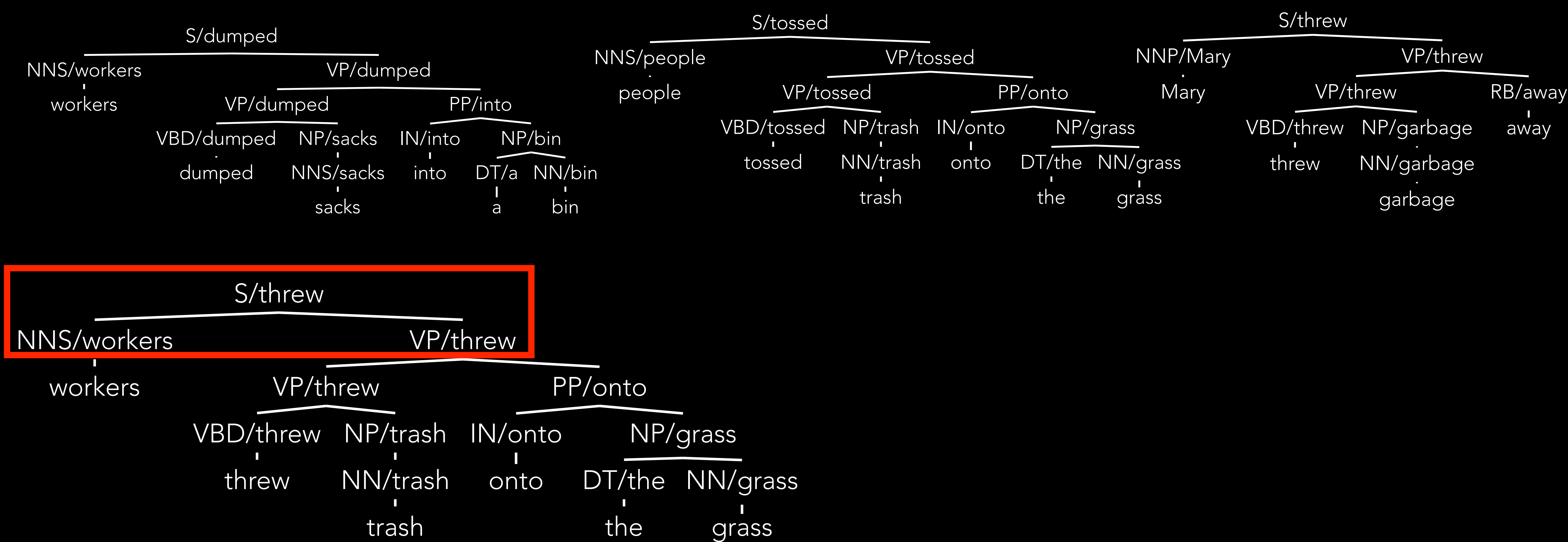

Head lexicalization

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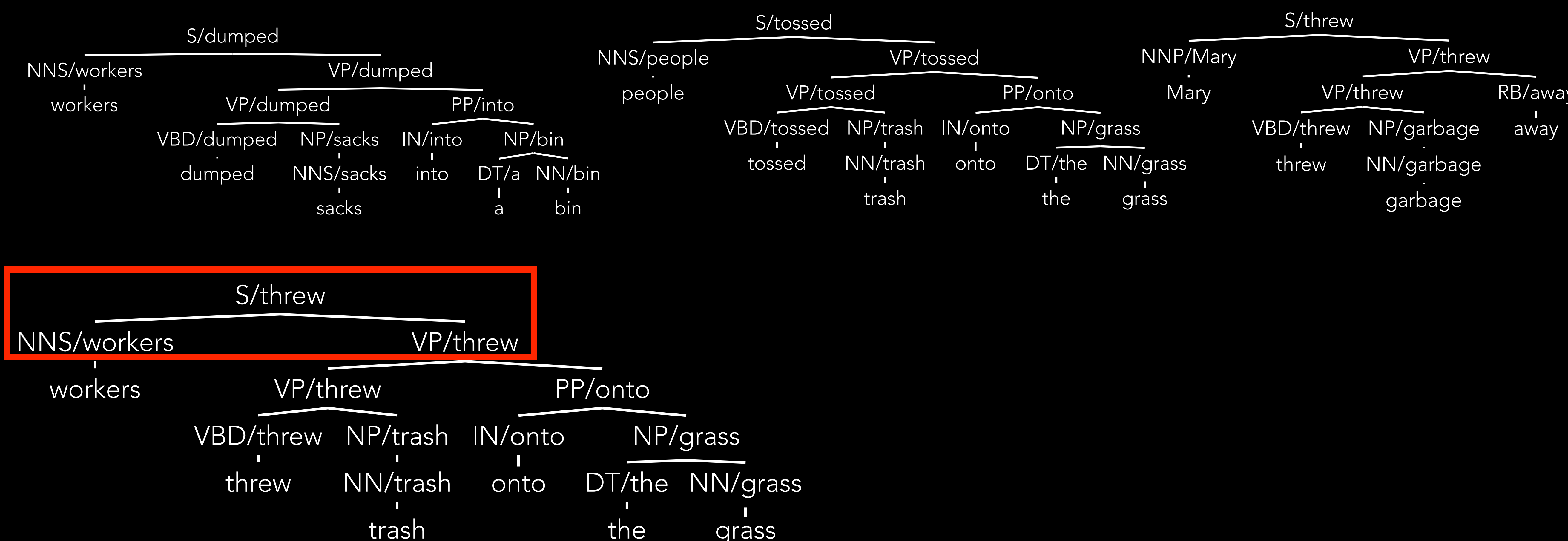

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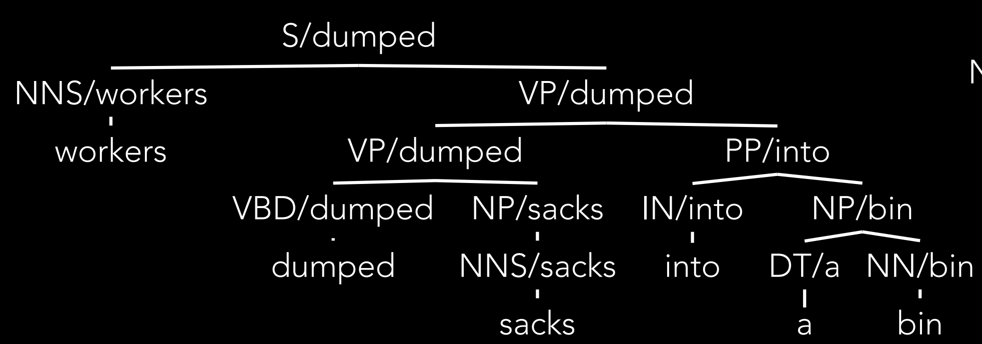

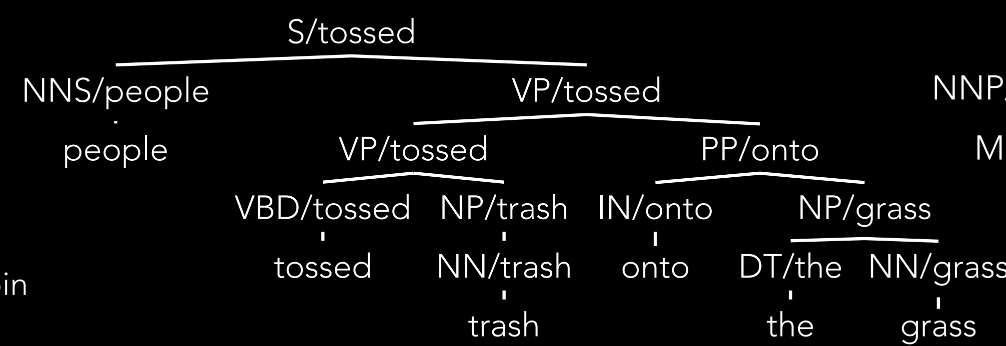

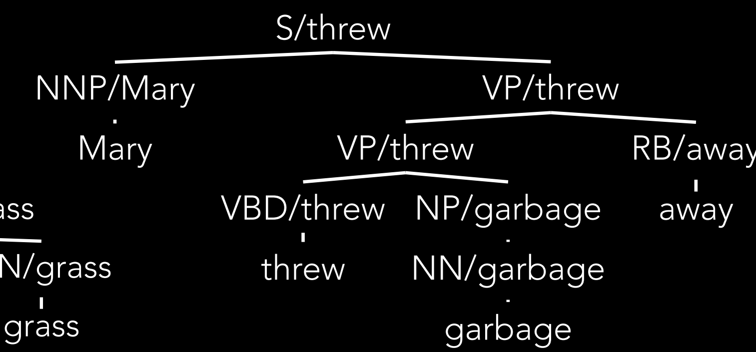

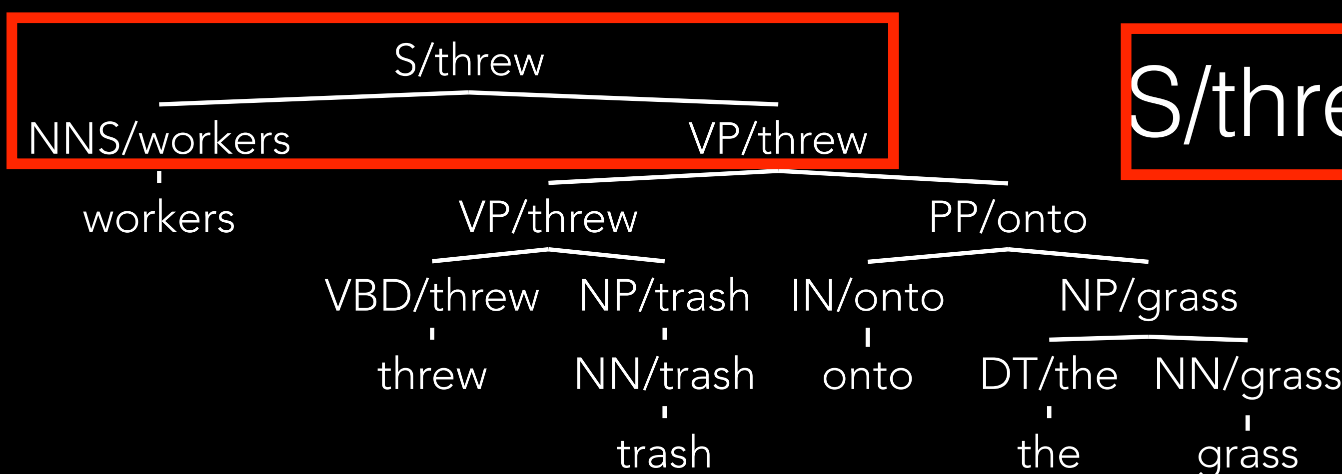

S/threw -> NNS/workers VP/threw

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Head lexicalization

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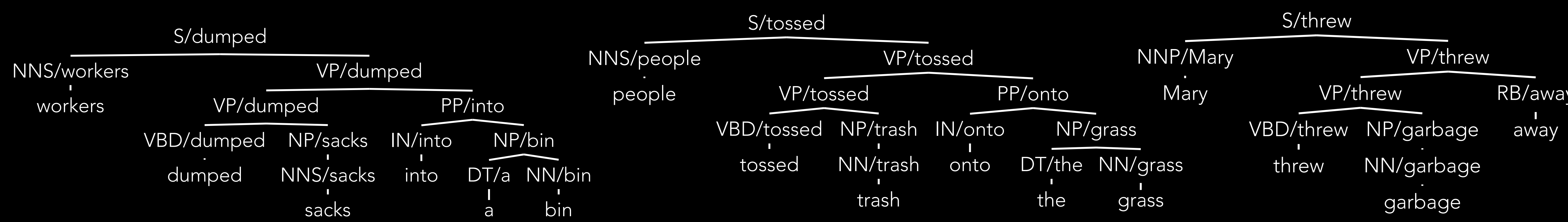

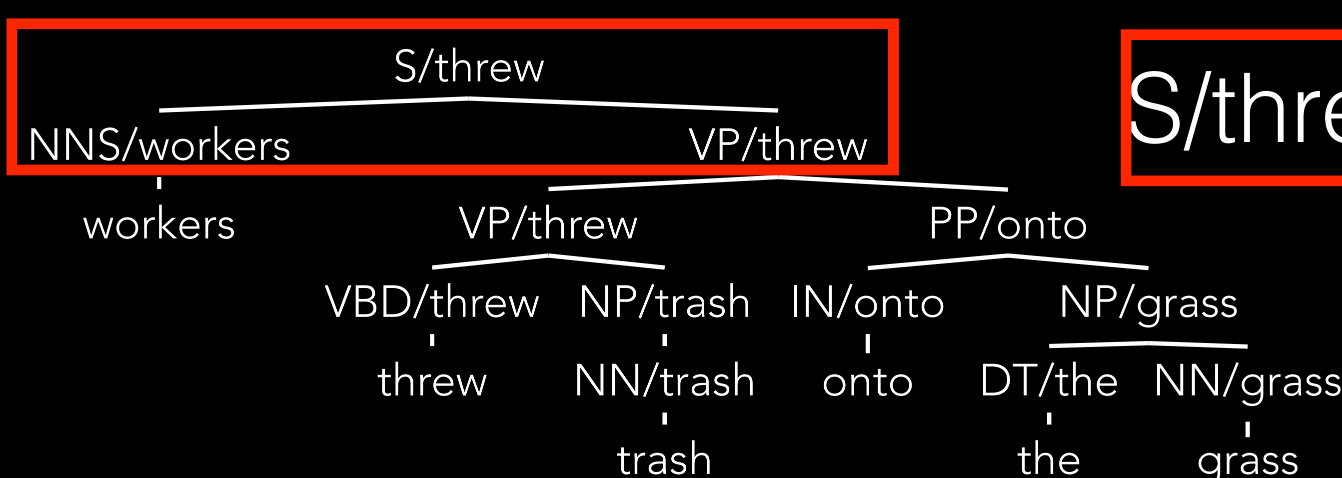

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S/threw -> …

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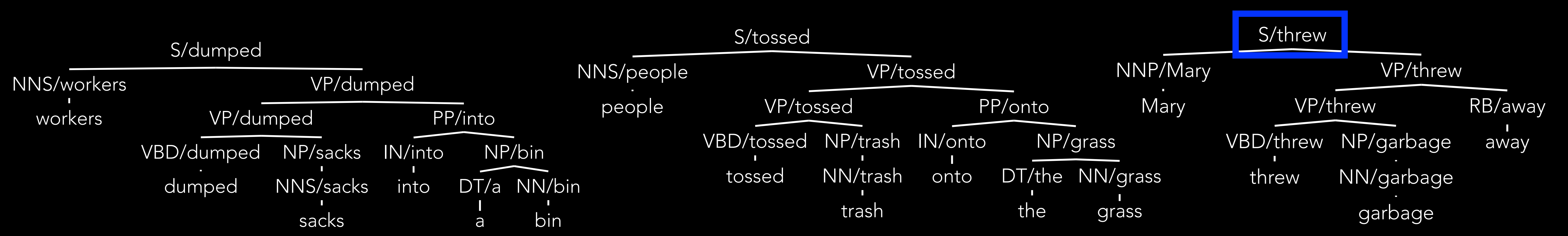

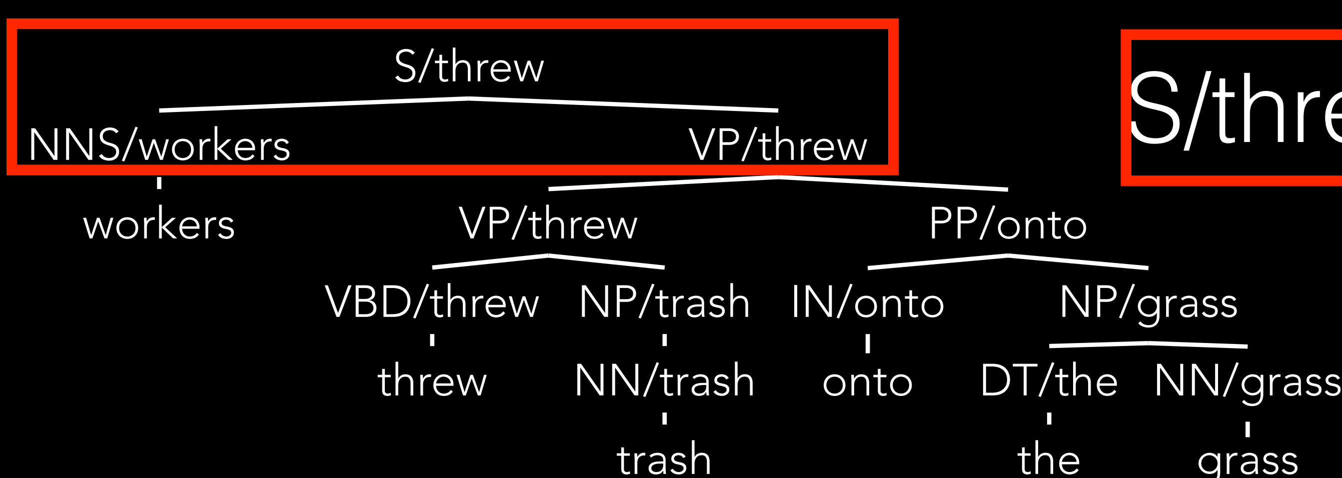

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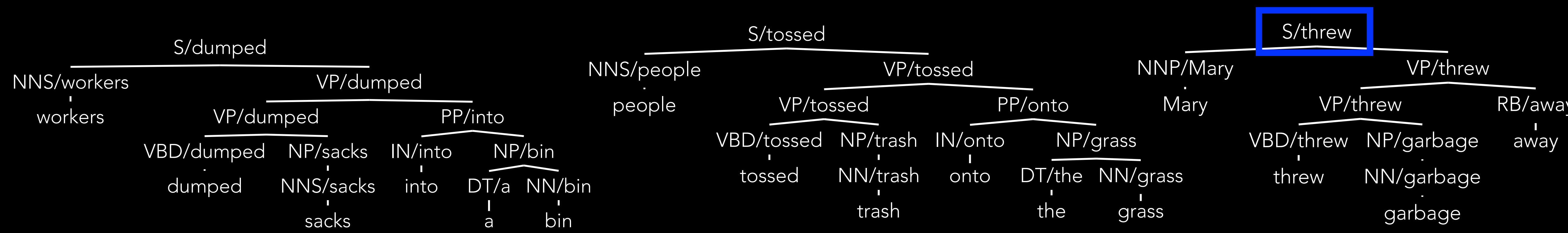

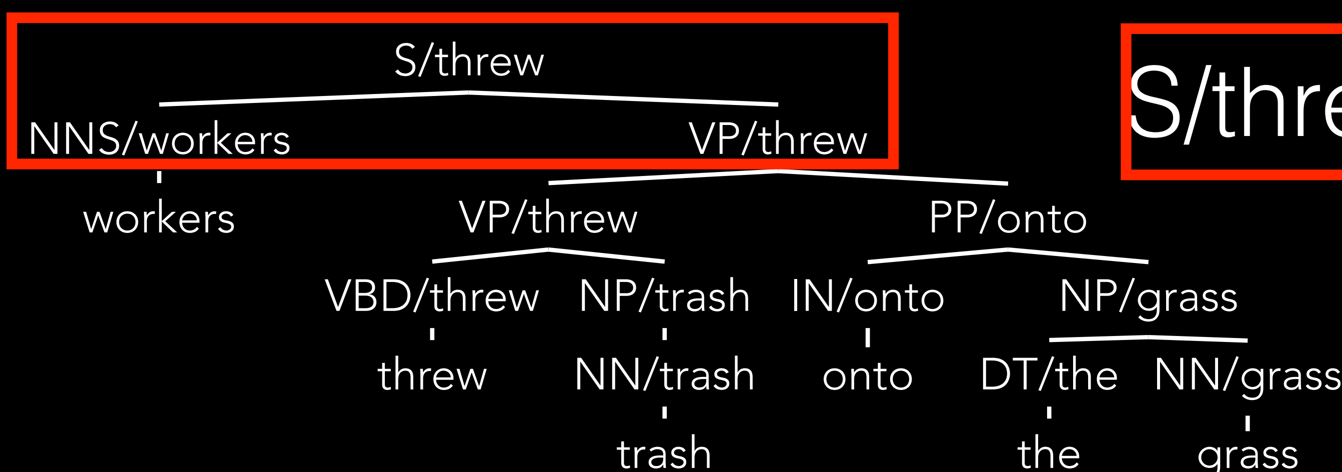

S/threw -> NNS/workers VP/threw

S/threw -> NNS VP/threw

S/threw -> …

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0/20

Head lexicalization

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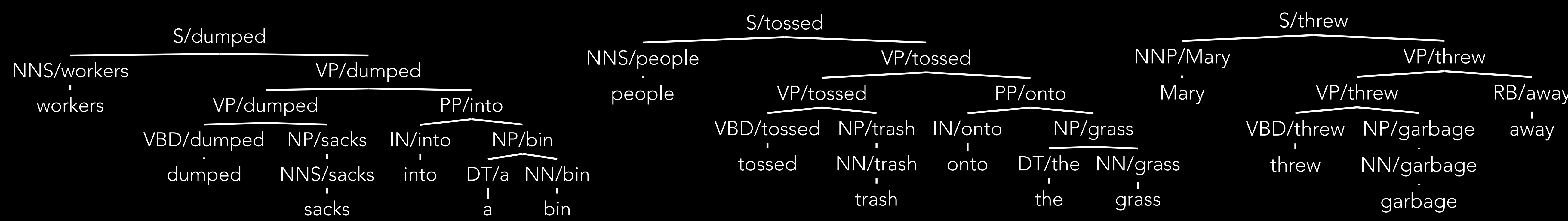

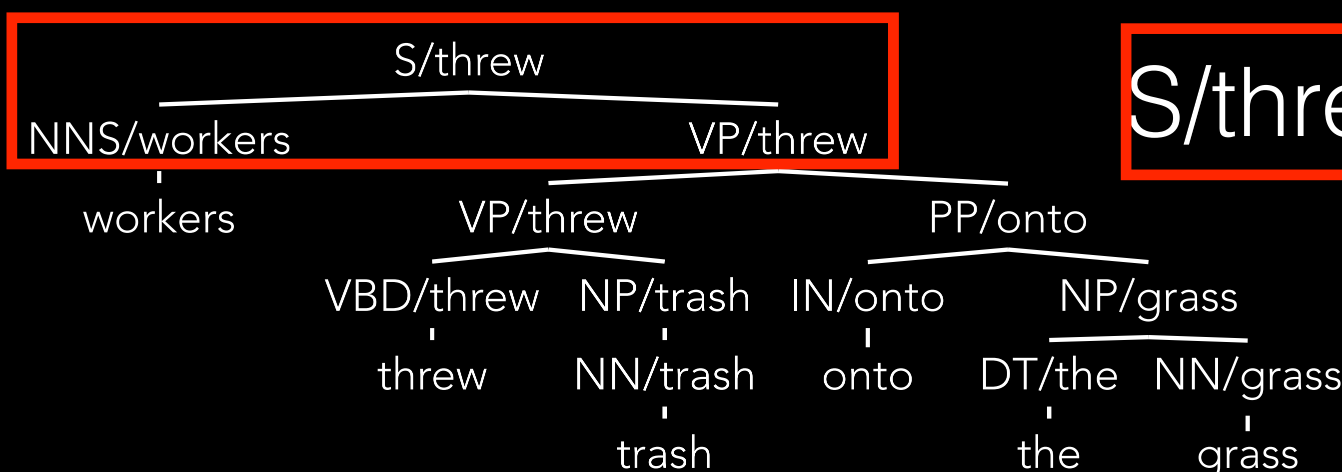

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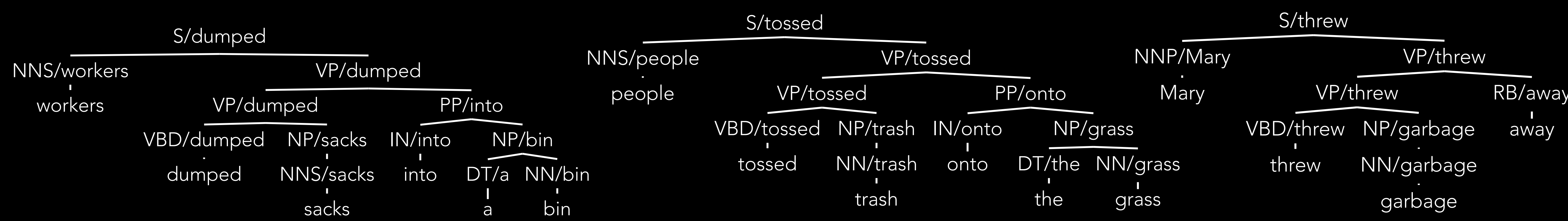
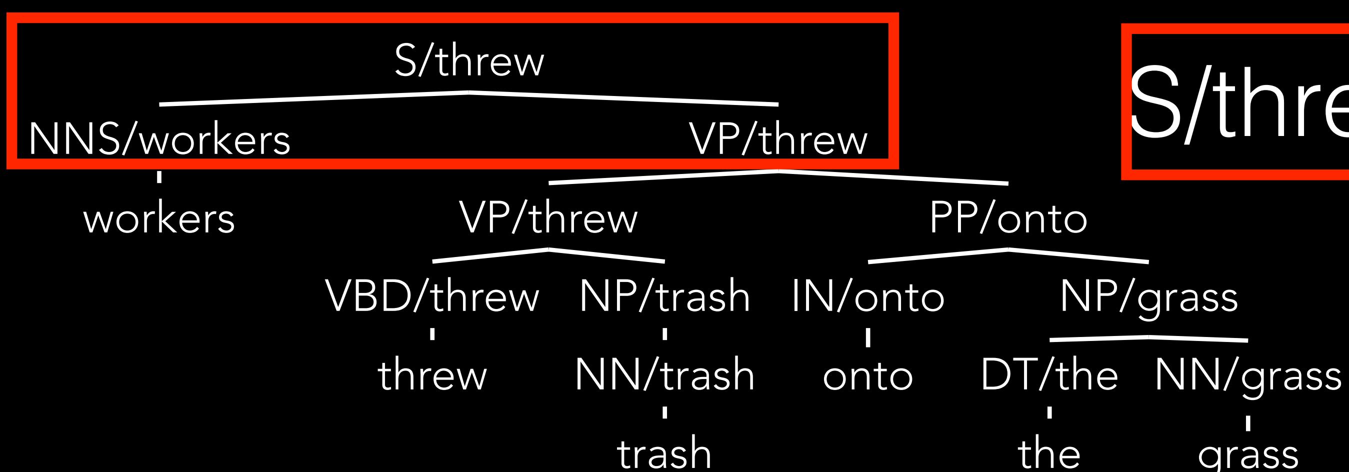




S/threw -> NNS/workers VP/threw

S -> NNS VP

S -> …

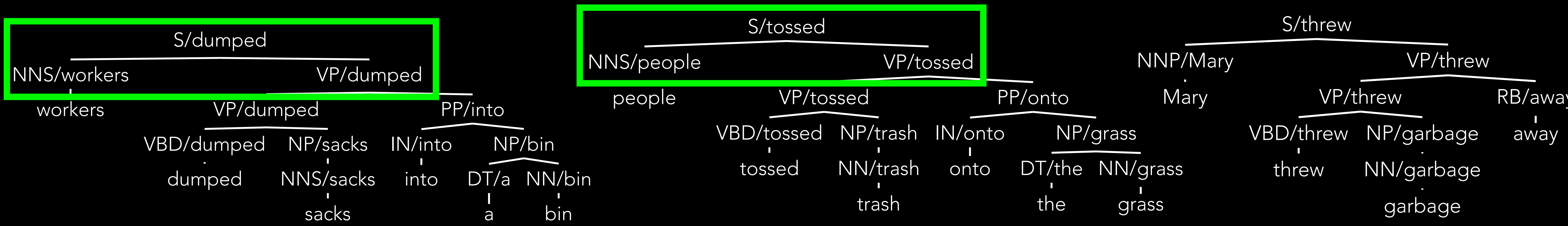
$$P(r \mid X, h) = \lambda_1 P_{ML}(r \mid X, h) + (1-\lambda_1) P_{ML}(r \mid X)$$

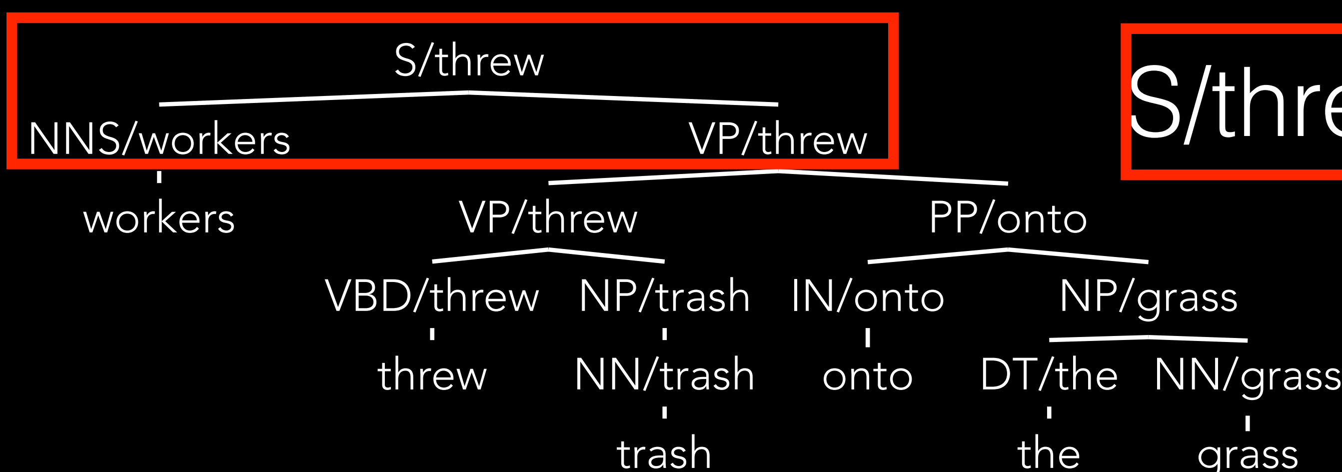
0/20

Head lexicalization

By decomposing we can estimate unseen lexicalized rules

Assume we saw each training tree 20 times





S/threw -> NNS/workers VP/threw

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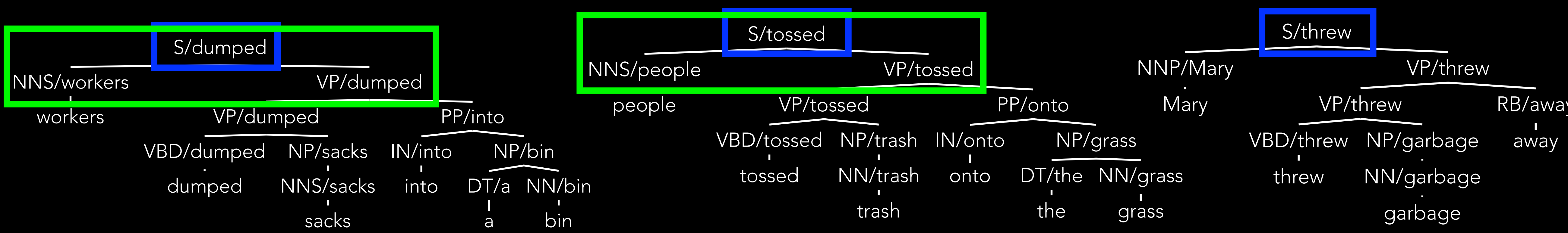

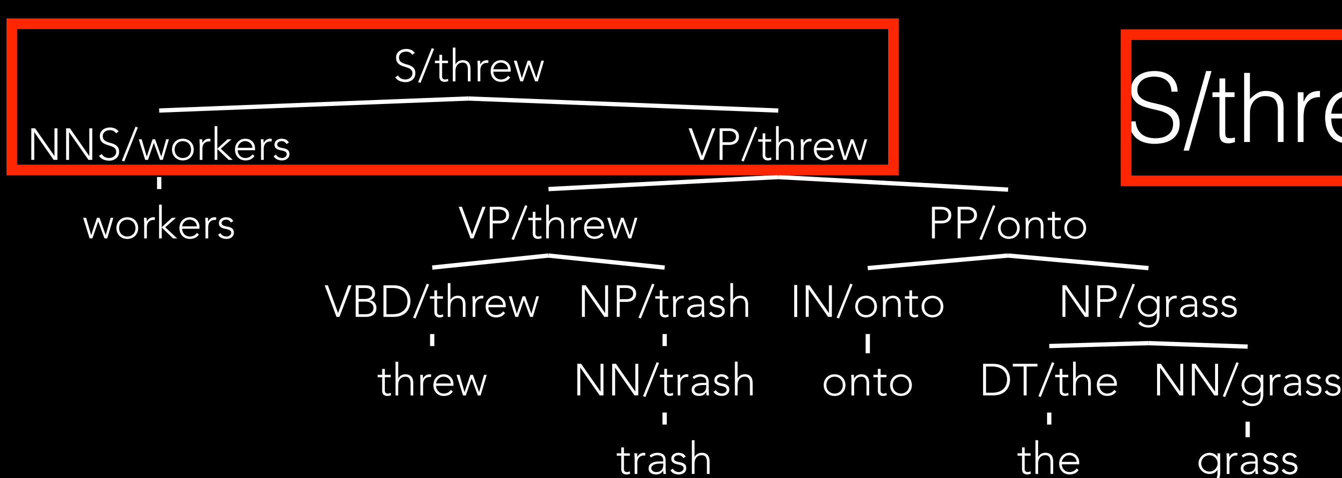

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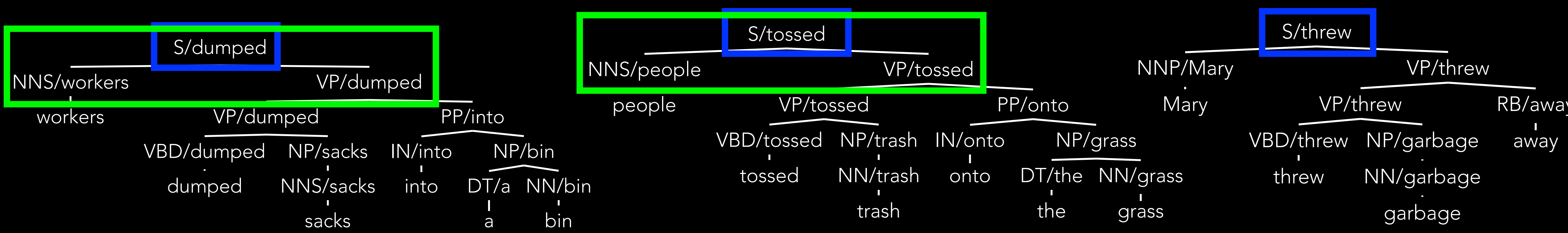

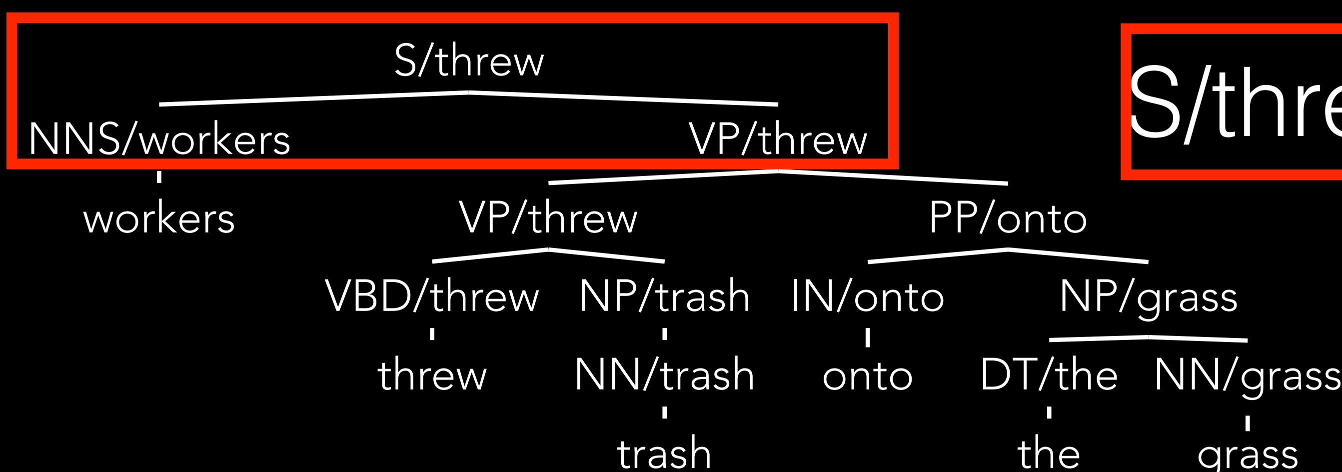

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0/20 40/60

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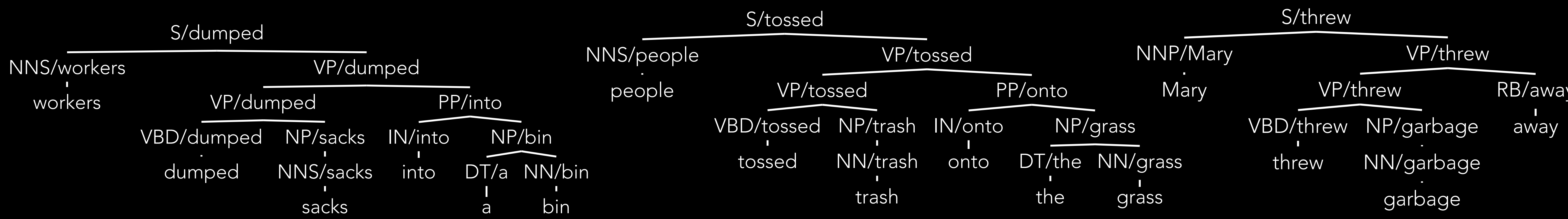

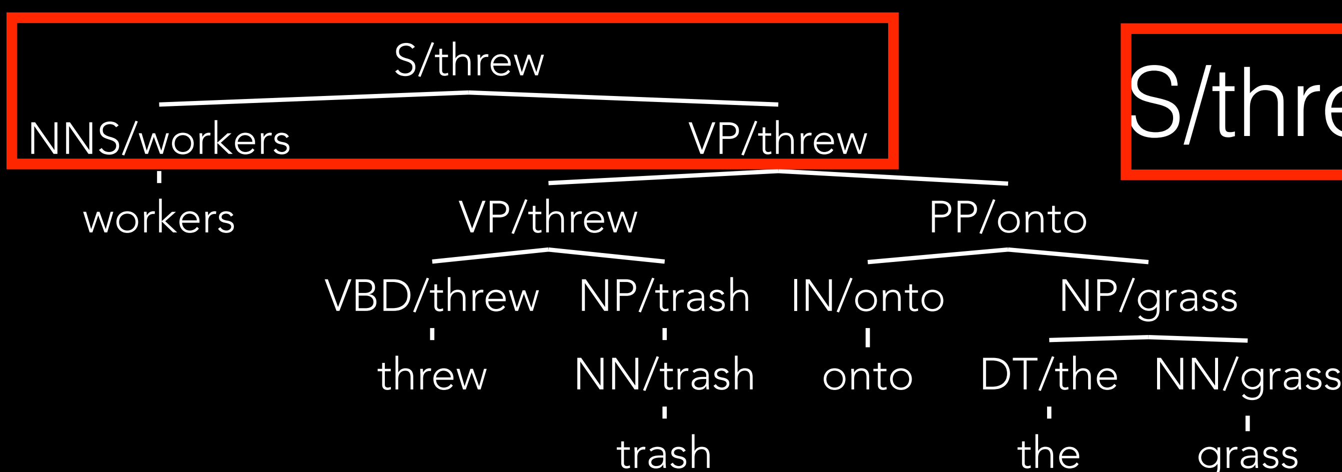

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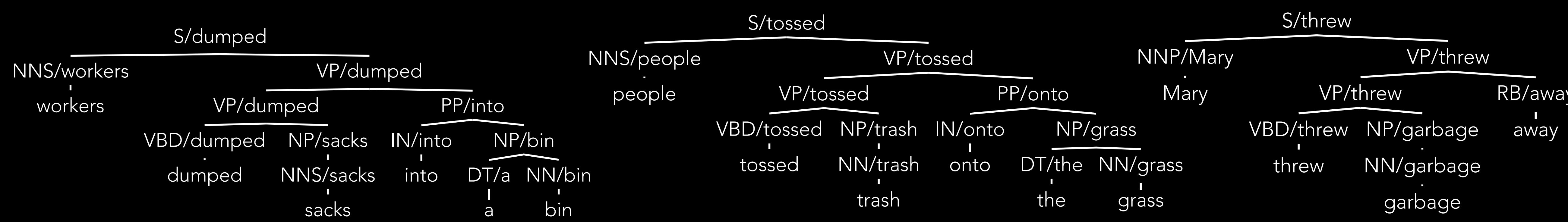

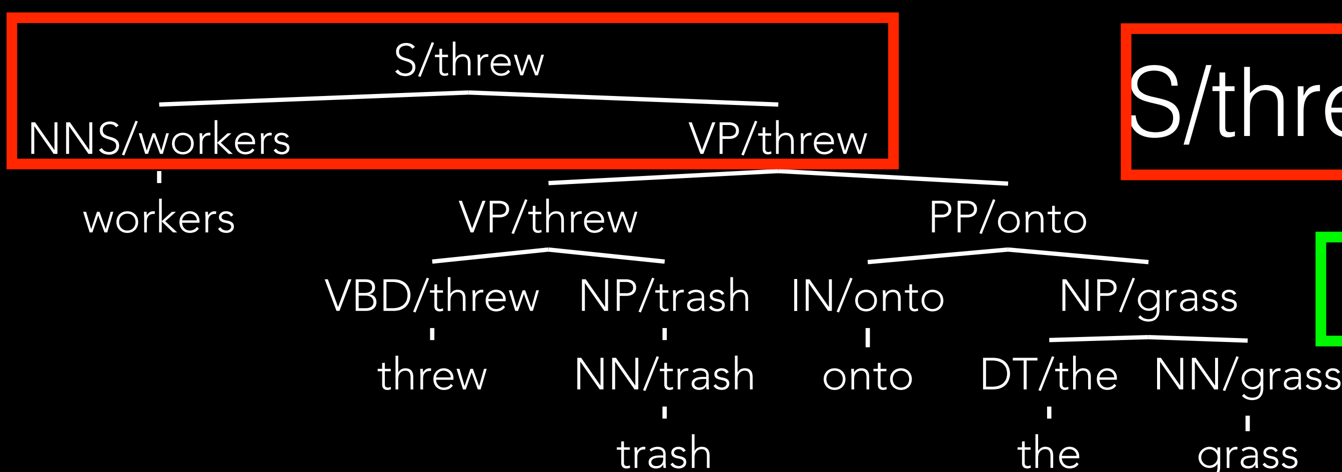

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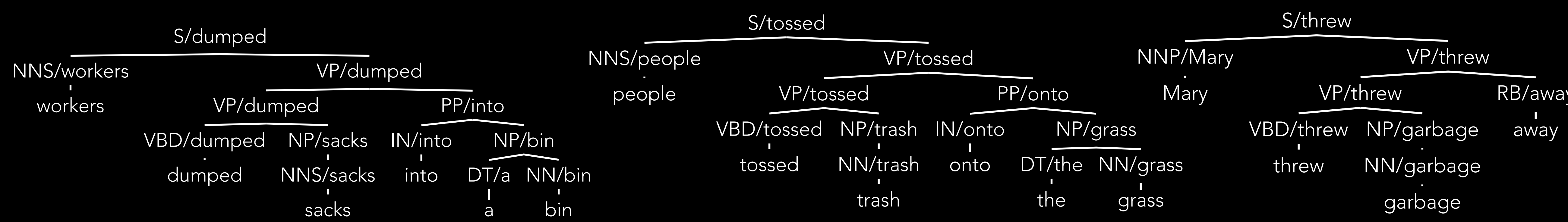

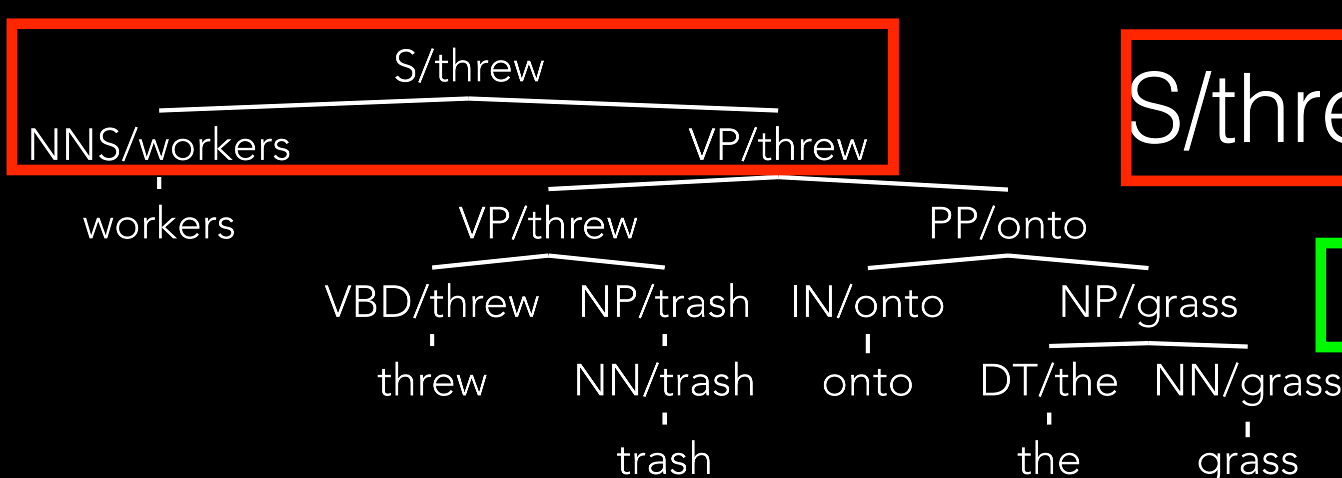

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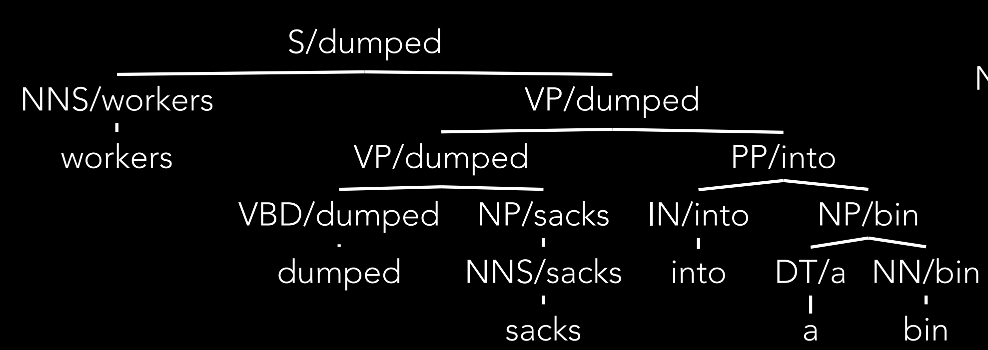

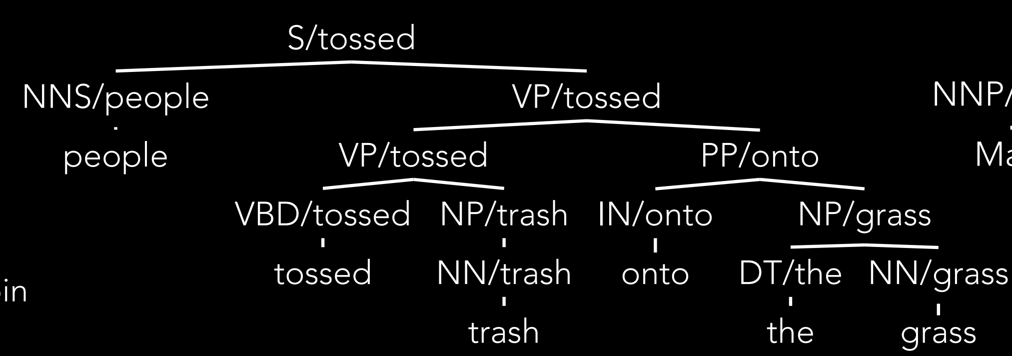

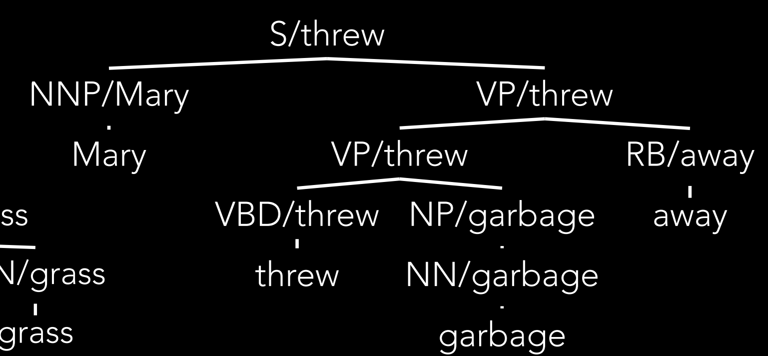

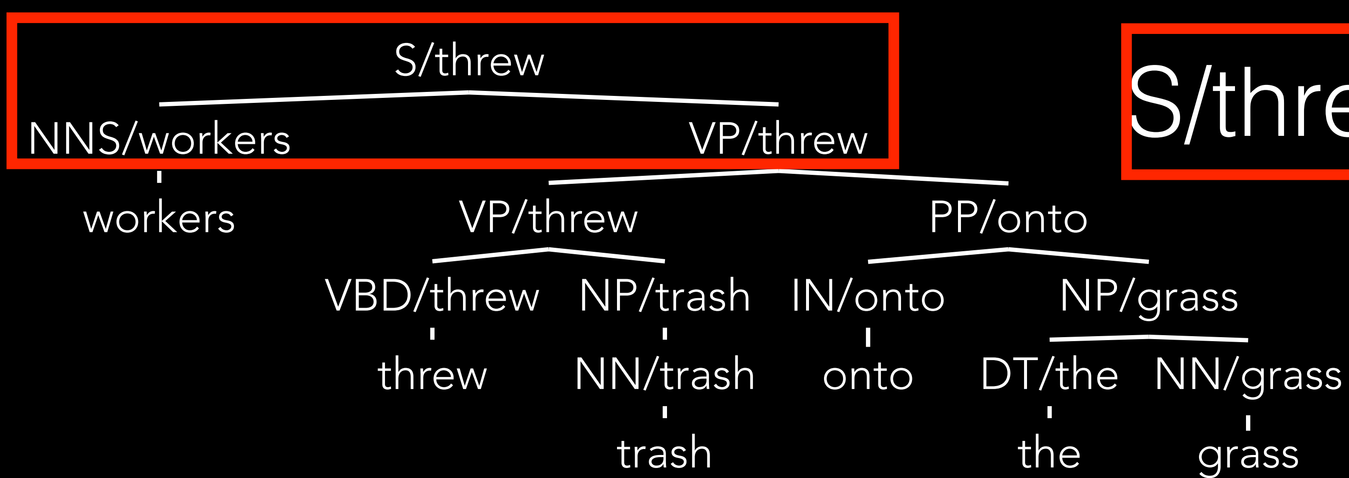

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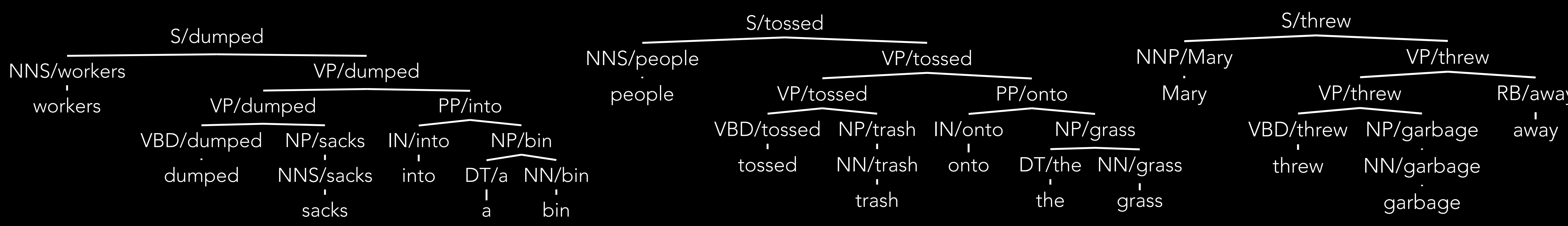

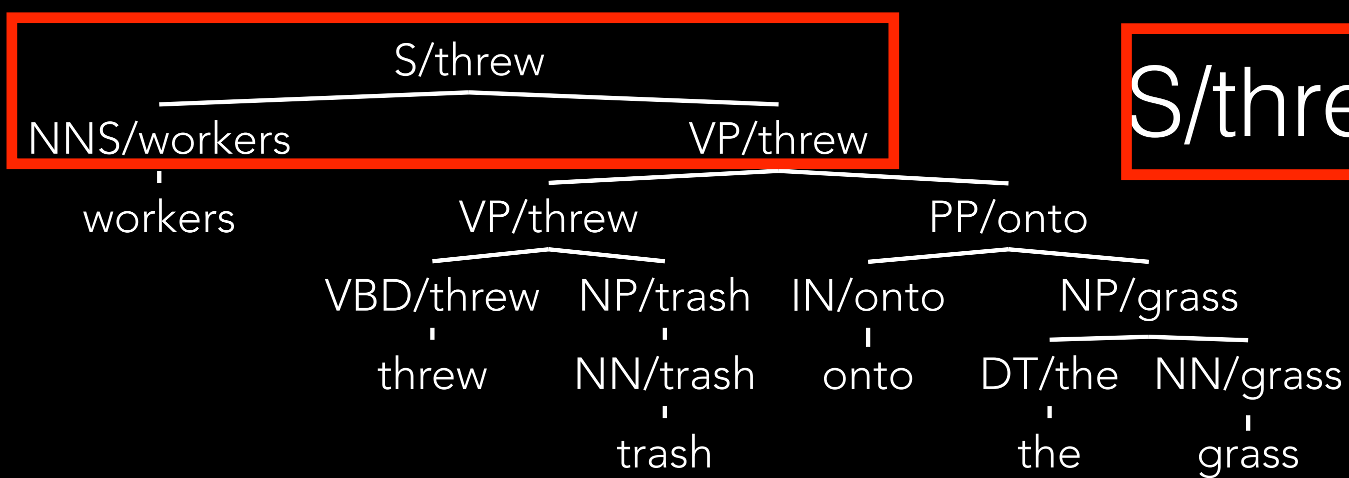

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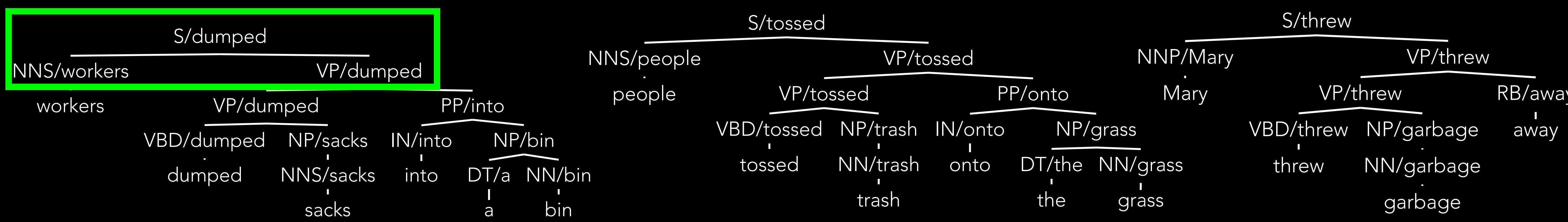

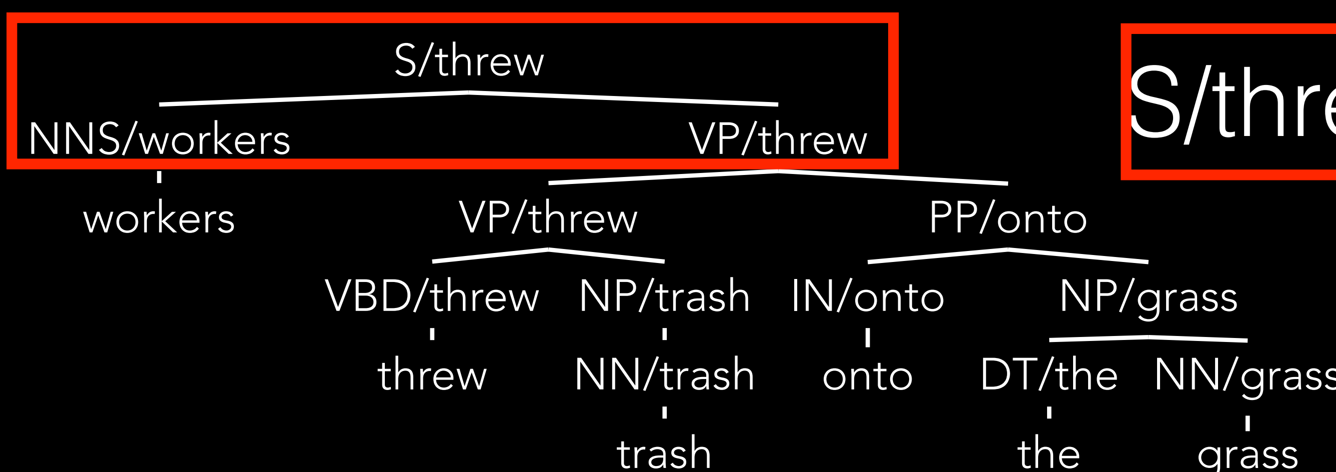

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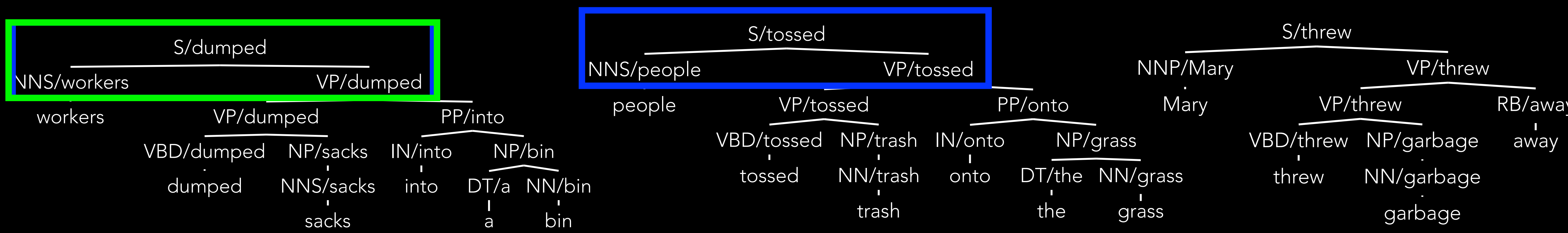

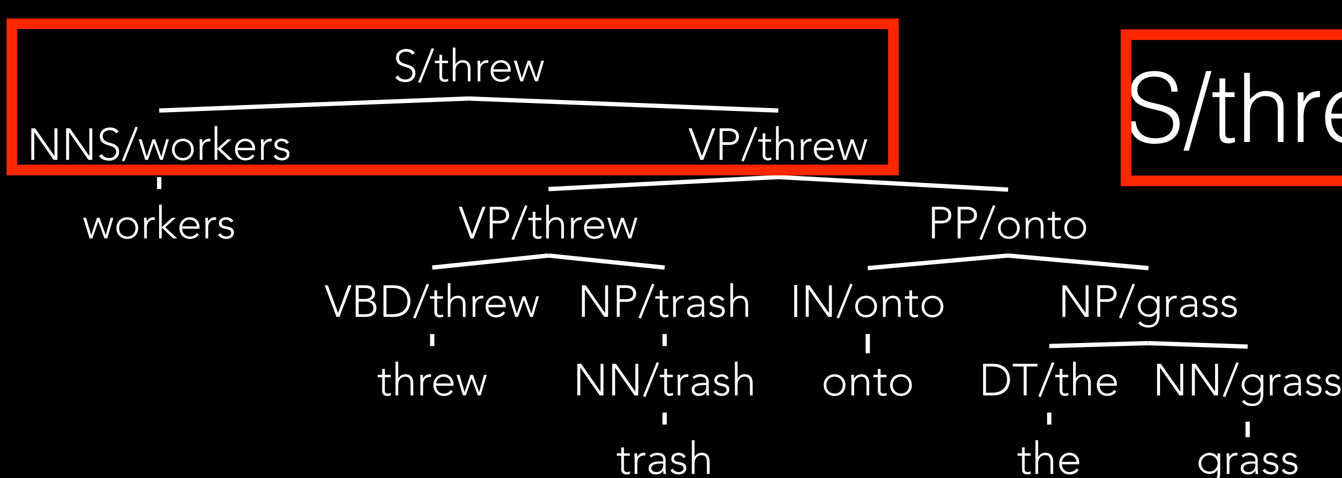

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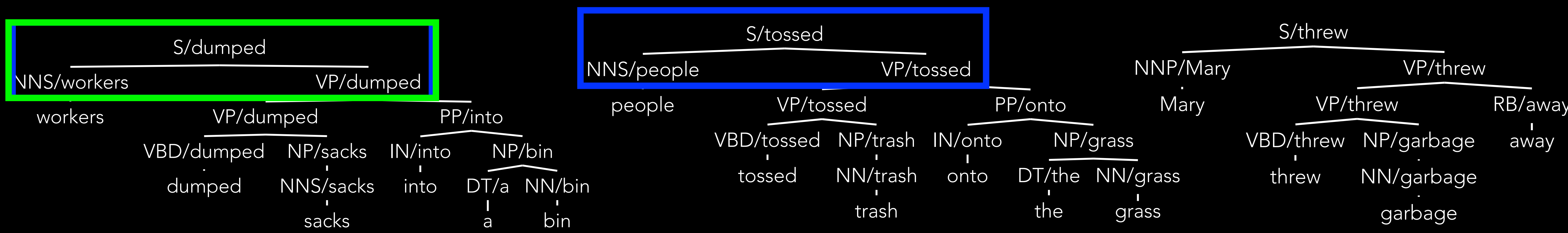

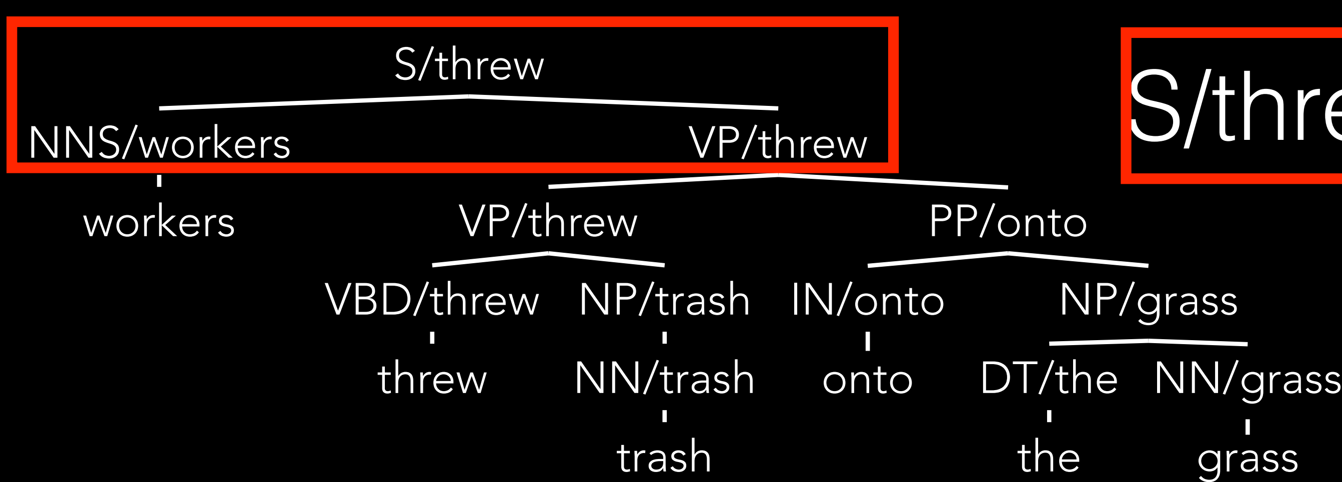

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0/0

20/40

Smoothing Lexicalized PCFGs

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- What about $\lambda 1$ and $\lambda 2$?

Smoothing Lexicalized PCFGs

- What about λ1 and λ2?
- Can do grid search on dev data (all 121 settings from 0.0 to 1.0 for each)

Smoothing Lexicalized PCFGs

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- Here we'll apply it to lexicalization, e.g.: $P_{ML}(r \mid X, h)$ and $P_{ML}(r \mid X)$

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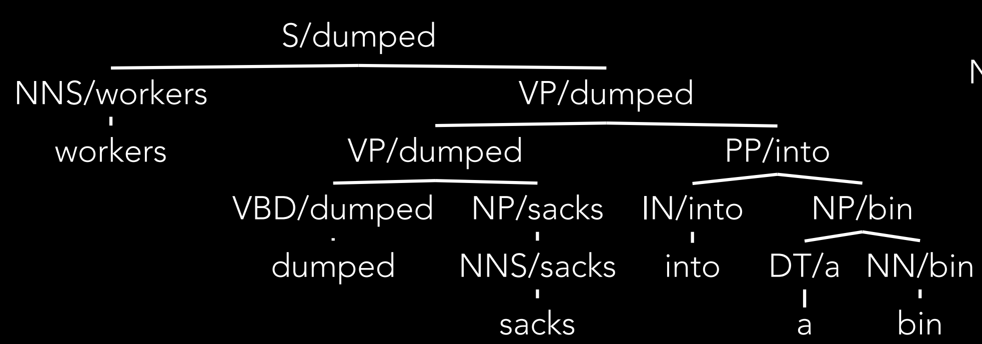
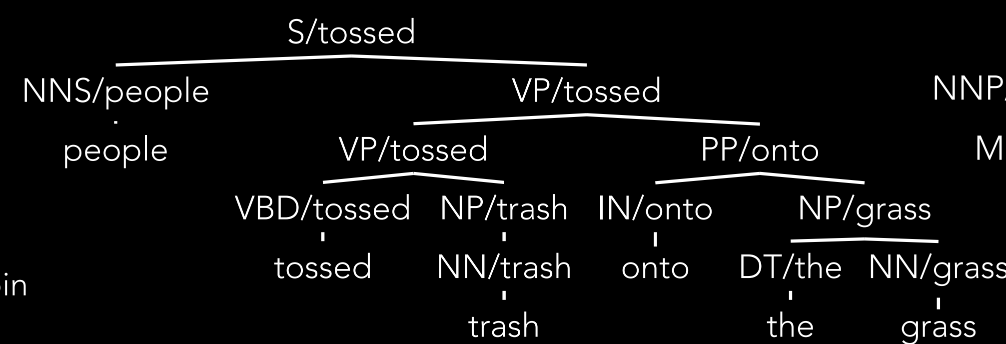
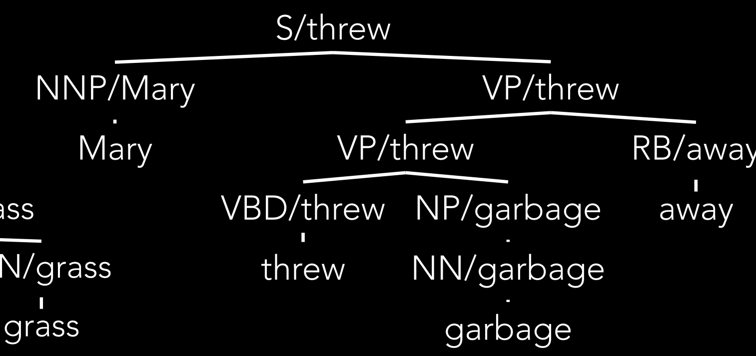
- λ_C=0 if C never seen

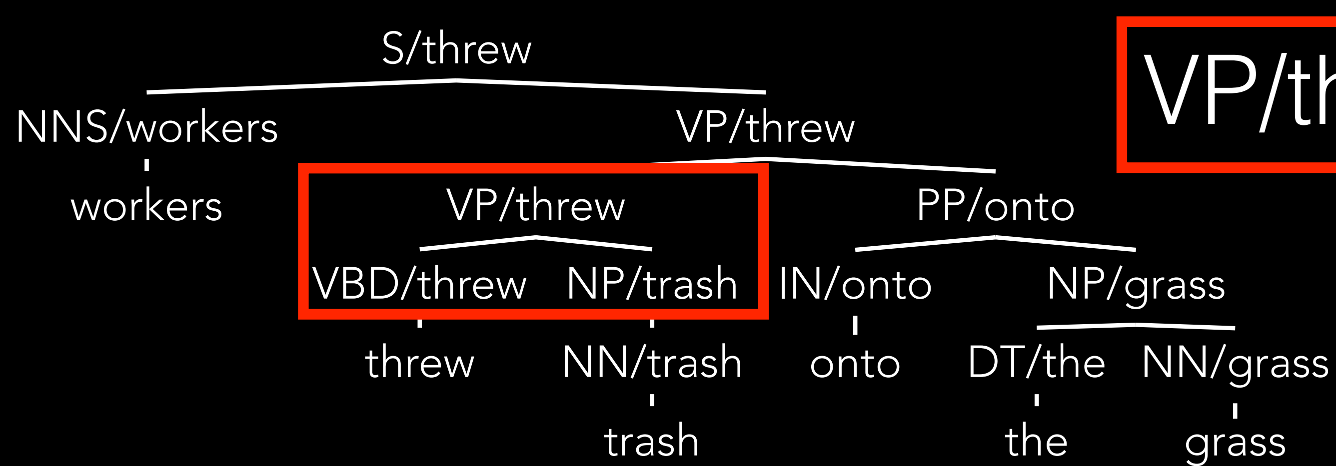
Incorporating Smoothing

Assume we saw each training tree 20 times









VP/threw -> VBD/threw NP/trash

$$P(r \mid X, h) = \lambda_1 P_{ML}(r \mid X, h) + (1-\lambda_1) P_{ML}(r \mid X)$$

20/40

60/120

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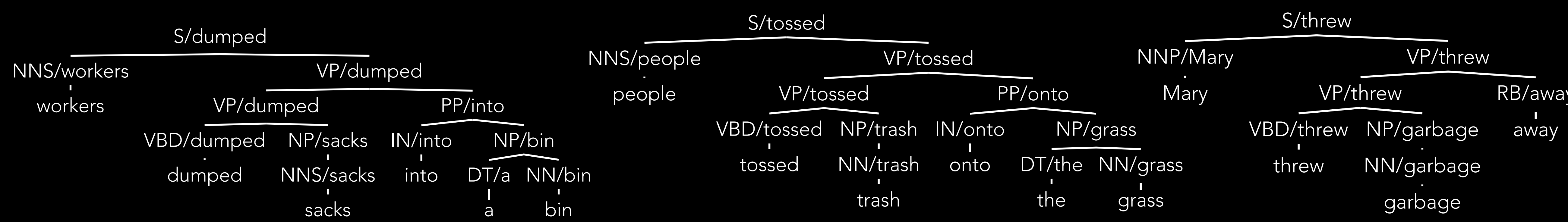

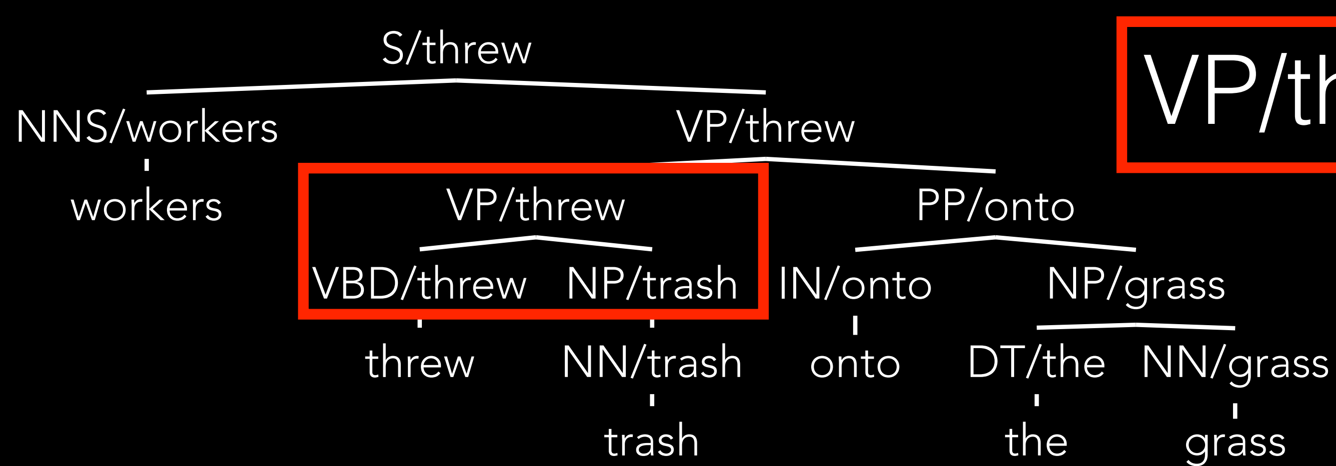

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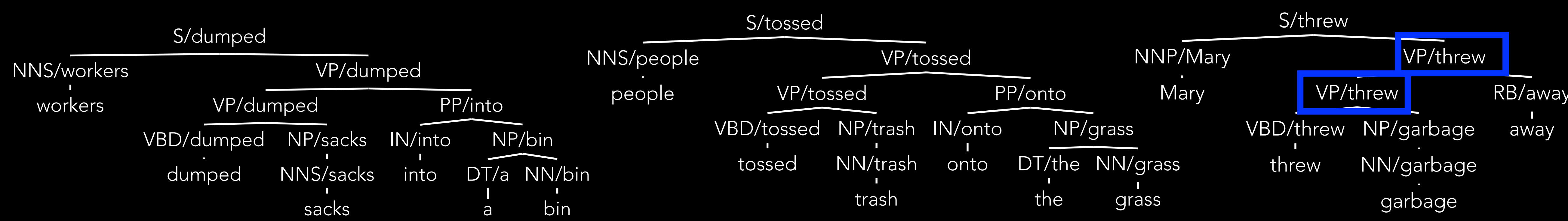

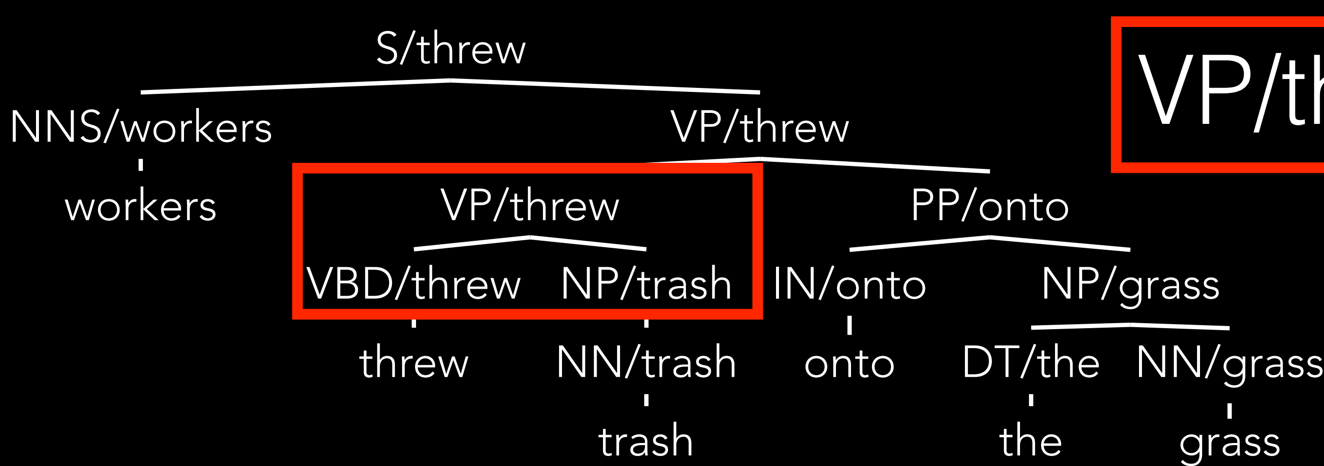

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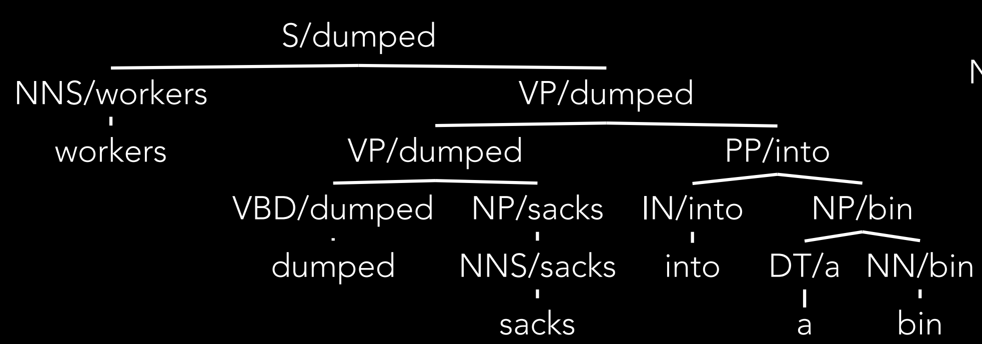

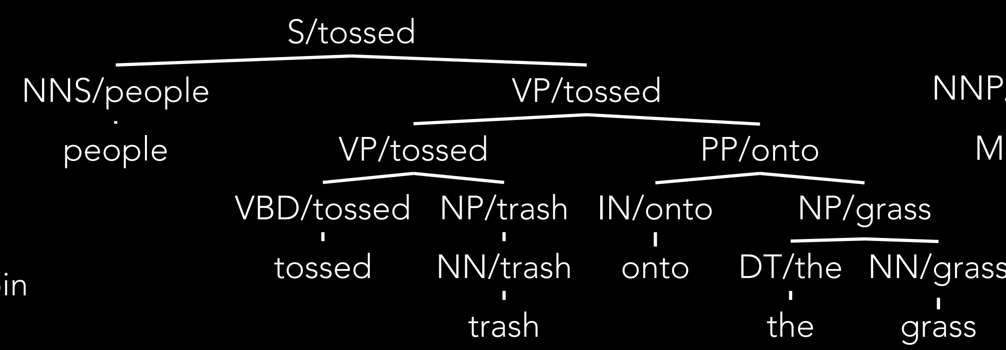

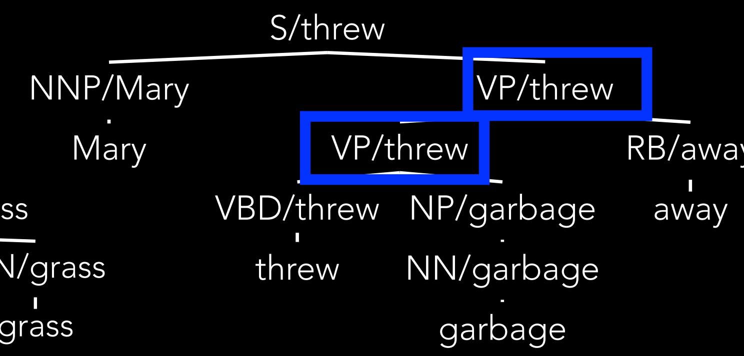

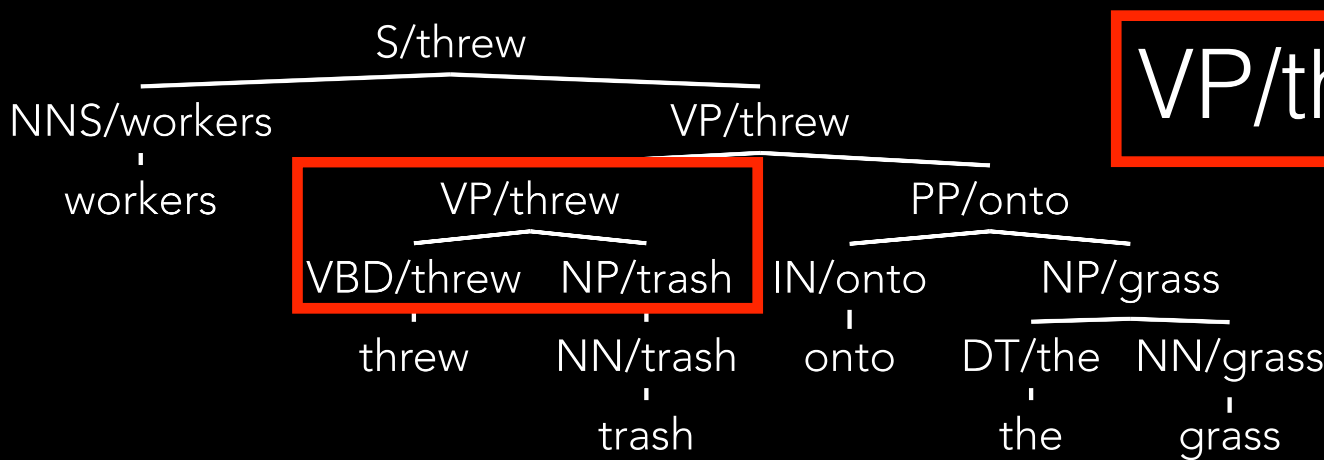

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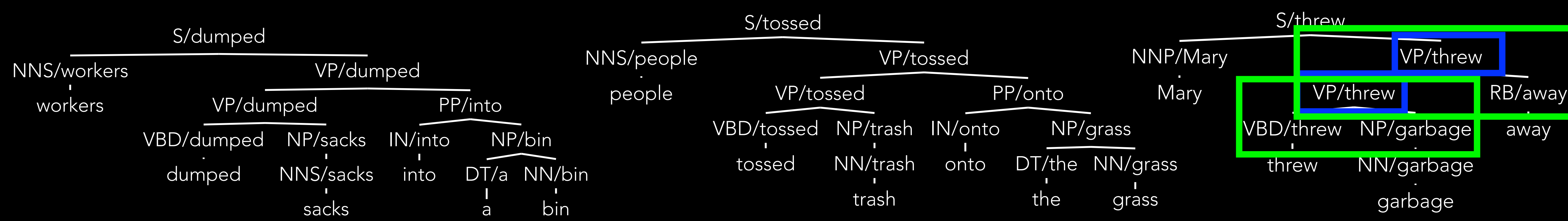

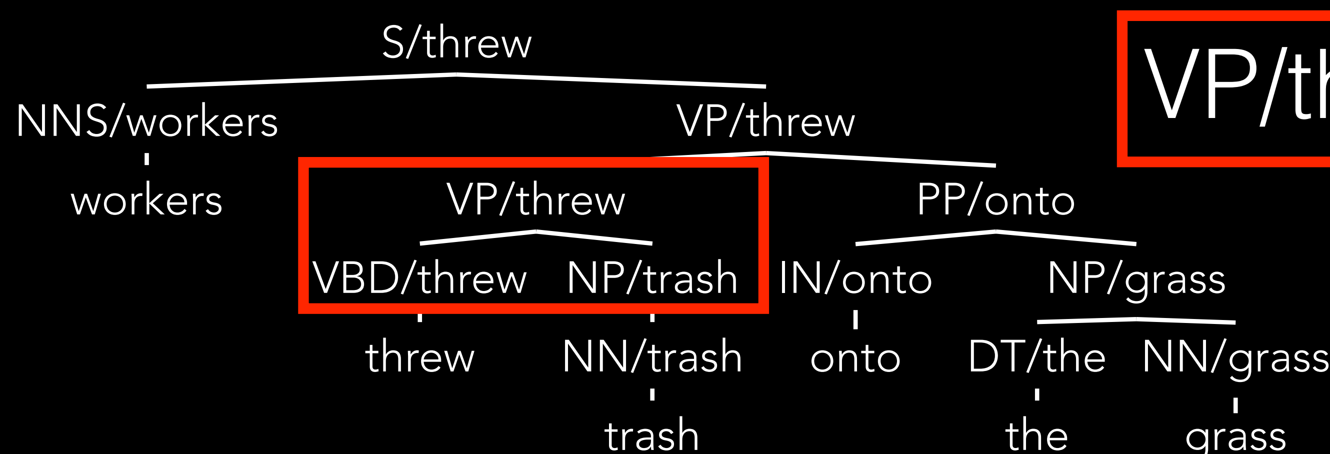

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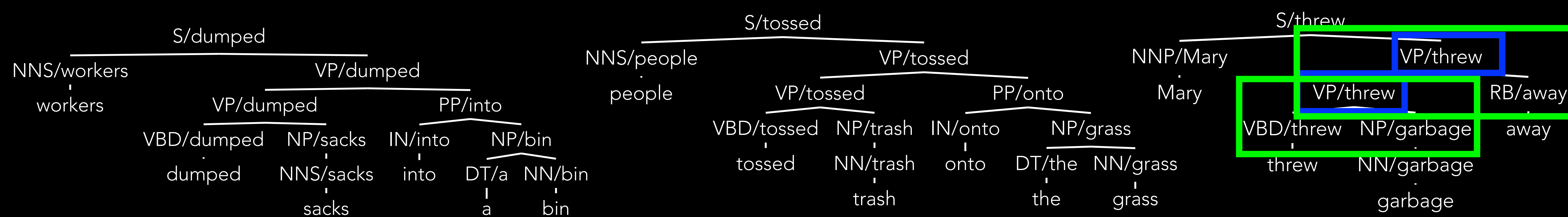

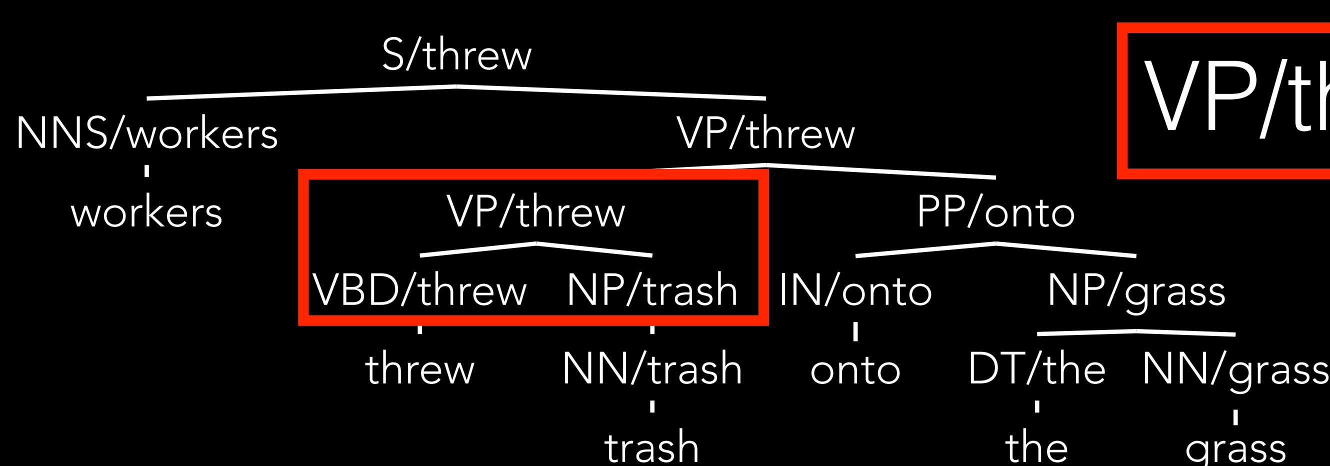

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40/42 x 20/40

60/120

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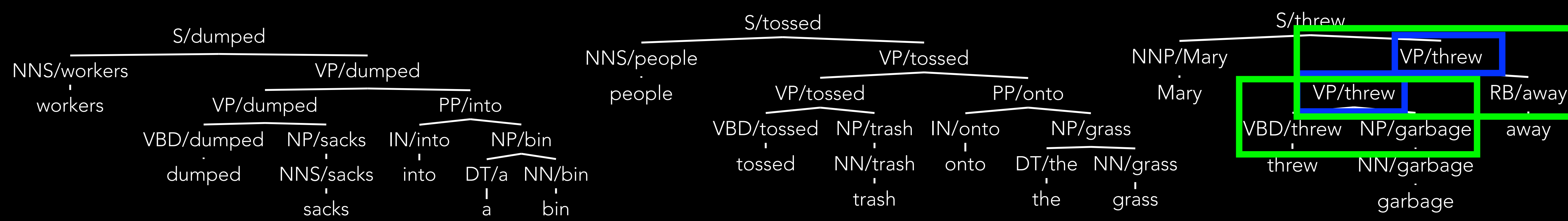

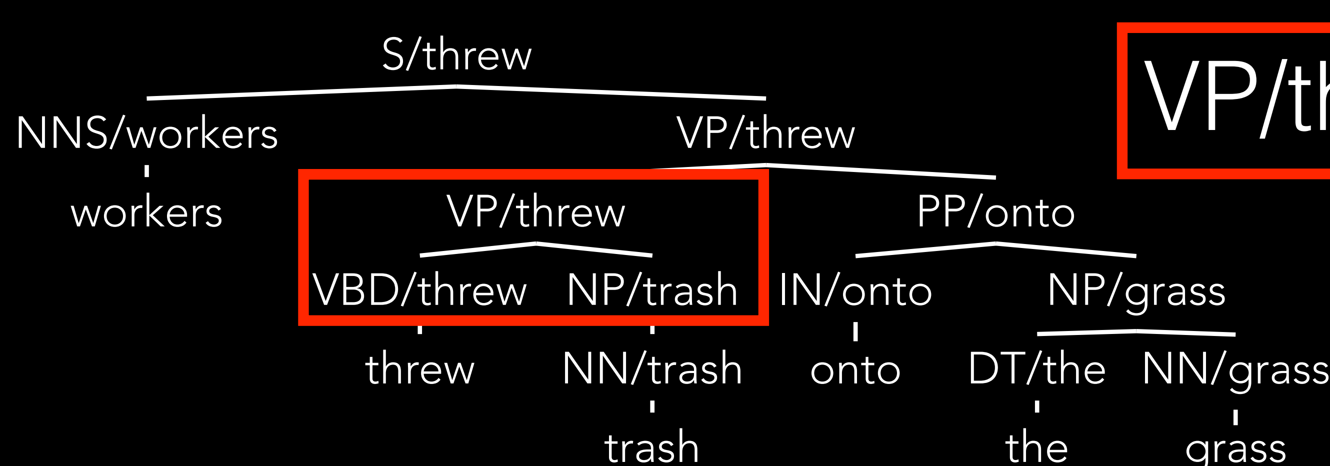

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40/42 x 20/40   2/42 x 60/120

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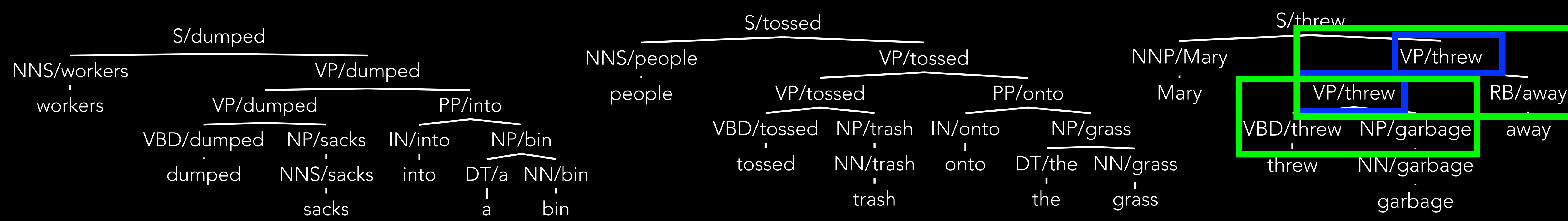

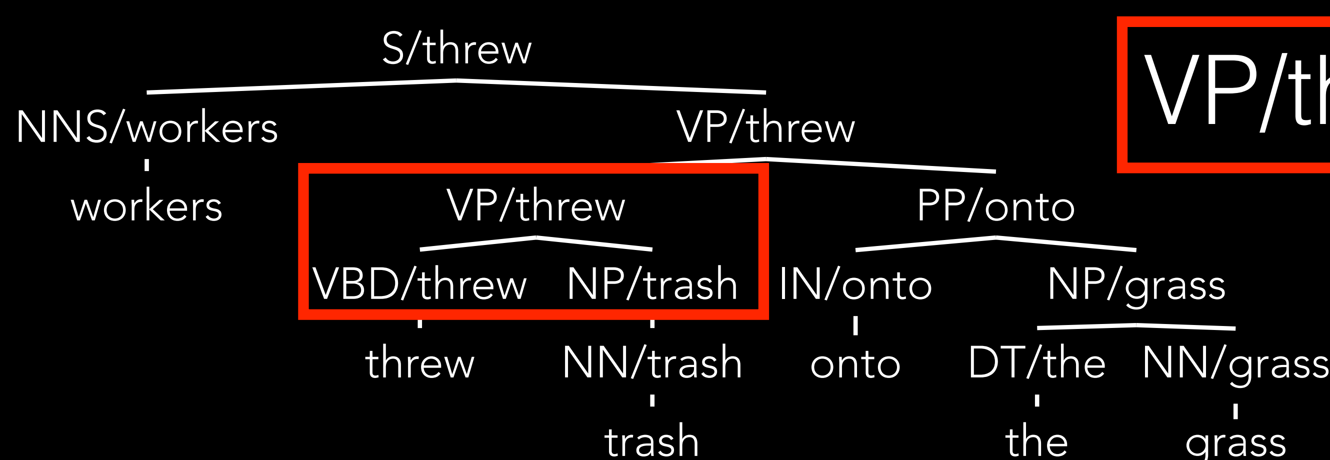

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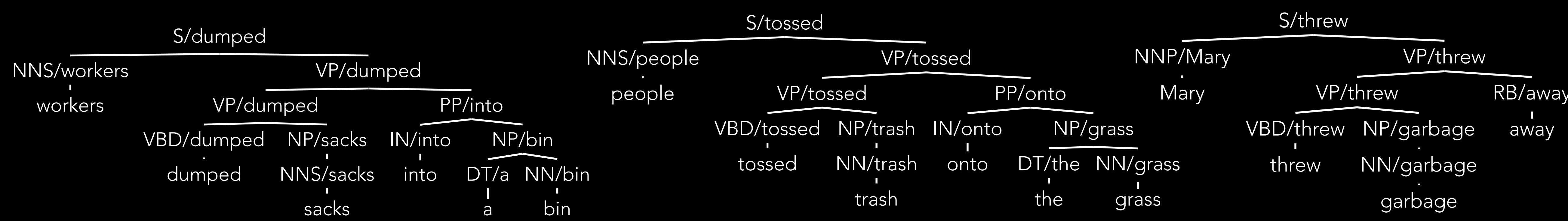
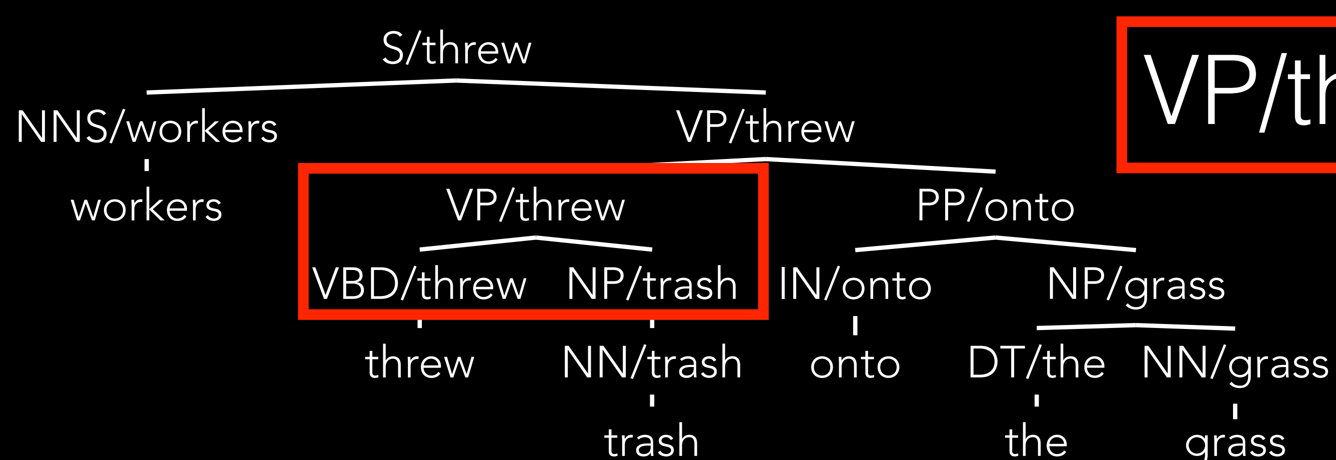




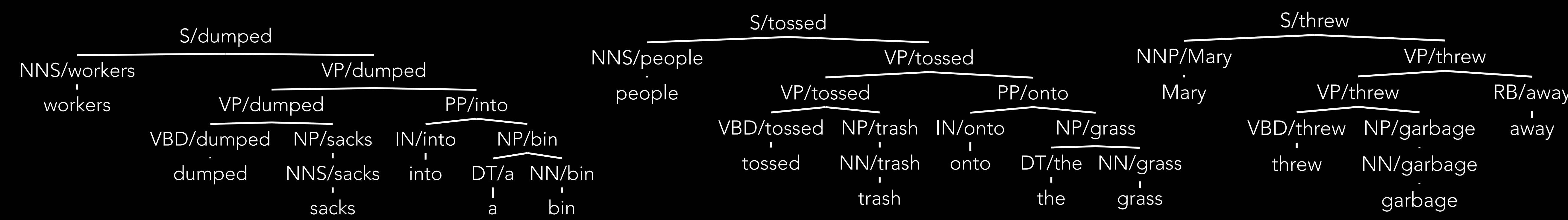
$\boxed{\text{VP/threw -> VBD/threw NP/trash}}$

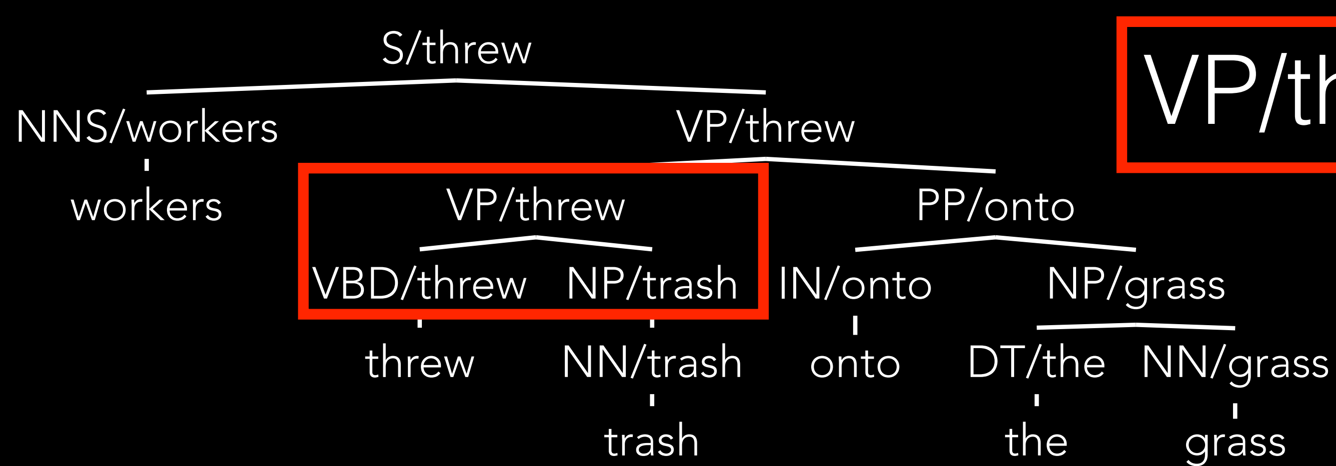
$$P(m \mid r, X, h) = \lambda_2 P_{ML}(m \mid r, X, h) + (1-\lambda_2) P_{ML}(m \mid r)$$

0/20 20/60

Incorporating Smoothing

Assume we saw each training tree 20 times





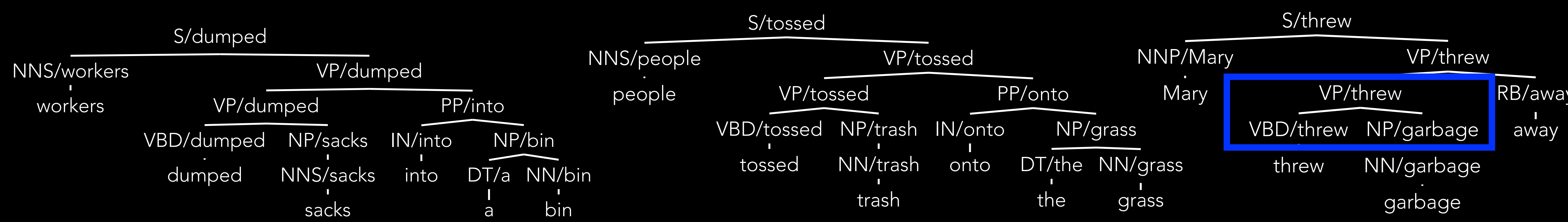
VP/threw -> VBD/threw NP/trash

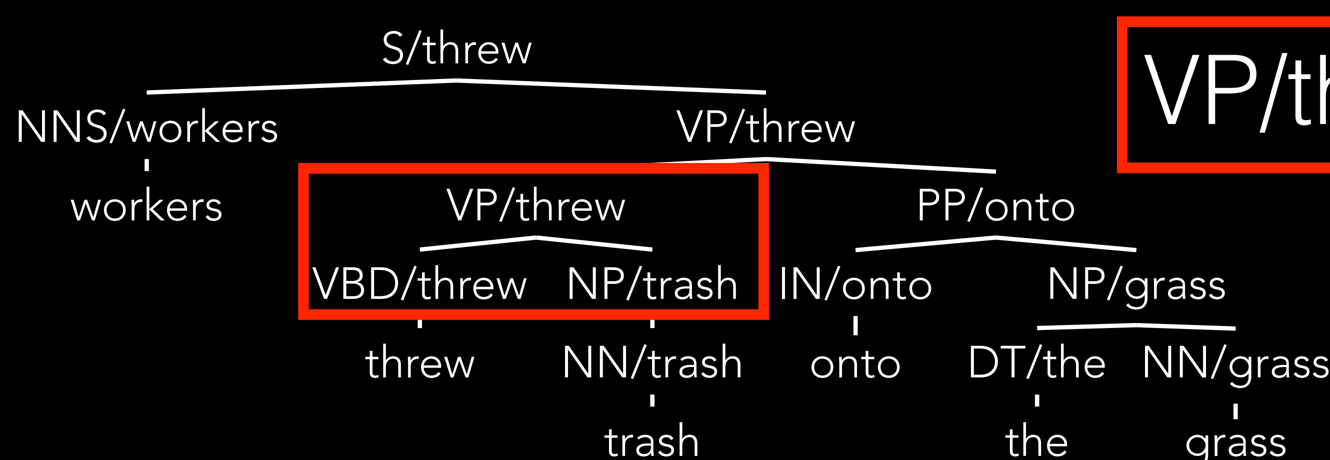
$$P(m \mid \boxed{r, X, h}) = \lambda_2 P_{ML}(m \mid r, X, h) + (1-\lambda_2) P_{ML}(m \mid r)$$

0/20 20/60

Incorporating Smoothing

Assume we saw each training tree 20 times





VP/threw -> VBD/threw NP/trash

$$P(m \mid \boxed{r, X, h}) = \lambda_2 P_{ML}(m \mid r, X, h) + (1-\lambda_2) P_{ML}(m \mid r)$$

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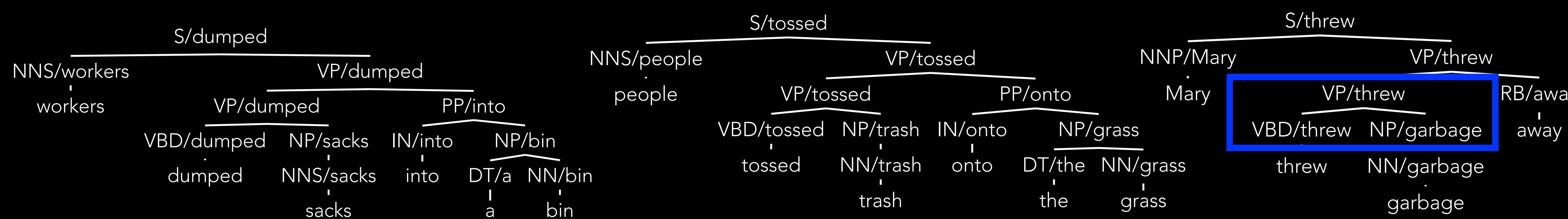
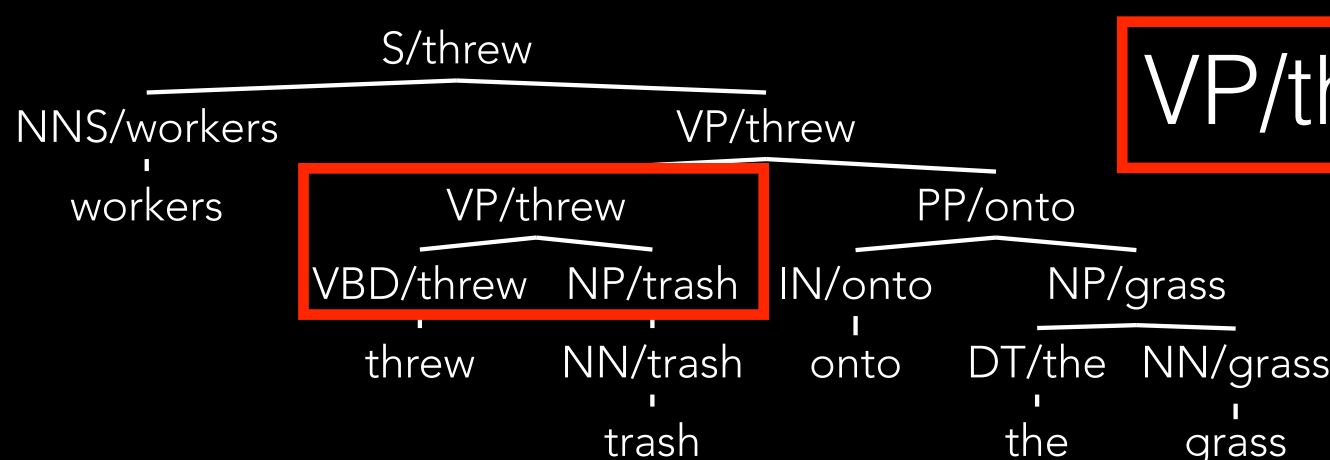
Assume we saw each training tree 20 times





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0/20 20/60

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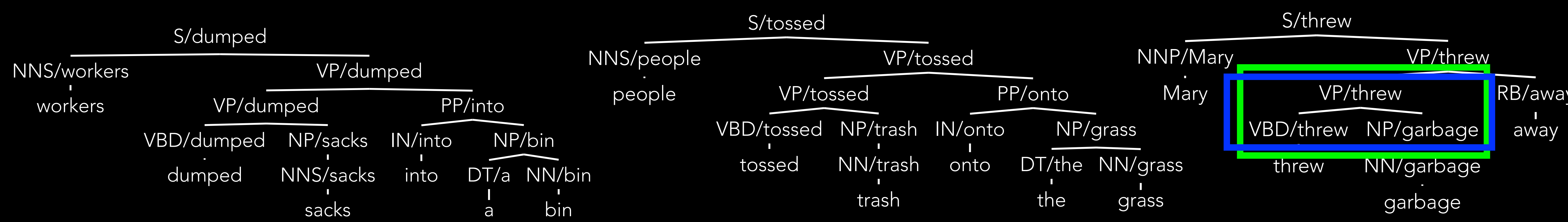
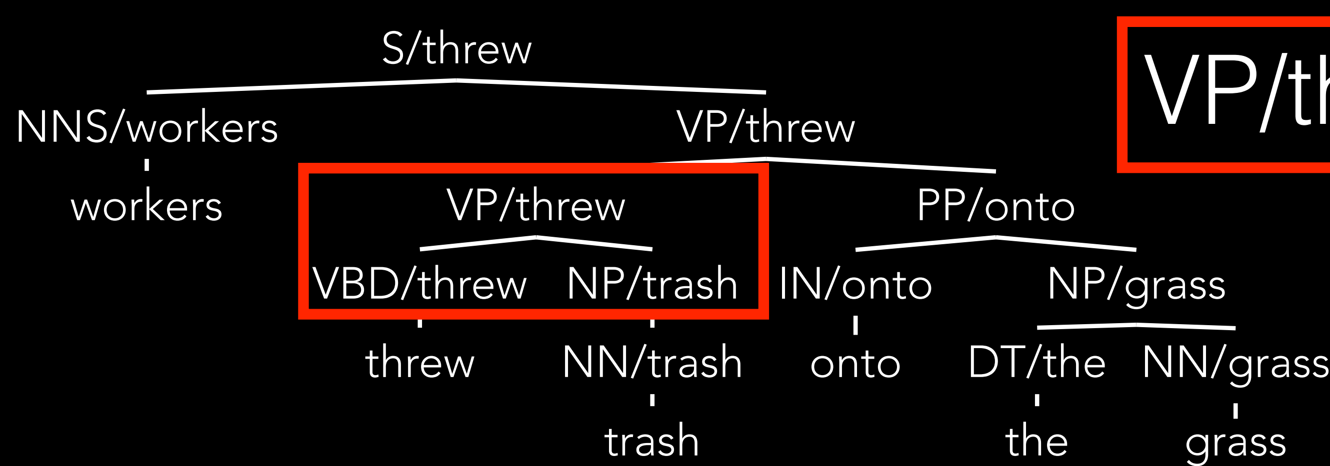
Assume we saw each training tree 20 times





VP/threw -> VBD/threw NP/trash

$$P(m \mid r, X, h) = \lambda_2 P_{ML}(m \mid r, X, h) + (1-\lambda_2) P_{ML}(m \mid r)$$

0/20 20/60

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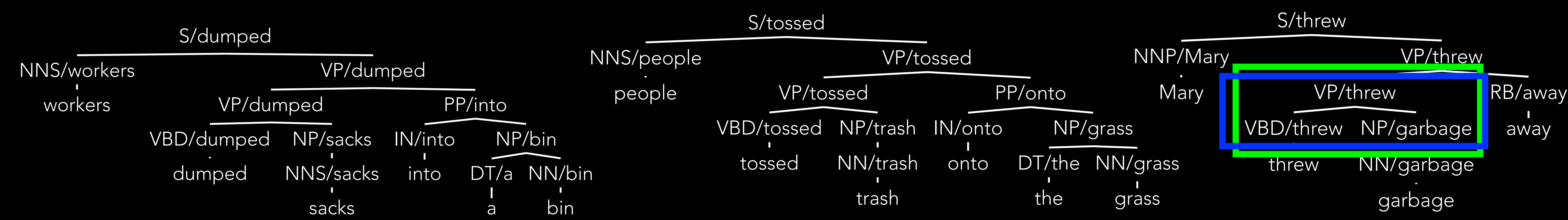
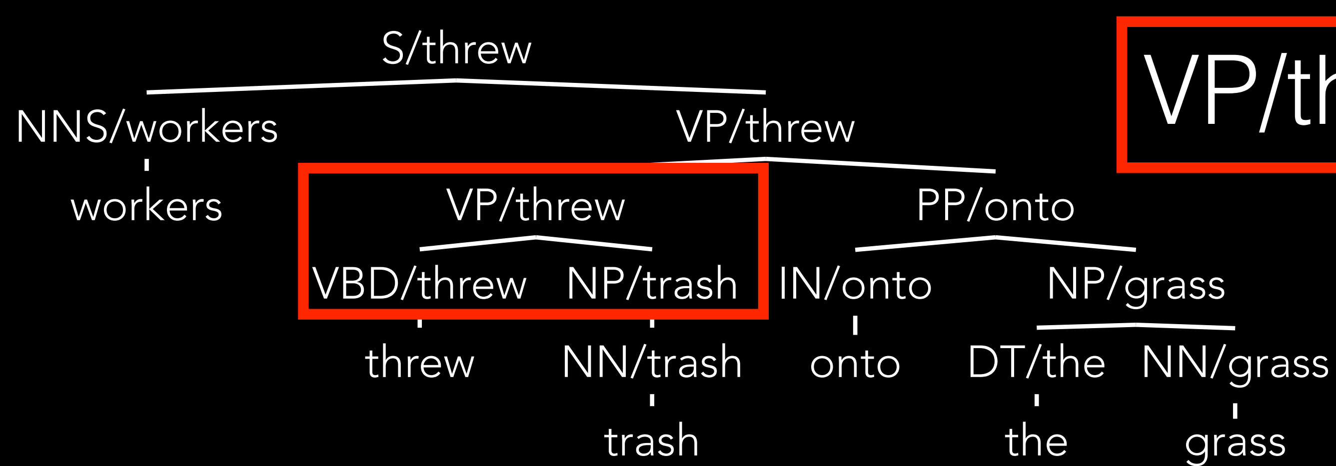
Assume we saw each training tree 20 times





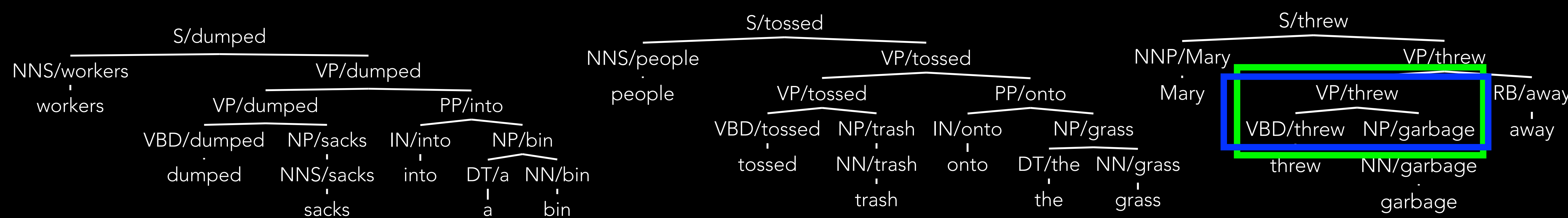
VP/threw -> VBD/threw NP/trash

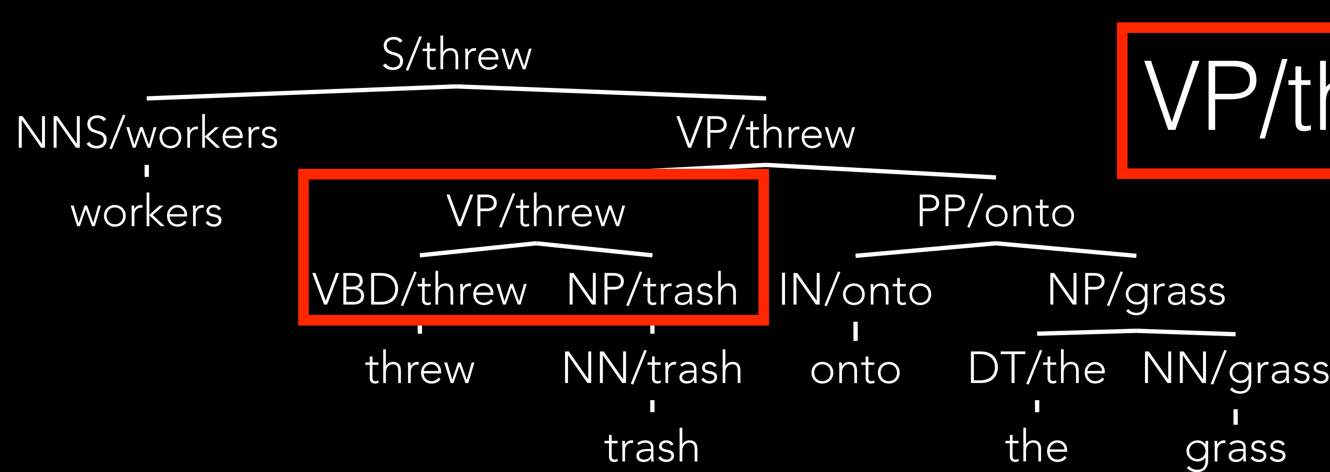
$$P(m \mid r, X, h) = \lambda_2 P_{ML}(m \mid r, X, h) + (1-\lambda_2) P_{ML}(m \mid r)$$

20/21 x 0/20 20/60

Incorporating Smoothing

Assume we saw each training tree 20 times





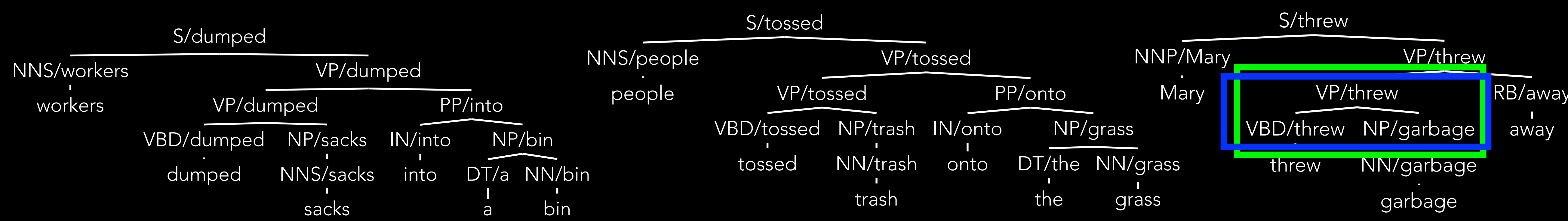
VP/threw -> VBD/threw NP/trash

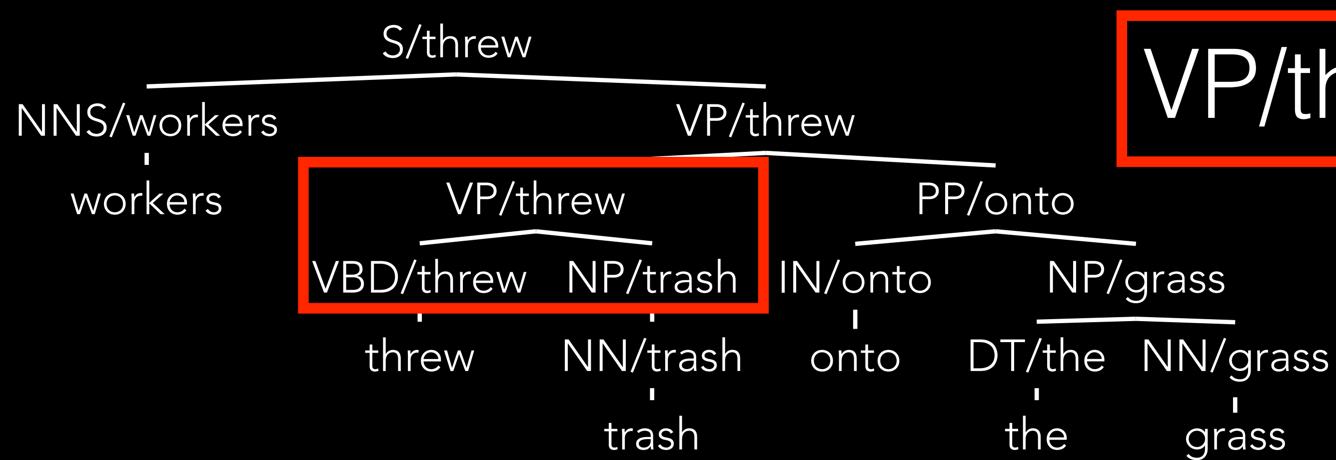
$$P(\boxed{m} \mid \boxed{r, X, h}) = \lambda_2 P_{ML}(m \mid r, X, h) + (1-\lambda_2) P_{ML}(m \mid r)$$

$$20/21 \times 0/20 \qquad 1/21 \times 20/60$$

Incorporating Smoothing

Assume we saw each training tree 20 times





VP/threw -> VBD/threw NP/trash

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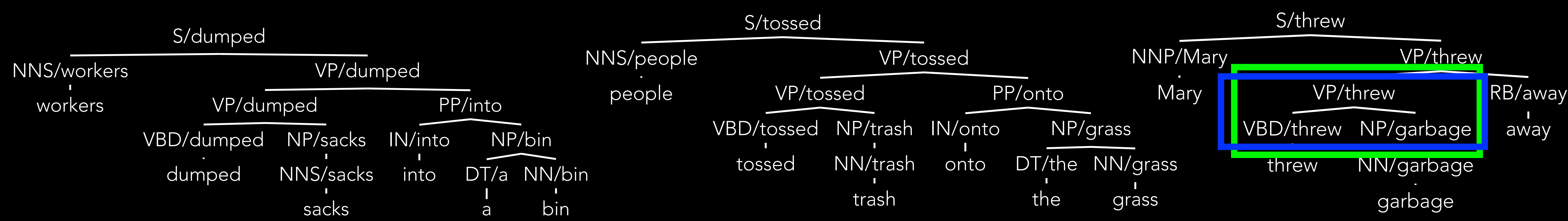
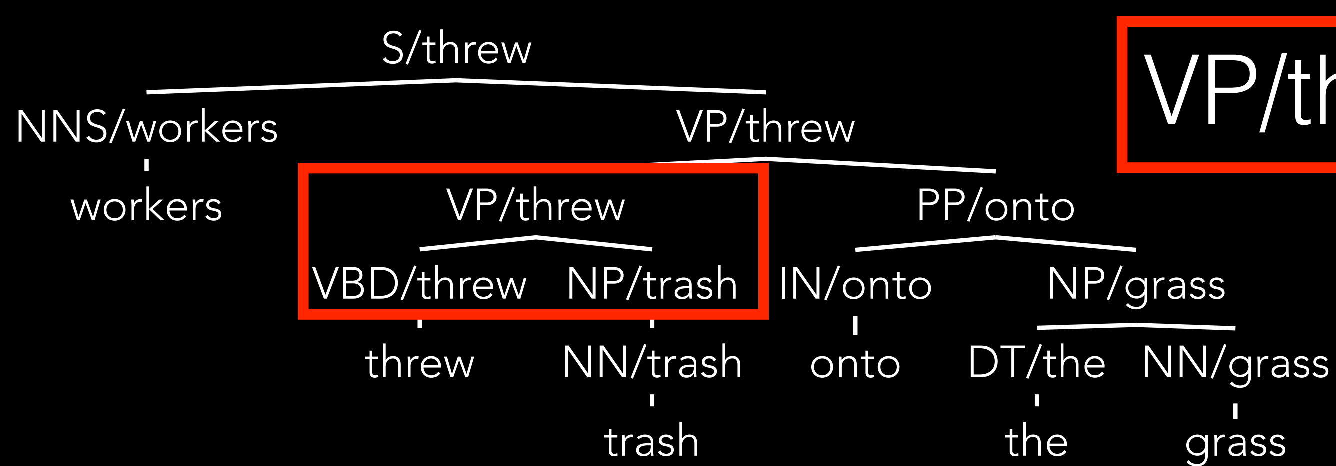
$$20/21 \times 0/20 \qquad 1/21 \times 20/60$$

$= .016$

Incorporating Smoothing

Assume we saw each training tree 20 times





VP/threw -> VBD/threw NP/trash

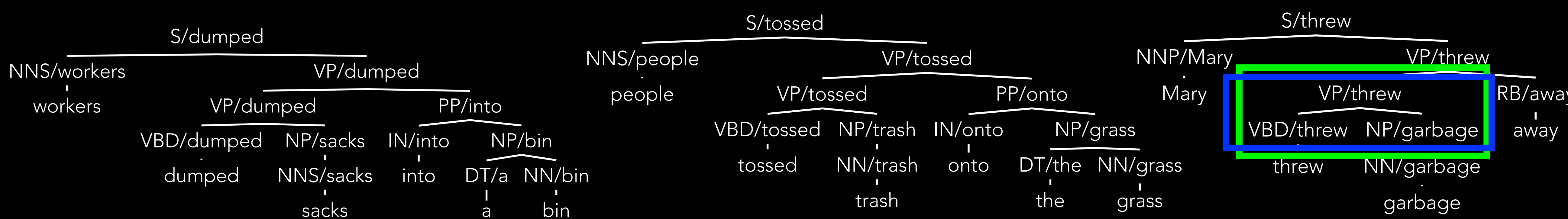
$$P(m \mid r, X, h) = \lambda_2 P_{ML}(m \mid r, X, h) + (1-\lambda_2) P_{ML}(m \mid r)$$

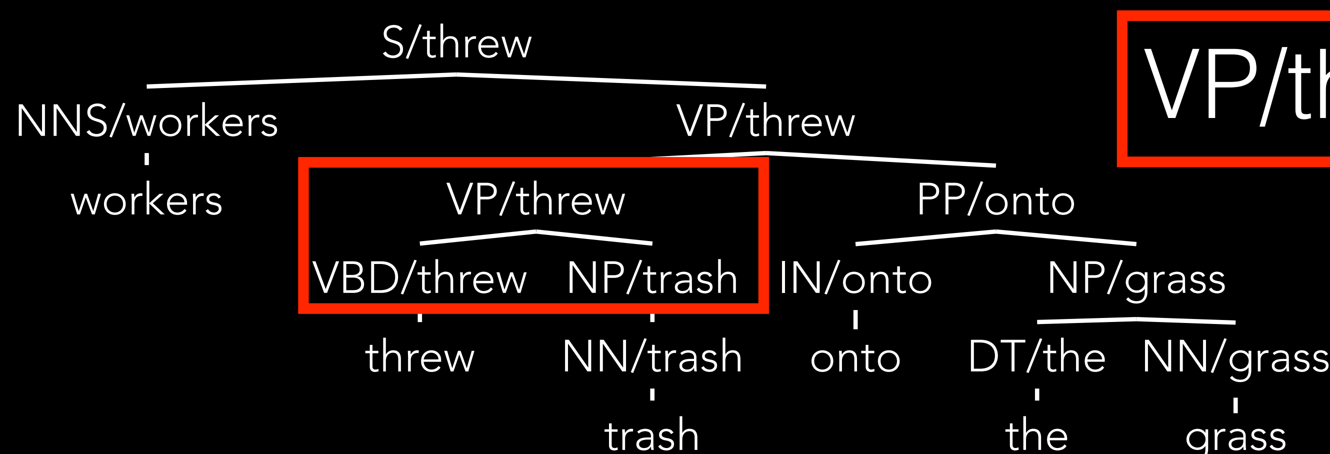
20/21 x 0/20 1/21 x 20/60

=.016 VP/threw -> VBD/threw NP/trash

Incorporating Smoothing

Assume we saw each training tree 20 times





VP/threw -> VBD/threw NP/trash

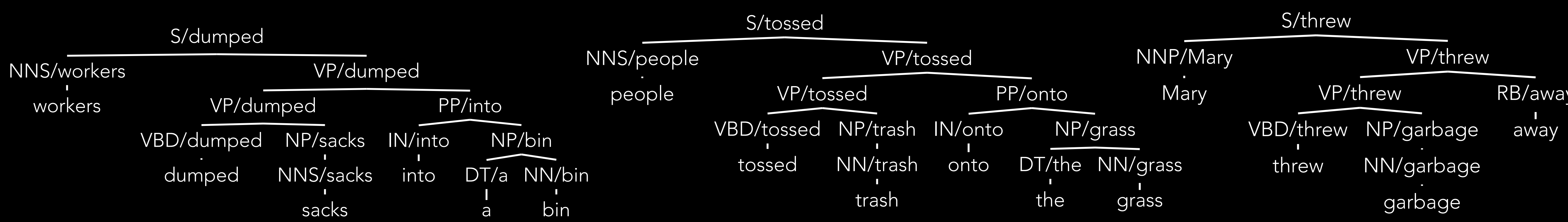
$$P(m \mid r, X, h) = \lambda_2 P_{ML}(m \mid r, X, h) + (1-\lambda_2) P_{ML}(m \mid r)$$

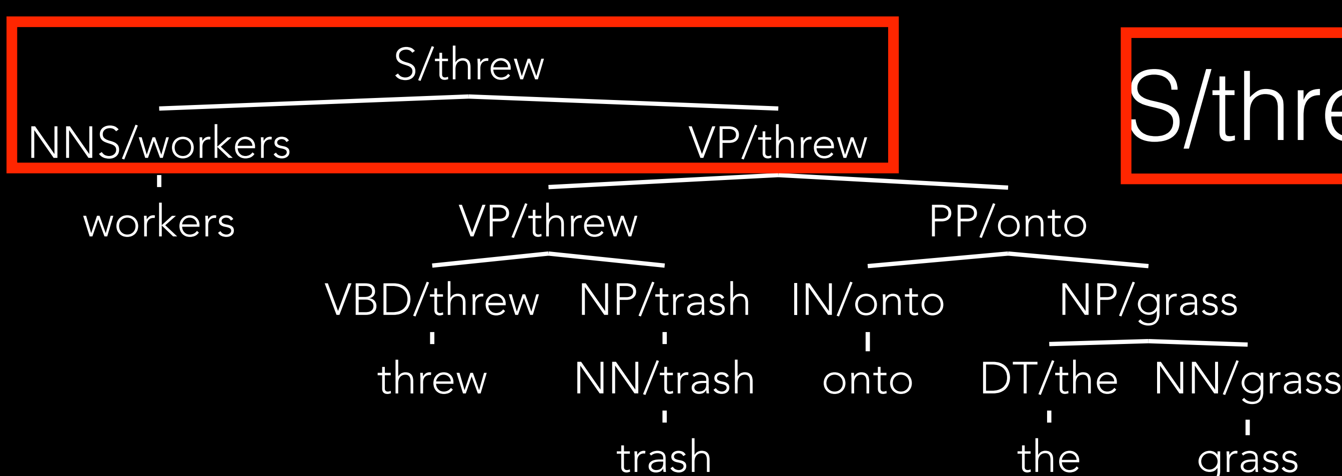
$20/21 \times 0/20$ $\quad$ $1/21 \times 20/60$

$=.016$ $\quad$ VP/threw -> VBD/threw NP/trash $=.5*.016 = .008$

Incorporating Smoothing

Assume we saw each training tree 20 times





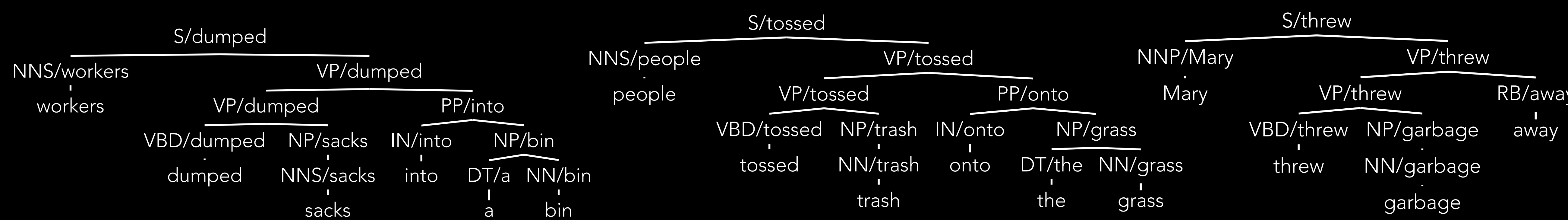
S/threw -> NNS/workers VP/threw

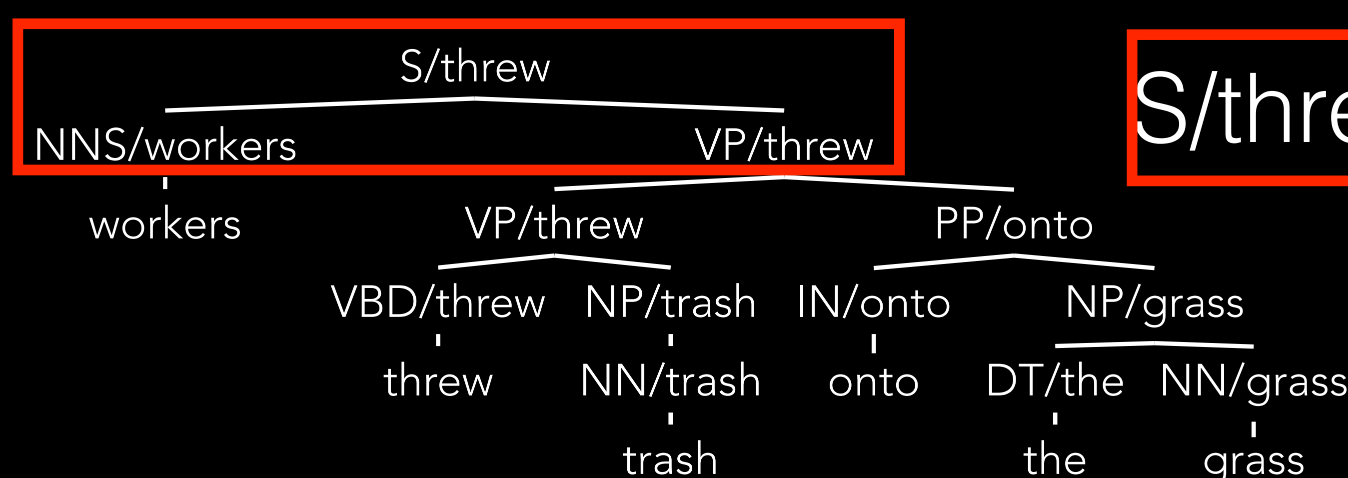
$$P(r \mid X, h) = \lambda_1 P_{ML}(r \mid X, h) + (1-\lambda_1) P_{ML}(r \mid X)$$

0/20 40/60

Incorporating Smoothing

Assume we saw each training tree 20 times





S/threw -> NNS/workers VP/threw

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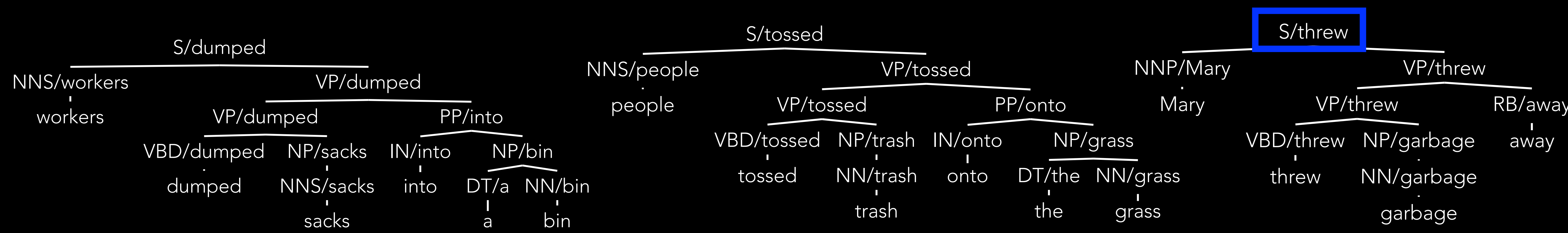
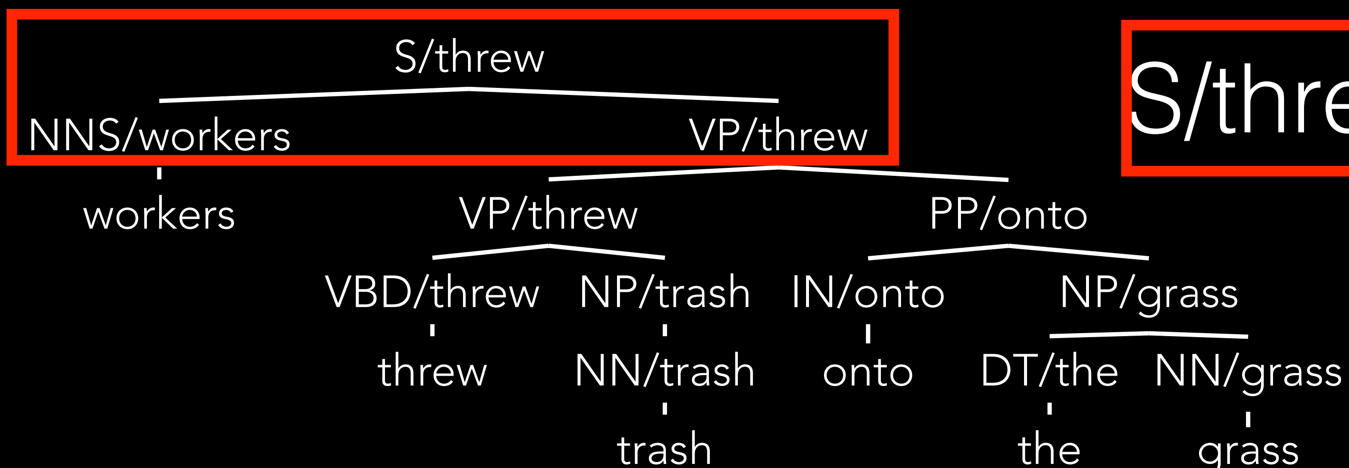
0/20 40/60

Incorporating Smoothing

Assume we saw each training tree 20 times





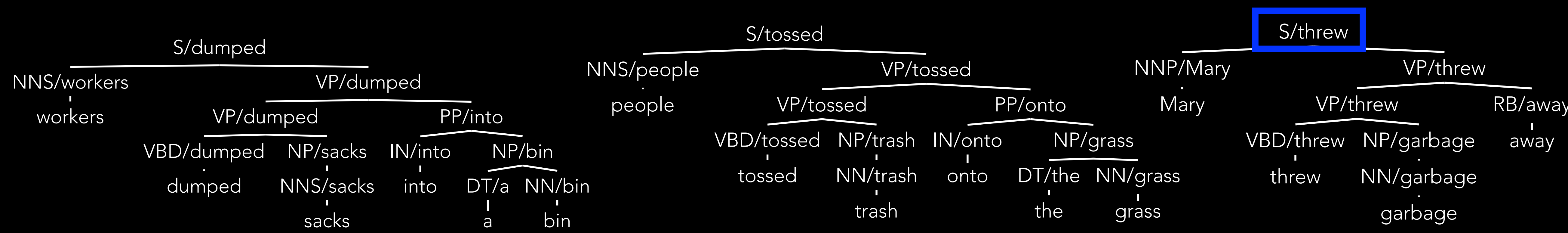
S/threw -> NNS/workers VP/threw

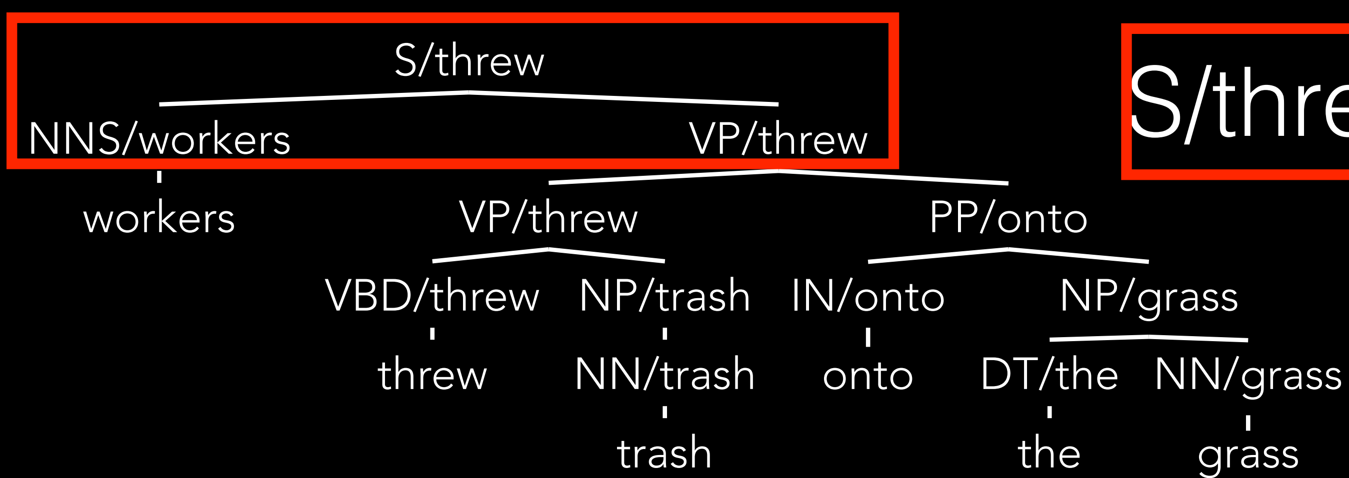
$$P(r \mid \boxed{X, h}) = \lambda_1 P_{ML}(r \mid X, h) + (1-\lambda_1) P_{ML}(r \mid X)$$

0/20 40/60

Incorporating Smoothing

Assume we saw each training tree 20 times





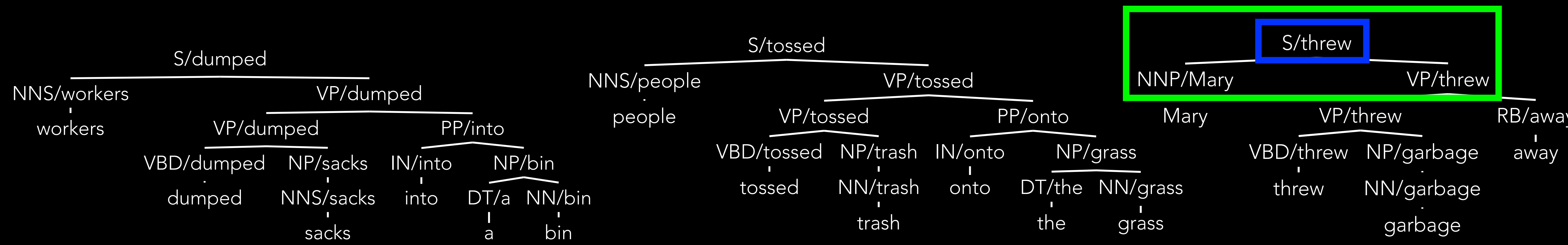
S/threw -> NNS/workers VP/threw

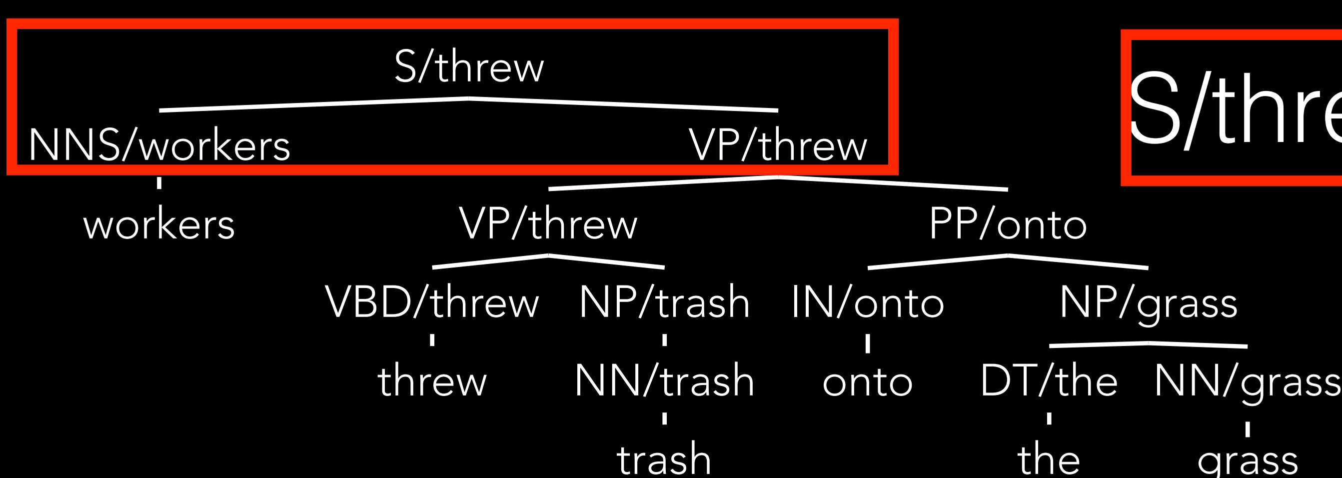
$$P(r \mid X, h) = \lambda_1 P_{ML}(r \mid X, h) + (1-\lambda_1) P_{ML}(r \mid X)$$

0/20 40/60

Incorporating Smoothing

Assume we saw each training tree 20 times





S/threw -> NNS/workers VP/threw

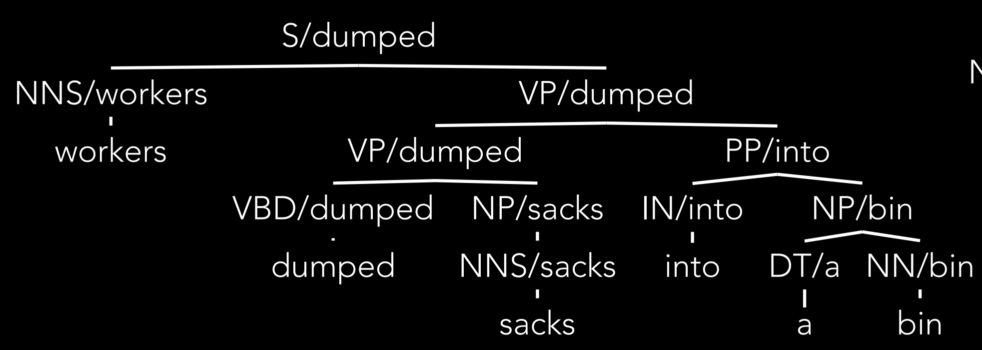
$$P(r \mid X, h) = \lambda_1 P_{ML}(r \mid X, h) + (1-\lambda_1) P_{ML}(r \mid X)$$

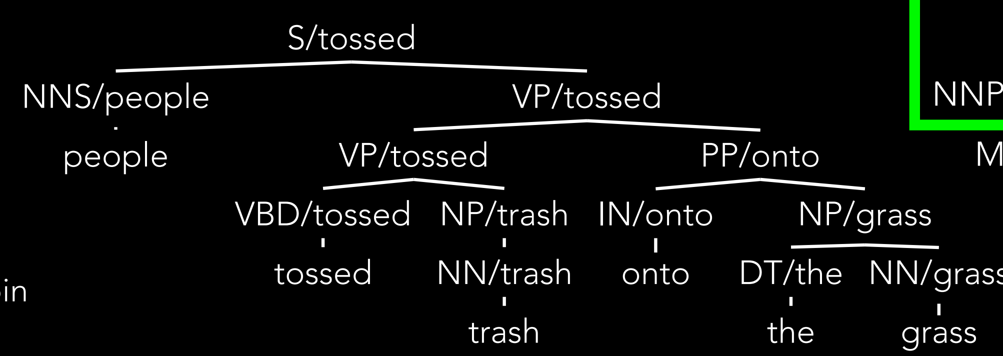
0/20

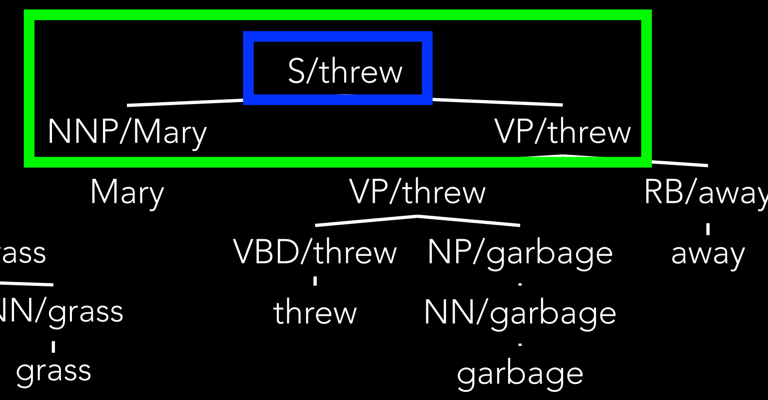
40/60

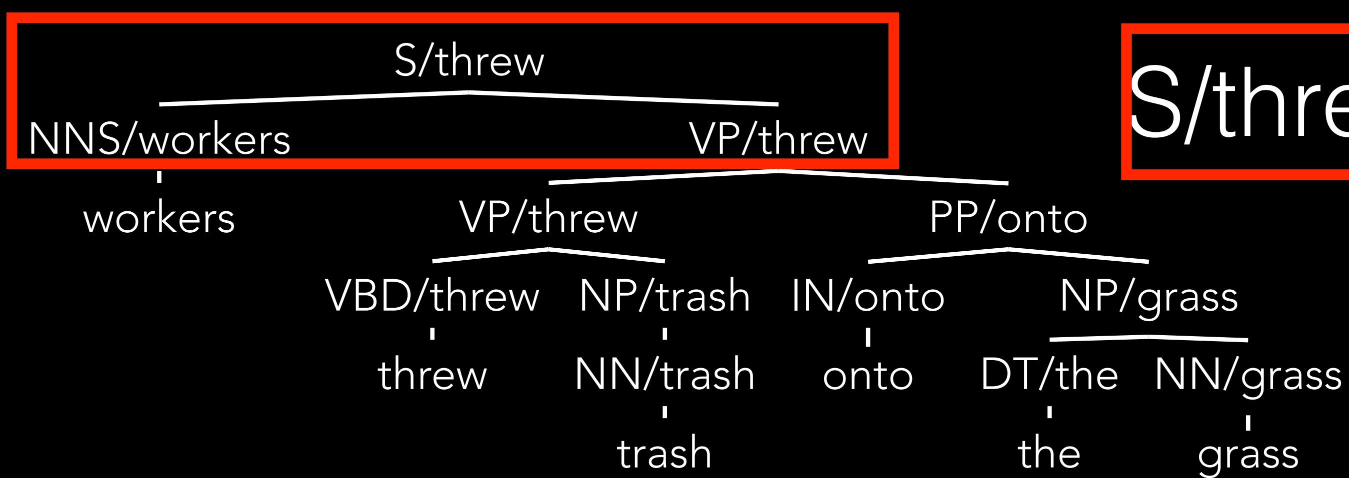
Incorporating Smoothing

Assume we saw each training tree 20 times









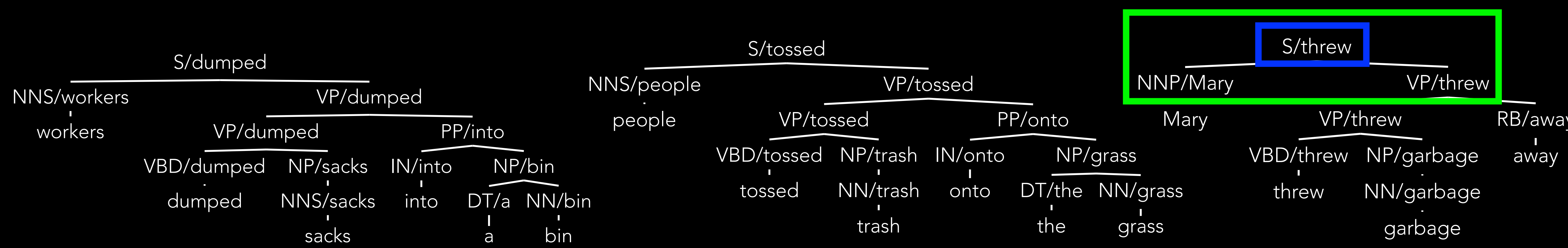
S/threw -> NNS/workers VP/threw

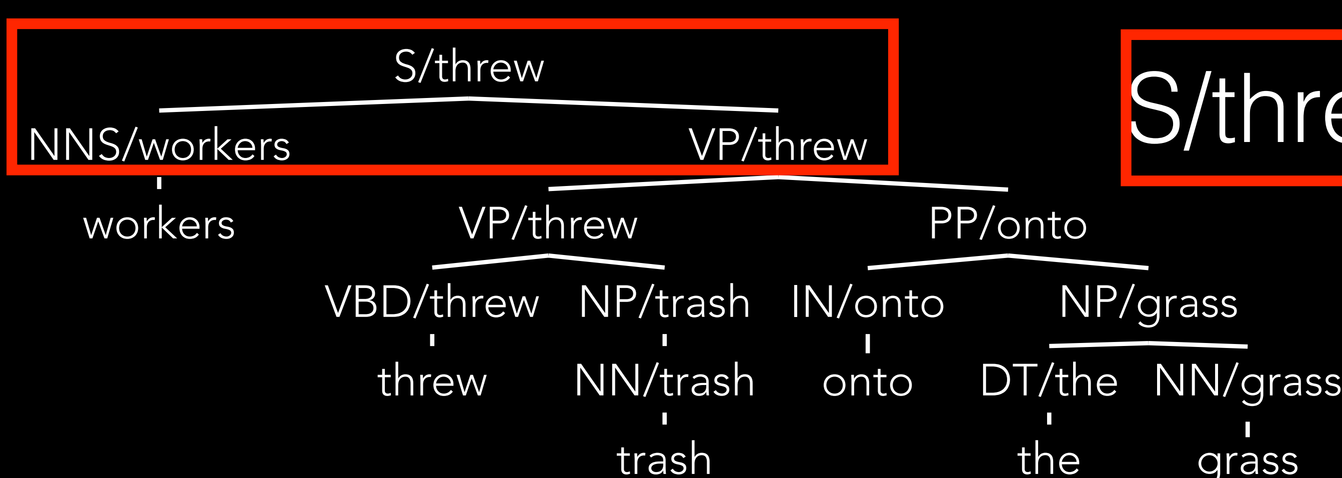
$$P(r \mid X, h) = \lambda_1 P_{ML}(r \mid X, h) + (1-\lambda_1) P_{ML}(r \mid X)$$

20/21 x 0/20 40/60

Incorporating Smoothing

Assume we saw each training tree 20 times





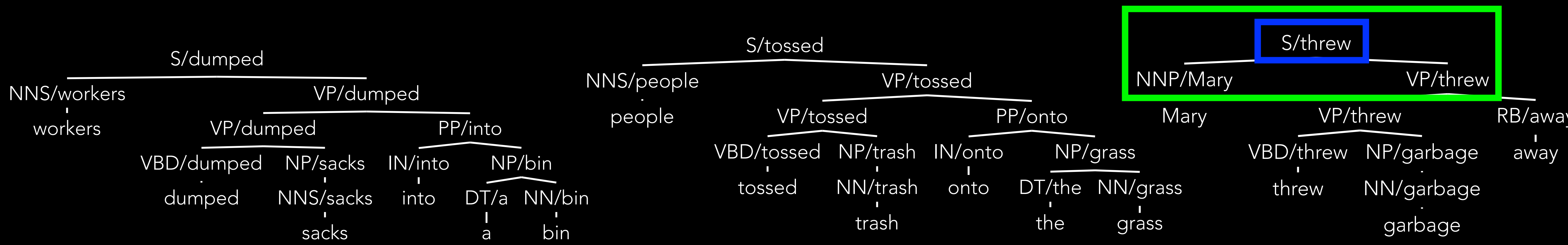
S/threw -> NNS/workers VP/threw

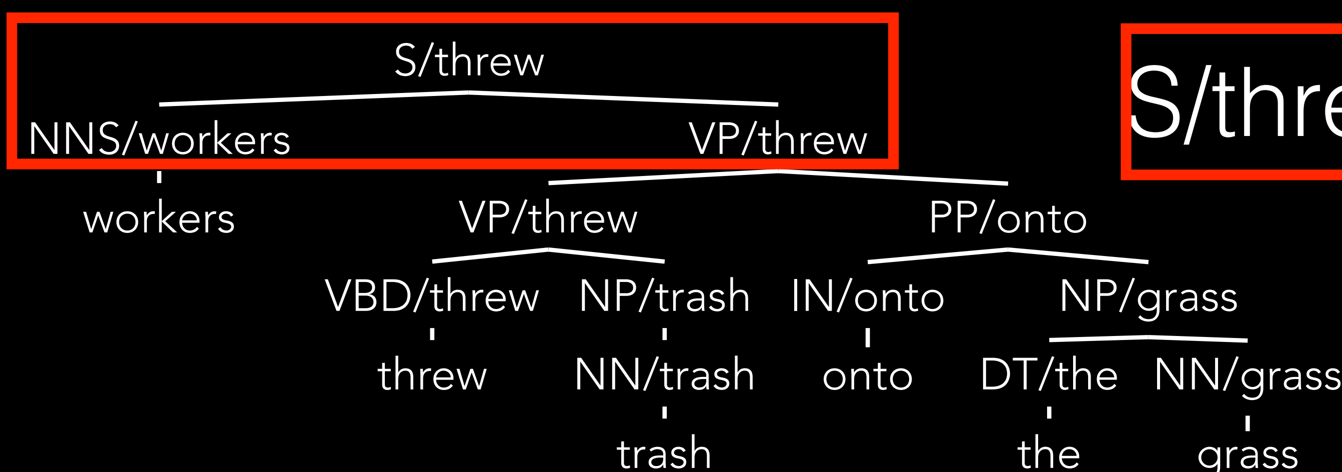
$$P(r \mid X, h) = \lambda_1 P_{ML}(r \mid X, h) + (1-\lambda_1) P_{ML}(r \mid X)$$

20/21 x 0/20   1/21 x 40/60

Incorporating Smoothing

Assume we saw each training tree 20 times





S/threw -> NNS/workers VP/threw

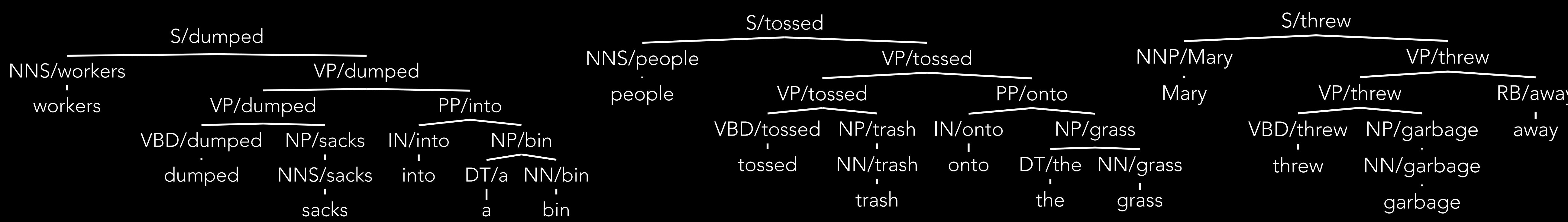
$$P(r \mid X, h) = \lambda_1 P_{ML}(r \mid X, h) + (1-\lambda_1) P_{ML}(r \mid X)$$

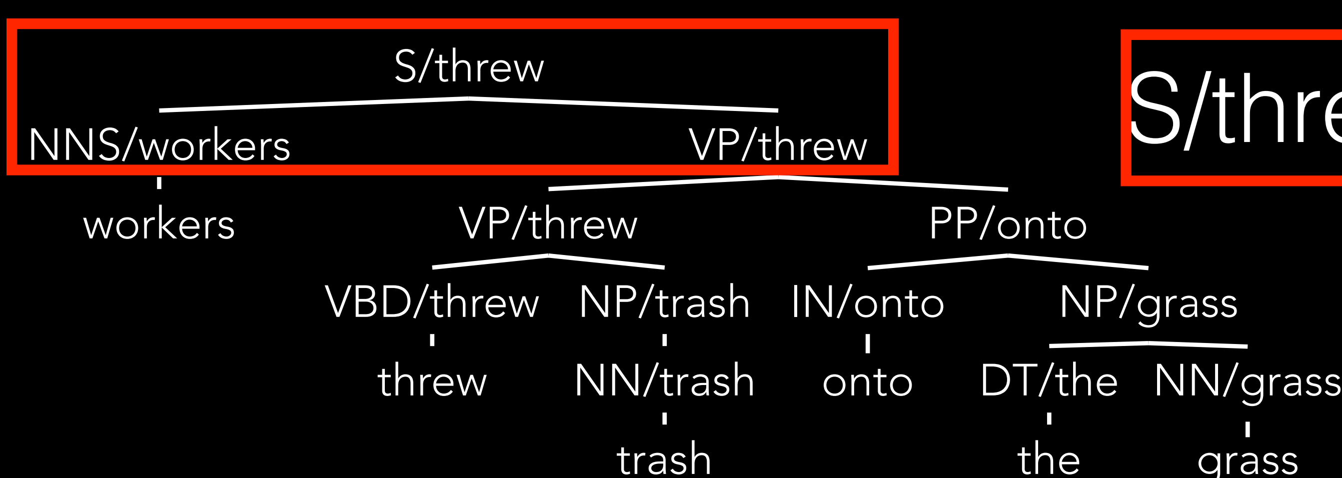
$20/21 \times 0/20 \qquad 1/21 \times 40/60$

$=.032$

Incorporating Smoothing

Assume we saw each training tree 20 times



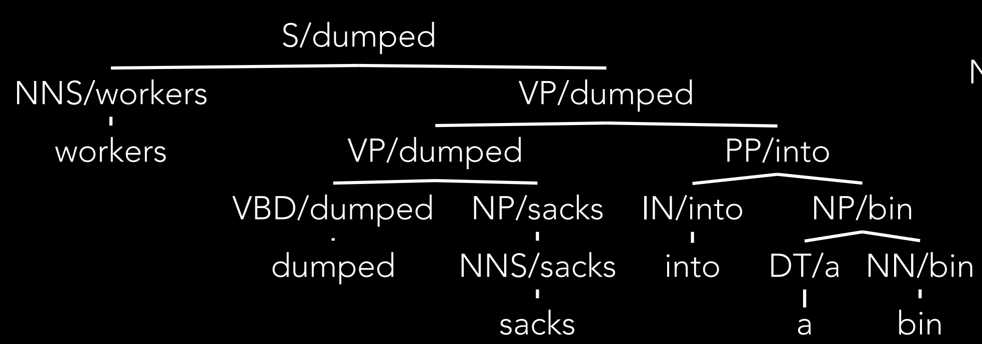


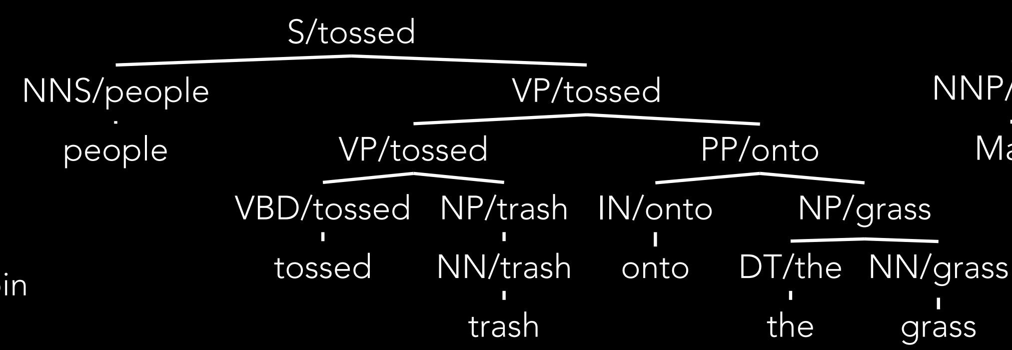
S/threw -> NNS/workers VP/threw

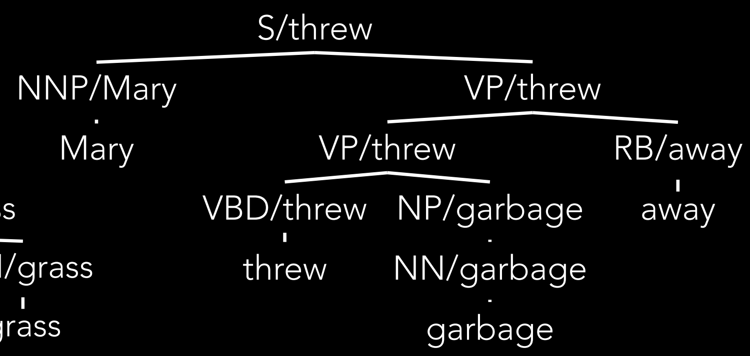
$$P(m \mid r, X, h) = \underbrace{\lambda_2 P_{ML}(m \mid r, X, h)}_{0/0} + \underbrace{(1-\lambda_2) P_{ML}(m \mid r)}_{20/40}$$

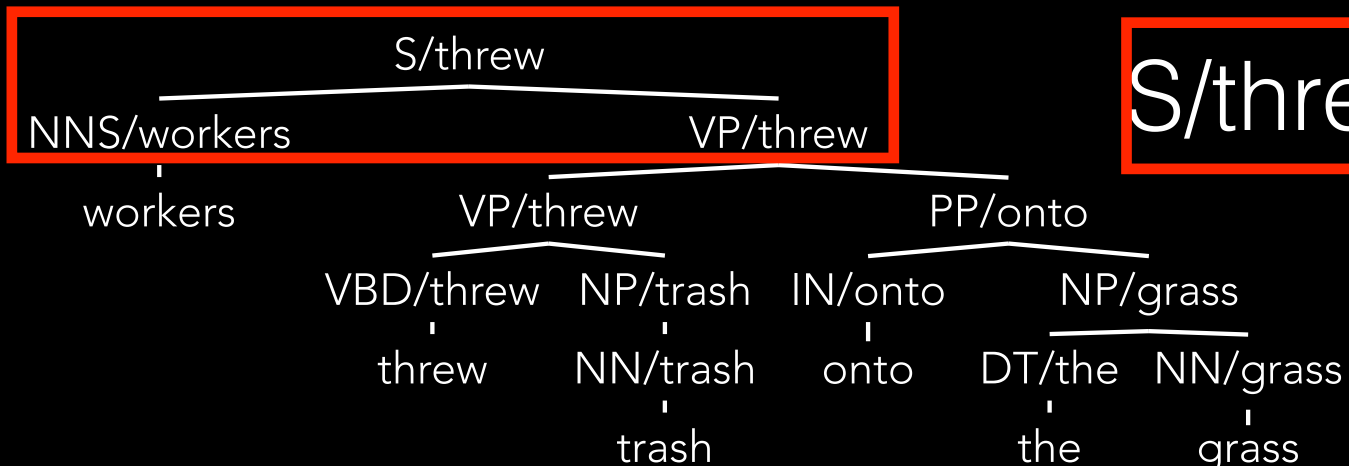
Incorporating Smoothing

Assume we saw each training tree 20 times







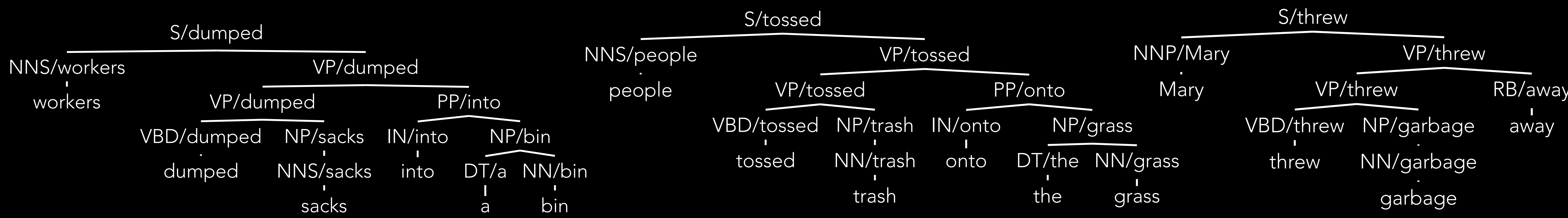


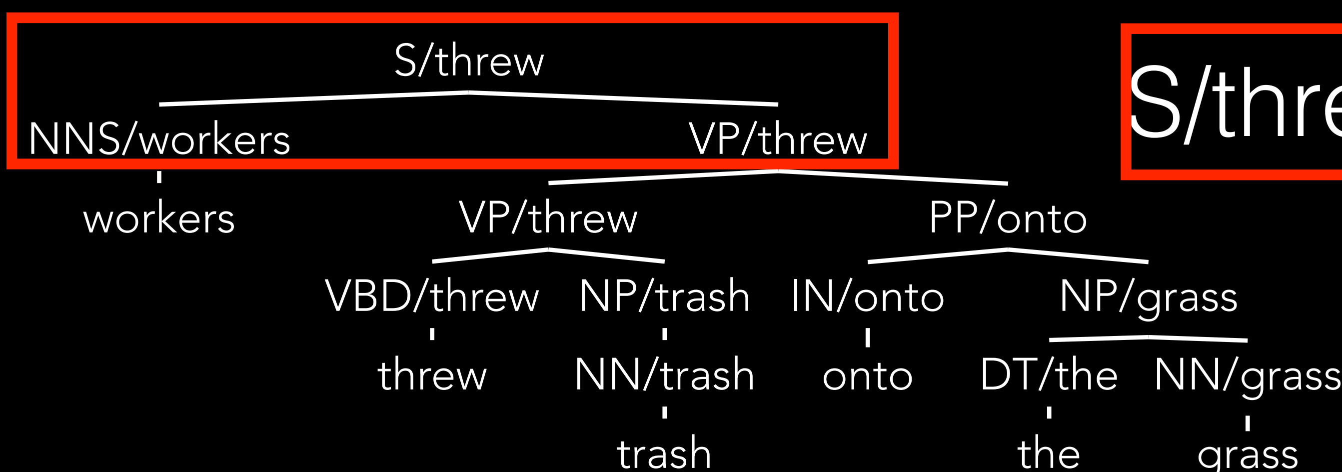
S/threw -> NNS/workers VP/threw

$$P(m \mid r, X, h) = \underbrace{\lambda_2}_{0} \times \underbrace{P_{ML}(m \mid r, X, h)}_{0/0} + (1-\lambda_2)\underbrace{P_{ML}(m \mid r)}_{20/40}$$

Incorporating Smoothing

Assume we saw each training tree 20 times





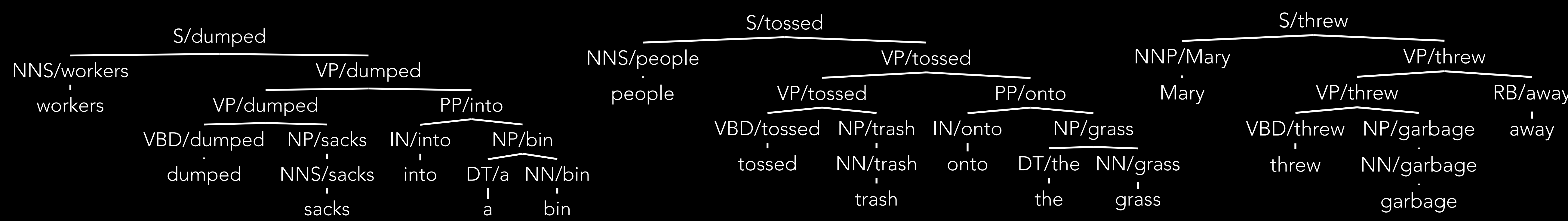
$\boxed{\text{S/threw -> NNS/workers VP/threw}}$

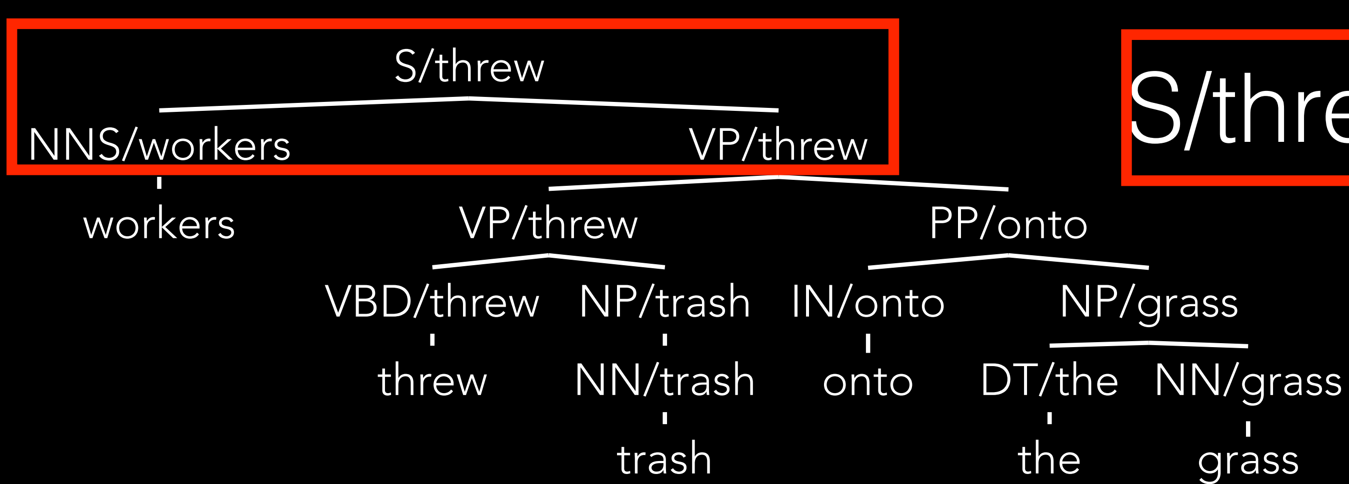
$$P(m \mid r, X, h) = \lambda_2 P_{ML}(m \mid r, X, h) + (1-\lambda_2) P_{ML}(m \mid r)$$

0 x 0/0   1 x 20/40

Incorporating Smoothing

Assume we saw each training tree 20 times





S/threw -> NNS/workers VP/threw

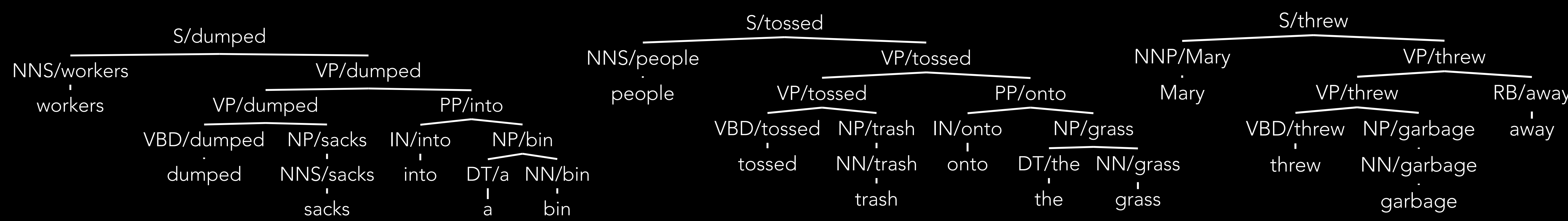
$$P(m \mid r, X, h) = \lambda_2 P_{ML}(m \mid r, X, h) + (1-\lambda_2) P_{ML}(m \mid r)$$

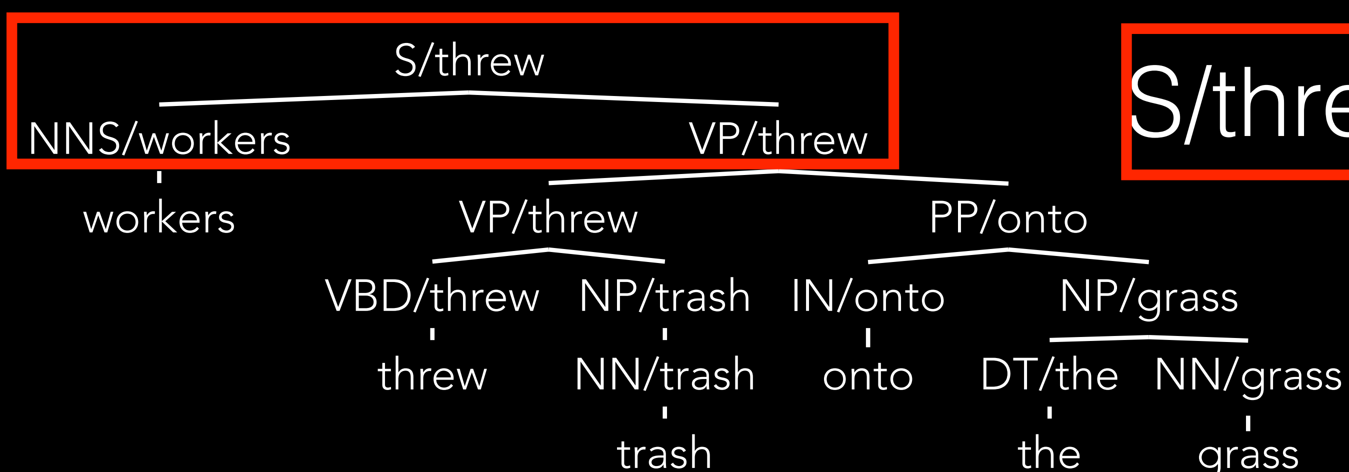
$$0 \times 0/0 \qquad\qquad 1 \times 20/40$$

$=0.5$

Incorporating Smoothing

Assume we saw each training tree 20 times





S/threw -> NNS/workers VP/threw

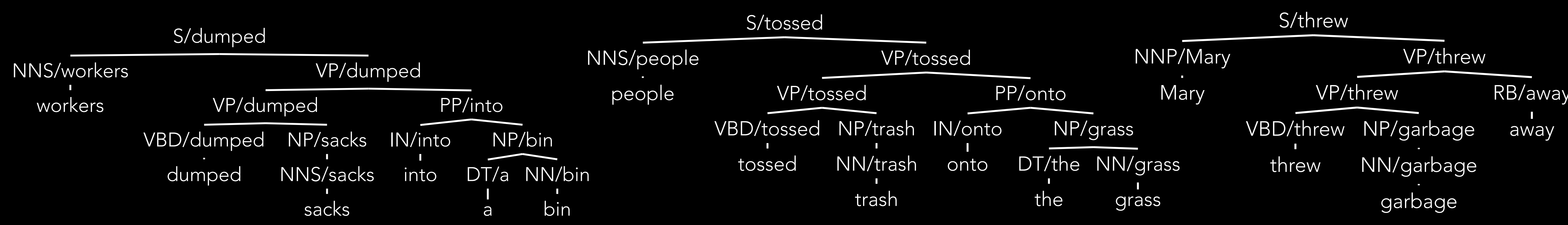
$$P(m \mid r, X, h) = \lambda_2 P_{ML}(m \mid r, X, h) + (1-\lambda_2) P_{ML}(m \mid r)$$

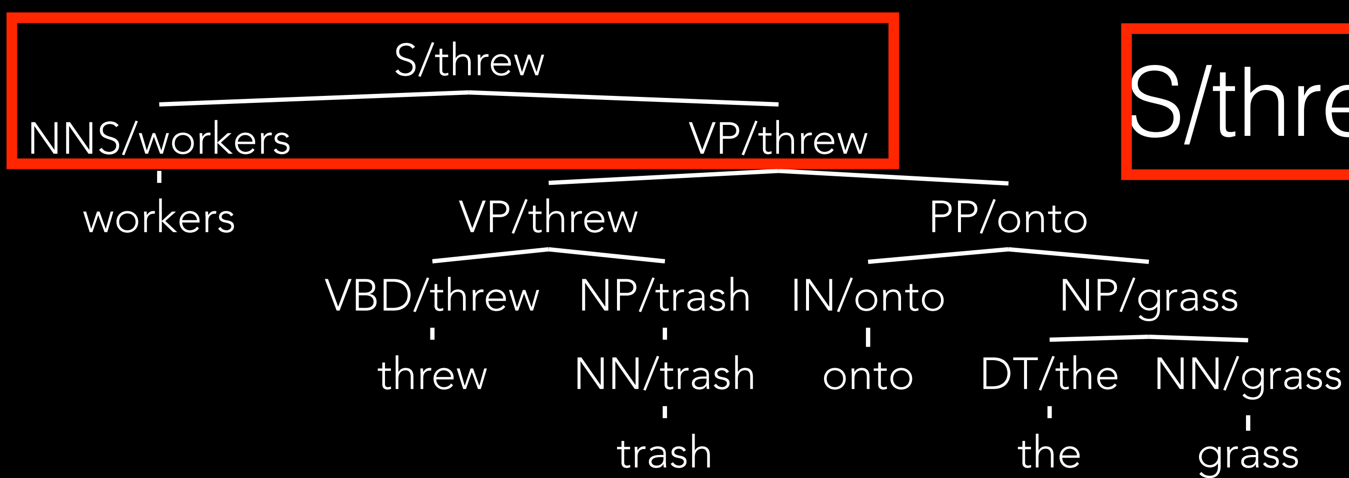
$0 \times 0/0$ $\quad$ $1 \times 20/40$

$=0.5$ S/threw -> NNS/workers VP/threw

Incorporating Smoothing

Assume we saw each training tree 20 times





S/threw -> NNS/workers VP/threw

$$P(m \mid r, X, h) = \lambda_2 P_{ML}(m \mid r, X, h) + (1-\lambda_2) P_{ML}(m \mid r)$$

$$0 \times 0/0 \qquad\qquad 1 \times 20/40$$

$=0.5$

S/threw -> NNS/workers VP/threw $= .032 * .5 = .016$

Other Ways To Smooth

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- Replace infrequently seen words with <unk> in training; map unseen words to <unk> when parsing

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- For interesting suffixes, stem infrequent words instead of replacing them; “working” becomes <unk>-ing

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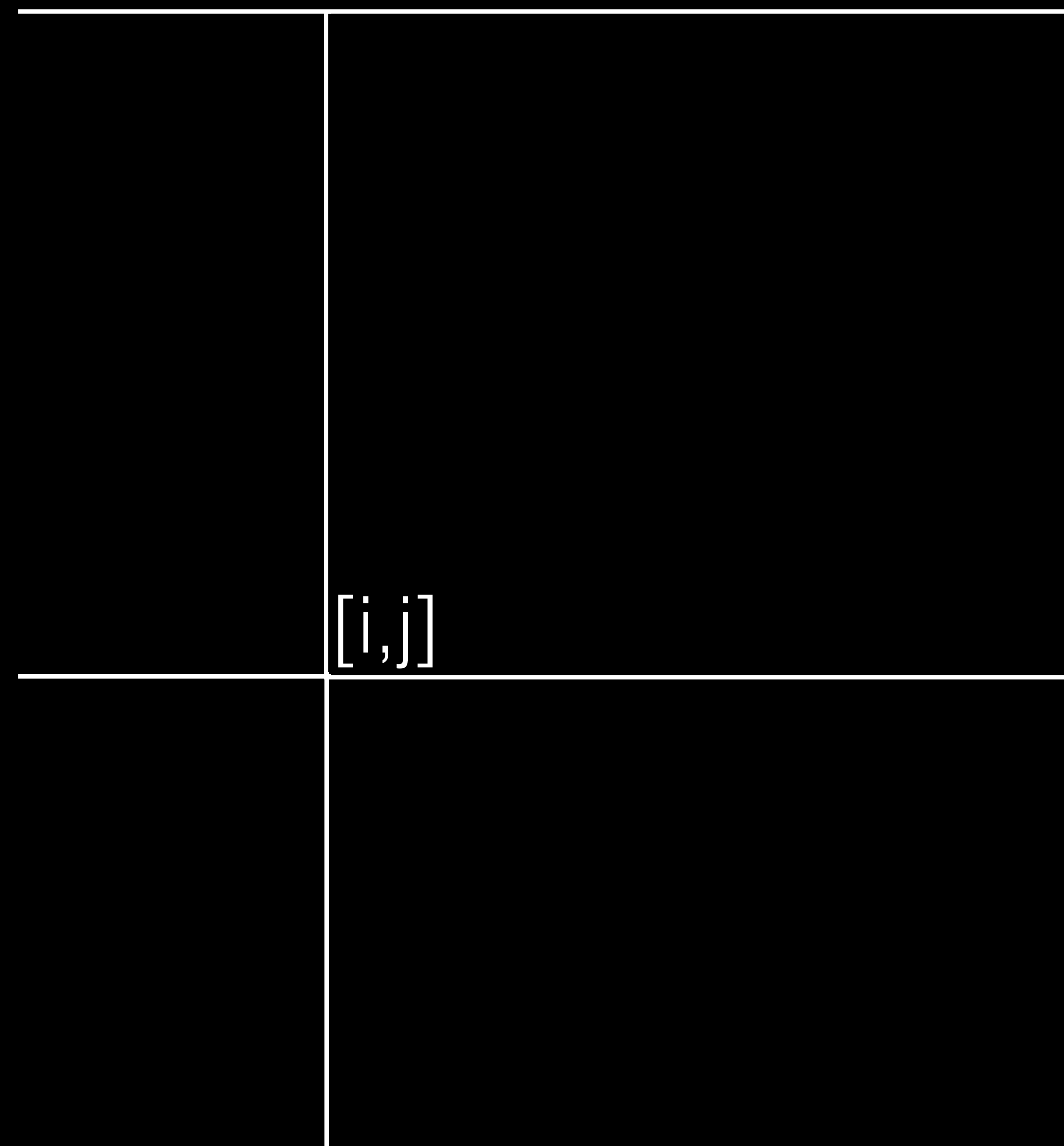
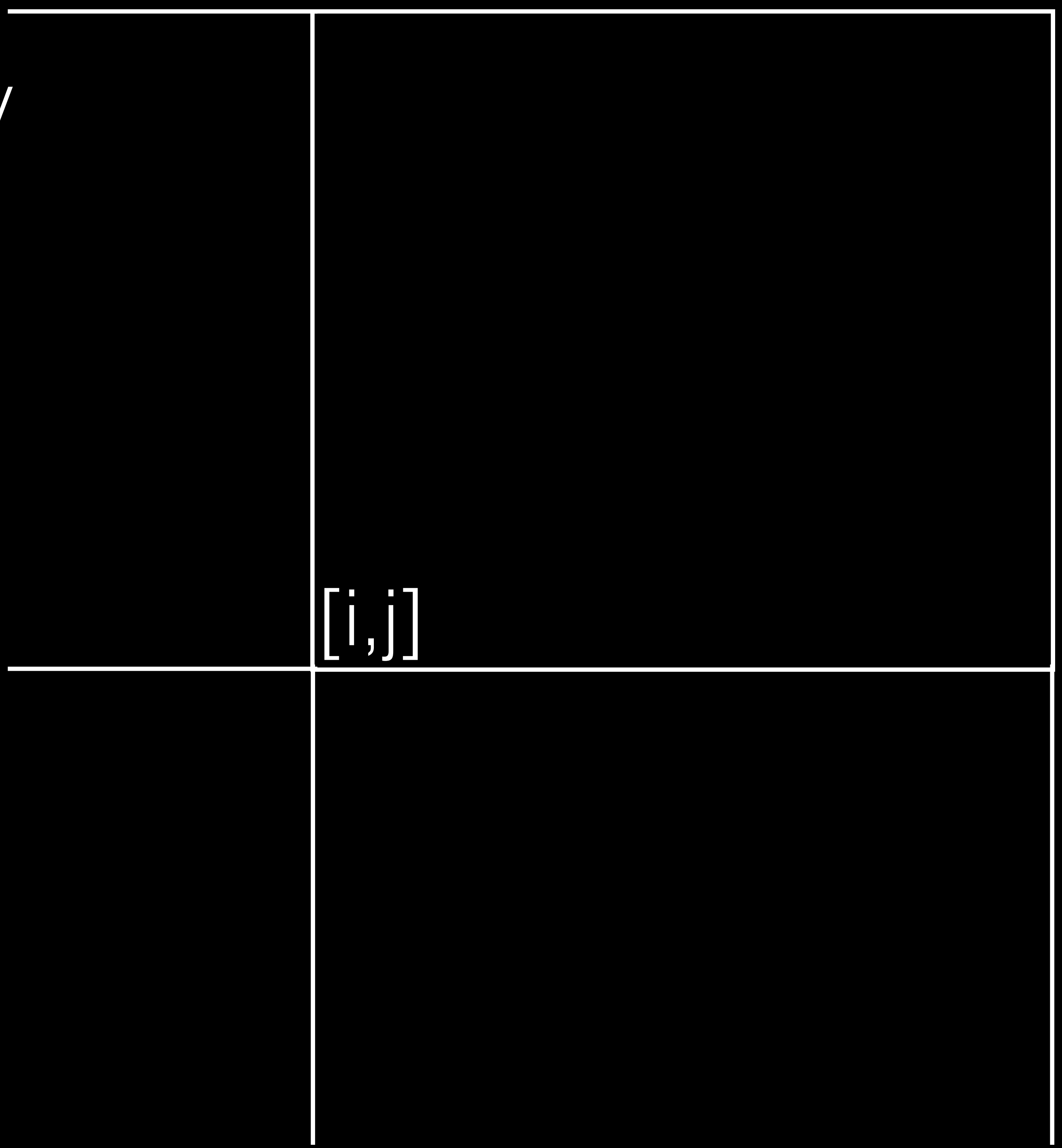
- Replace infrequently seen words with <unk> in training; map unseen words to <unk> when parsing
- For interesting suffixes, stem infrequent words instead of replacing them; “working” becomes <unk>-ing
- POS-tag ‘lexicalization’ instead of/in addition to true lexicalization

Beaming



Beaming

- Every state that gets created can be potentially combined to form new states higher up the chart



Beaming

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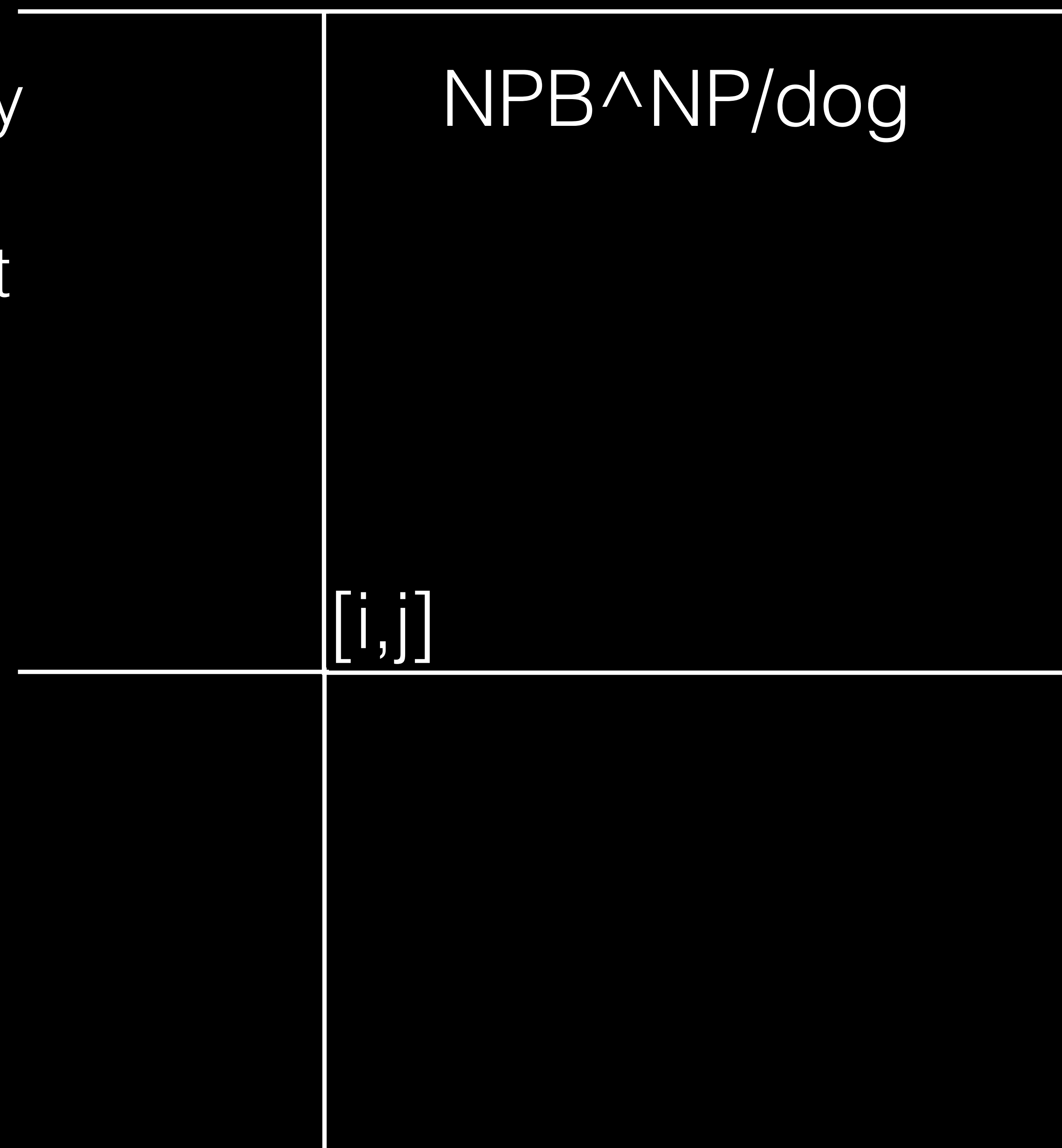

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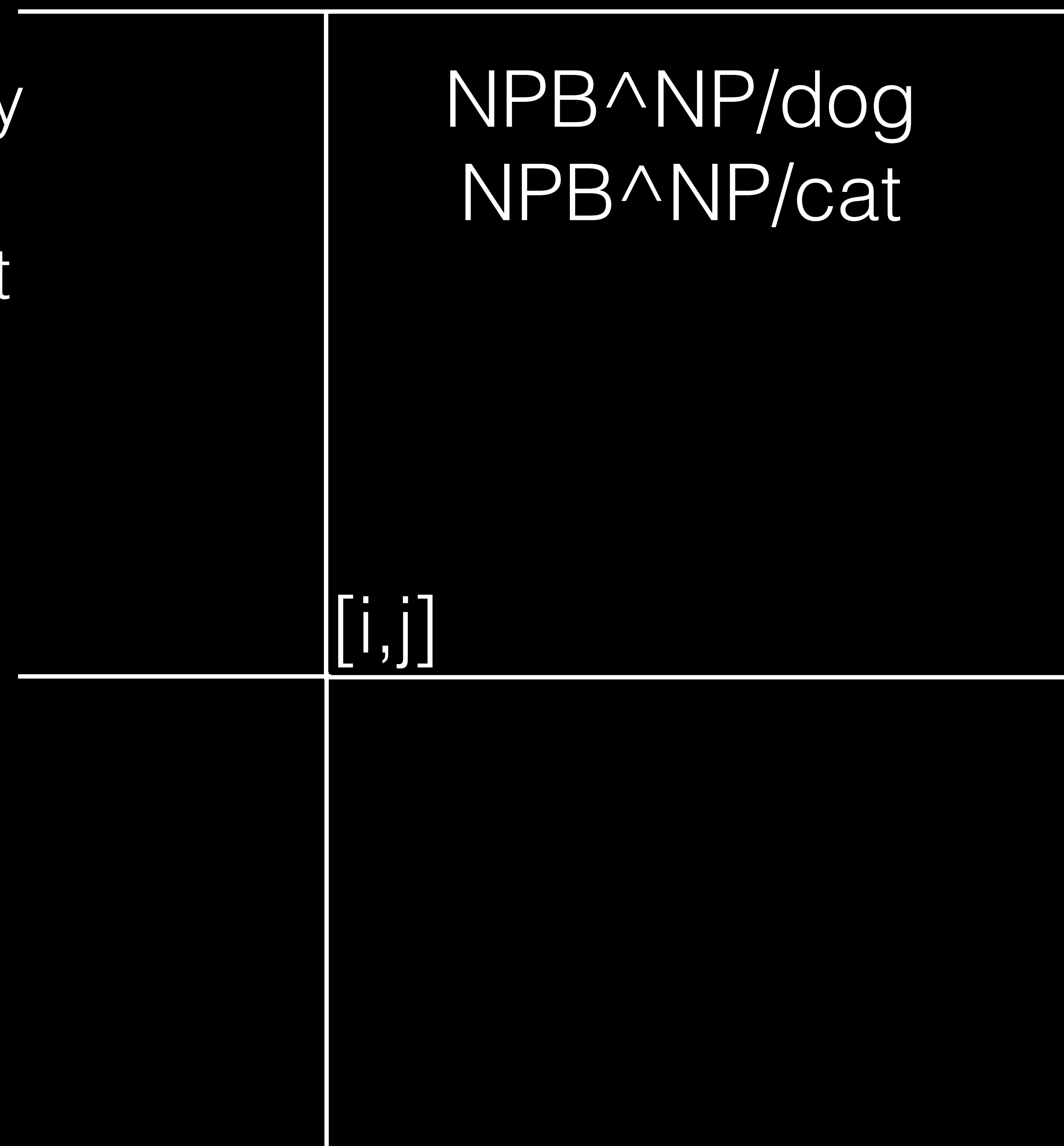

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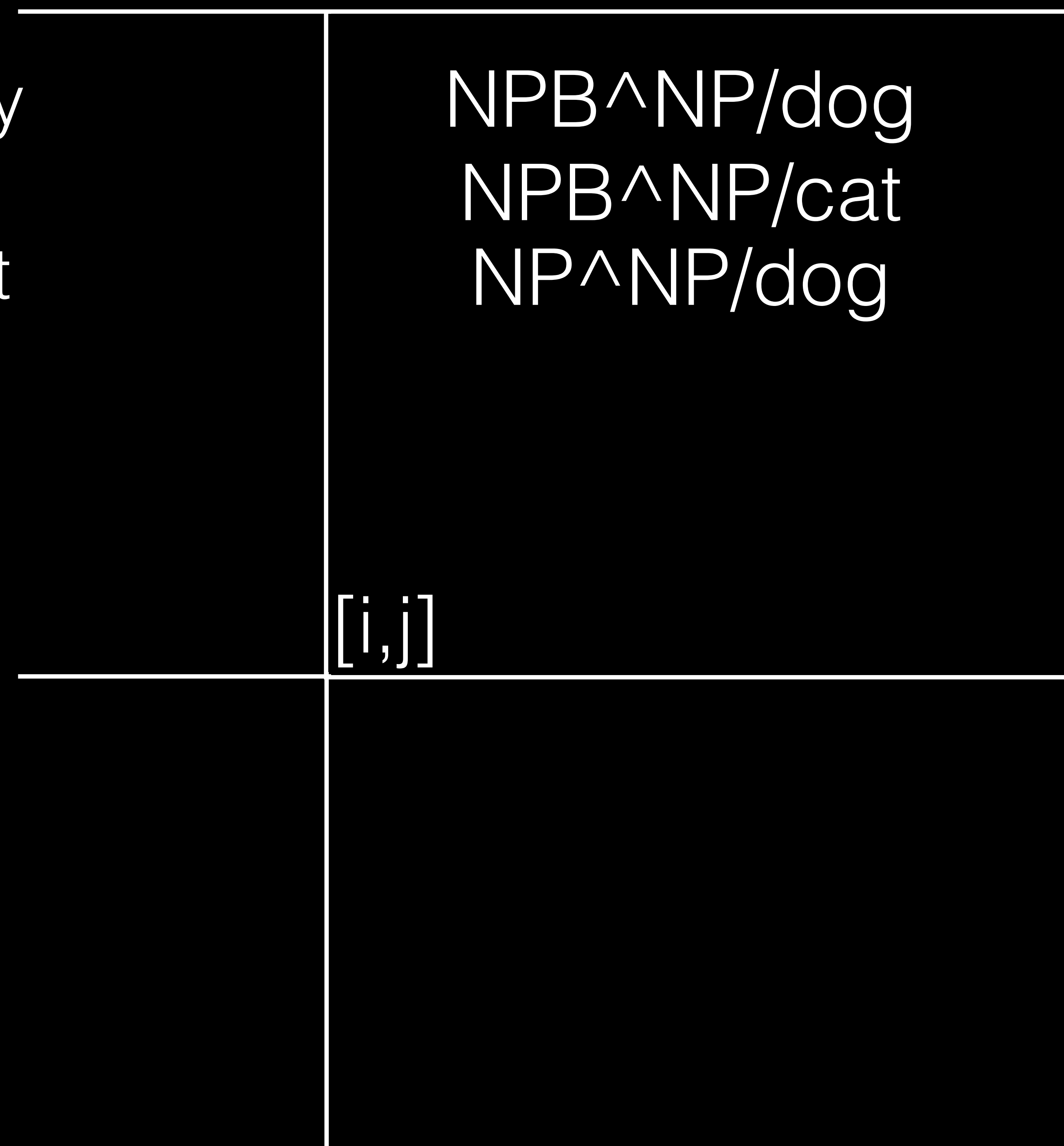

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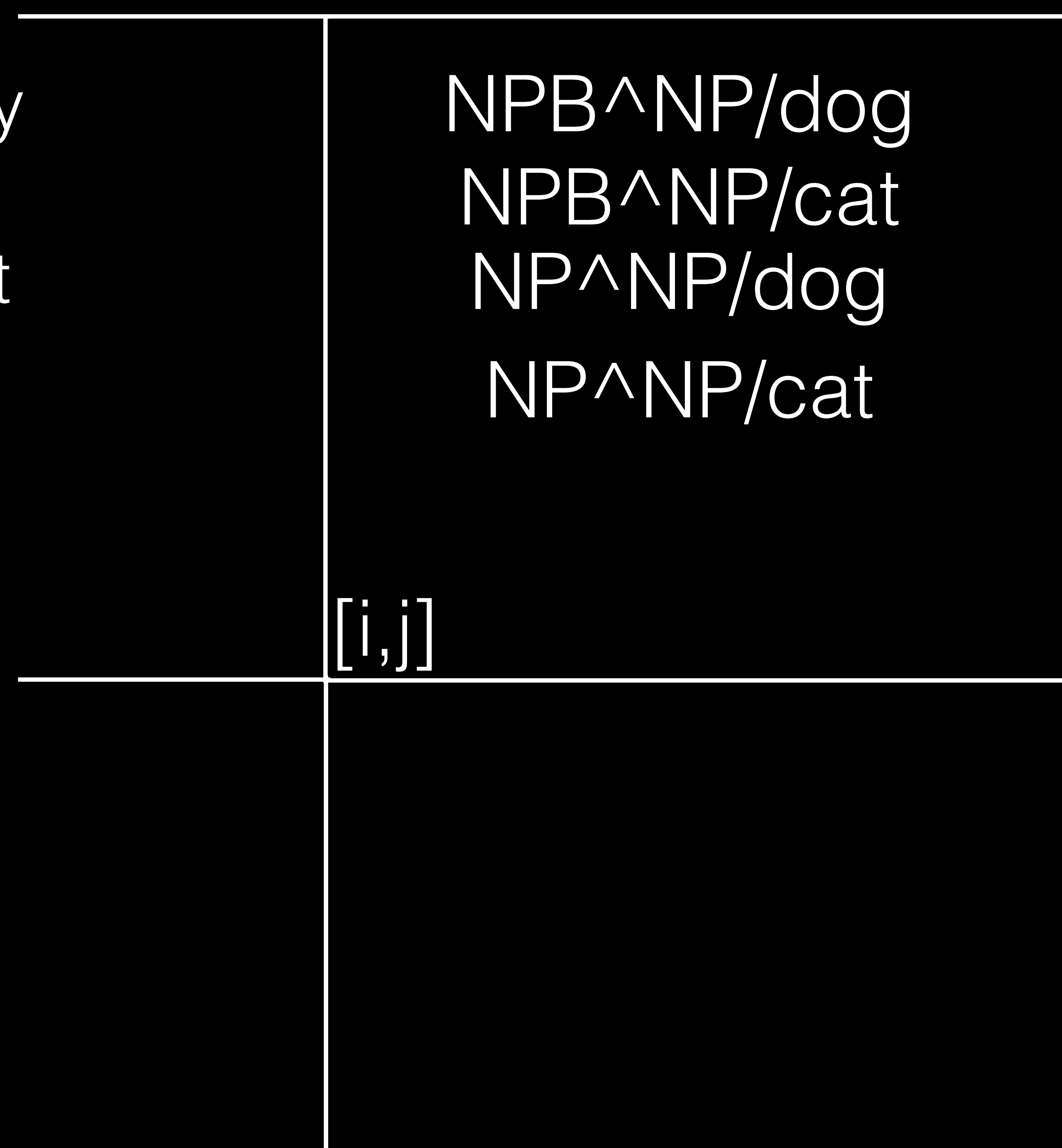


Beaming

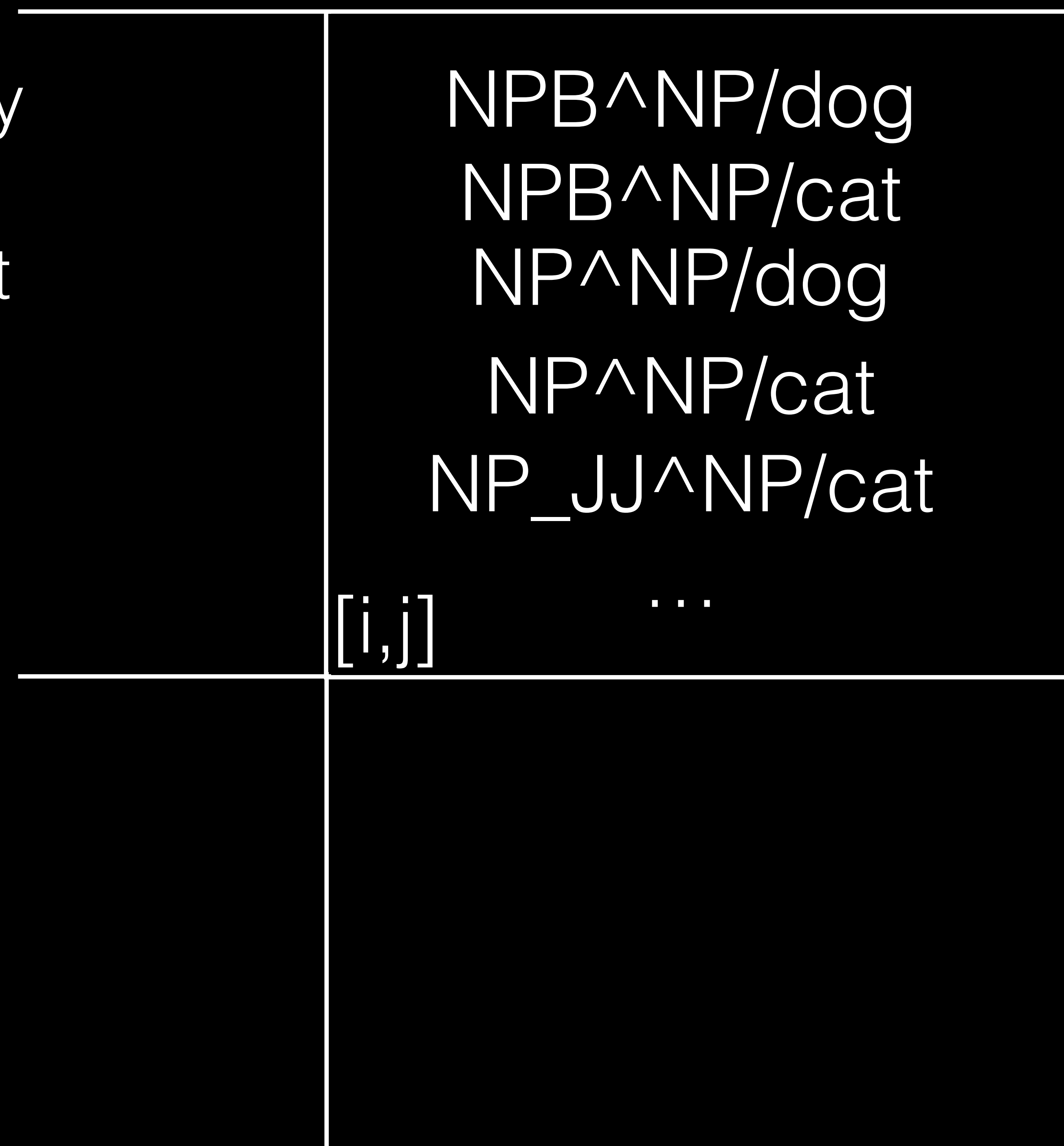
- Every state that gets created can be potentially combined to form new states higher up the chart

NPB^NP/dog
NPB^NP/cat
NP^NP/dog
NP^NP/cat
NP_JJ^NP/cat

[i,j]

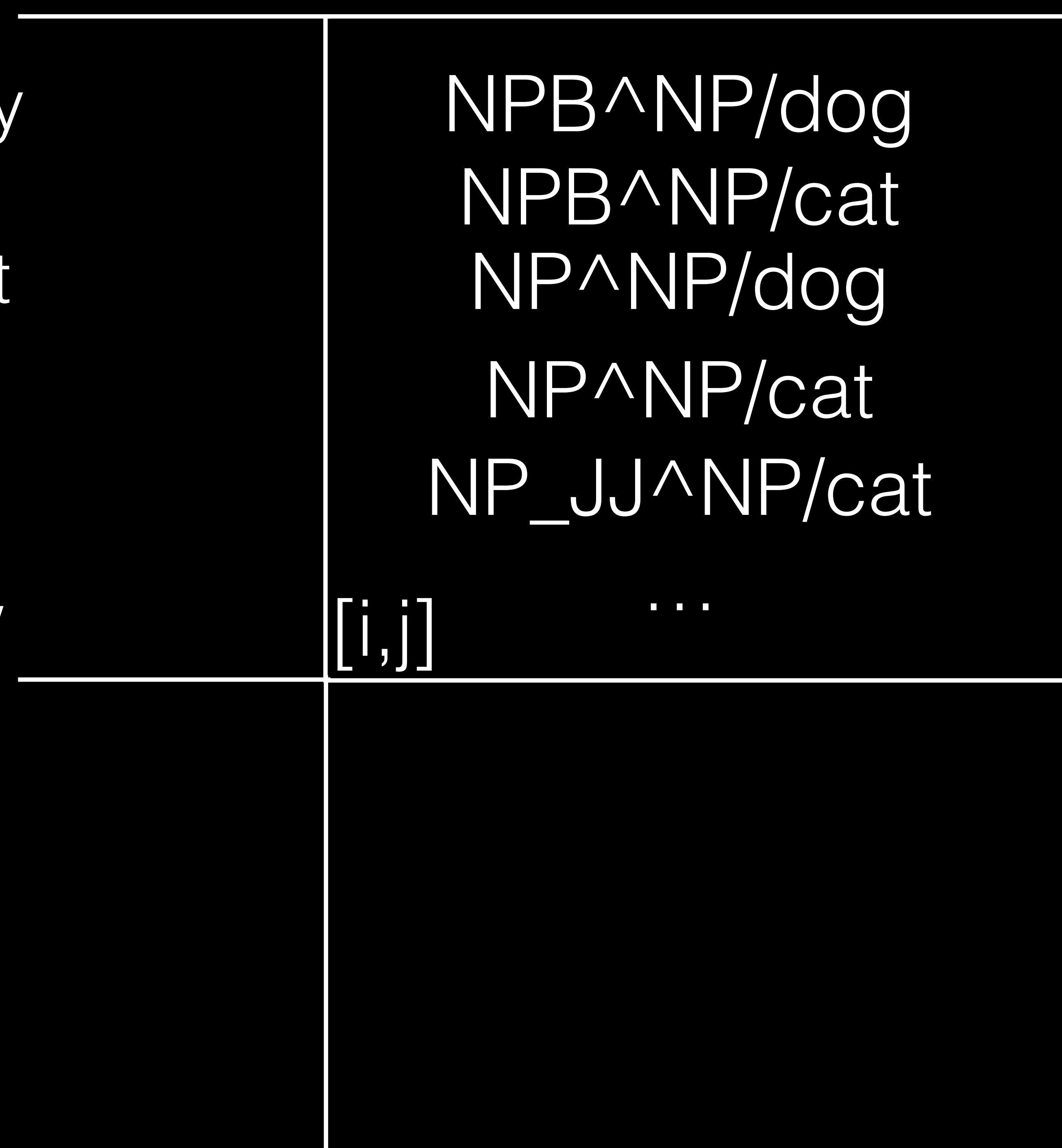
Beaming

- Every state that gets created can be potentially combined to form new states higher up the chart



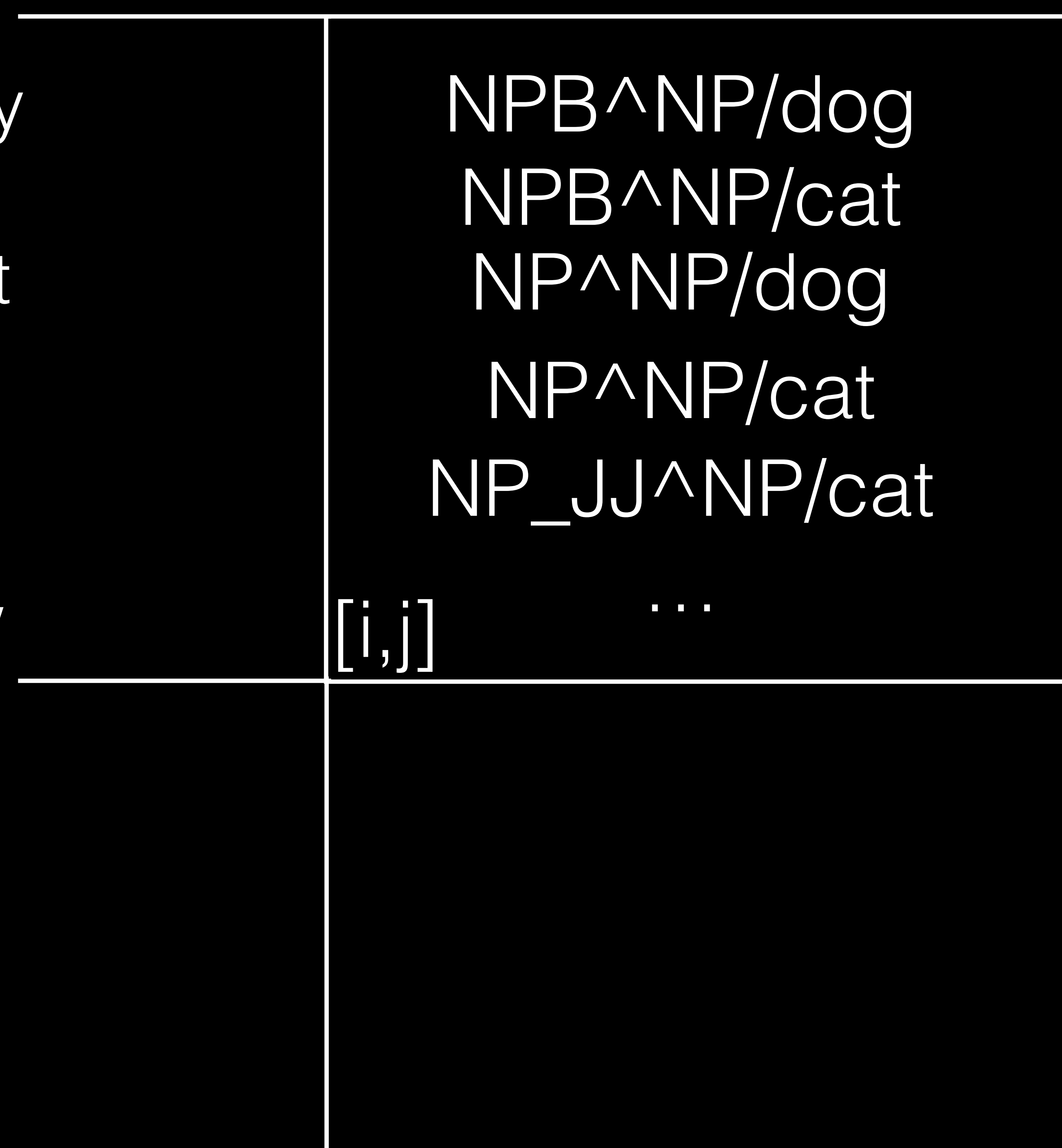
Beaming

- Every state that gets created can be potentially combined to form new states higher up the chart
- As grammars get more complex, number of states per span can grow



Beaming

- Every state that gets created can be potentially combined to form new states higher up the chart
- As grammars get more complex, number of states per span can grow
- Parsing will start to get slow unless something is done



Beaming

Beaming

- Beam search eliminates part of the chart as it is constructed

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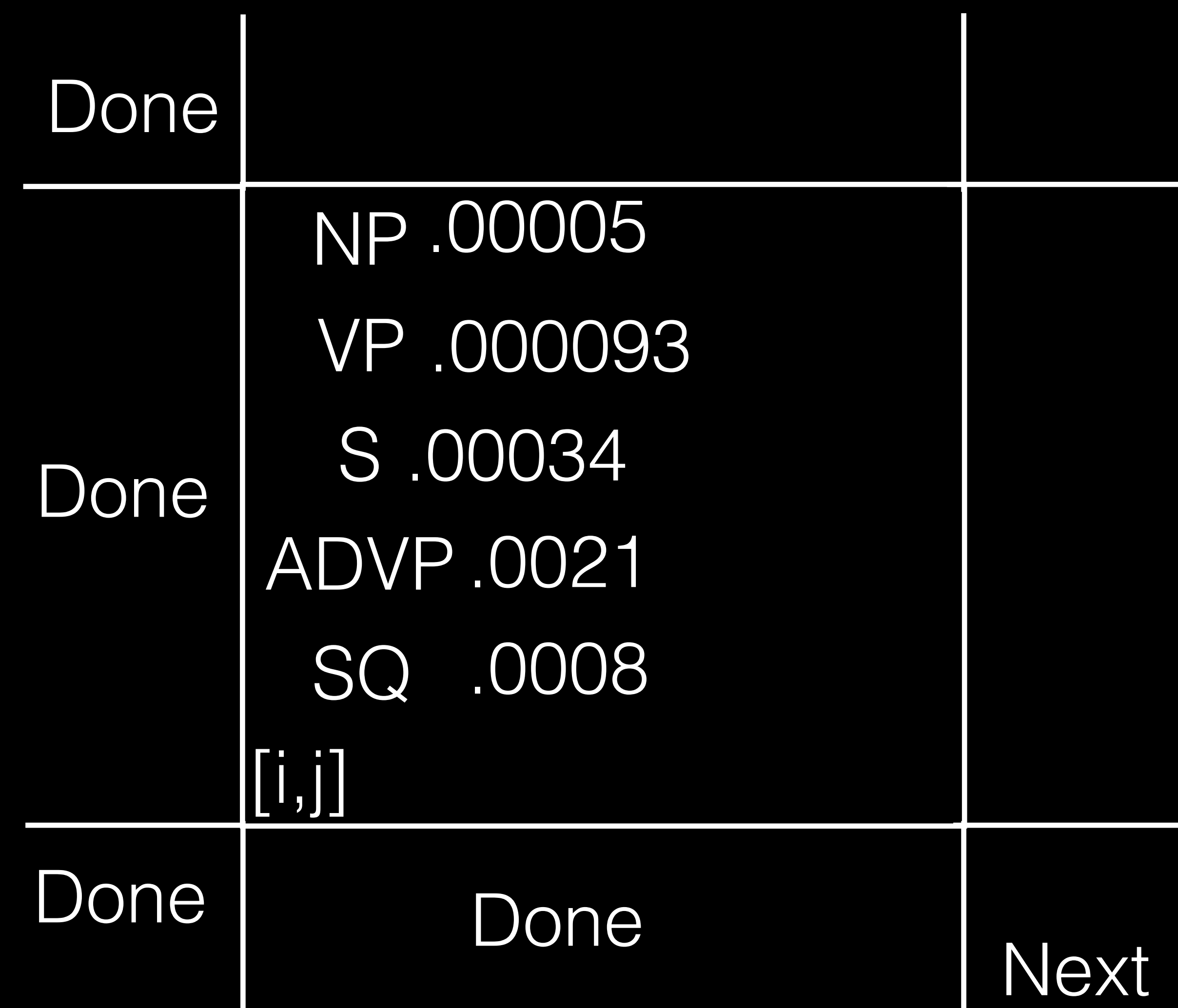
- Can cause search errors = best parse found is suboptimal

Beaming

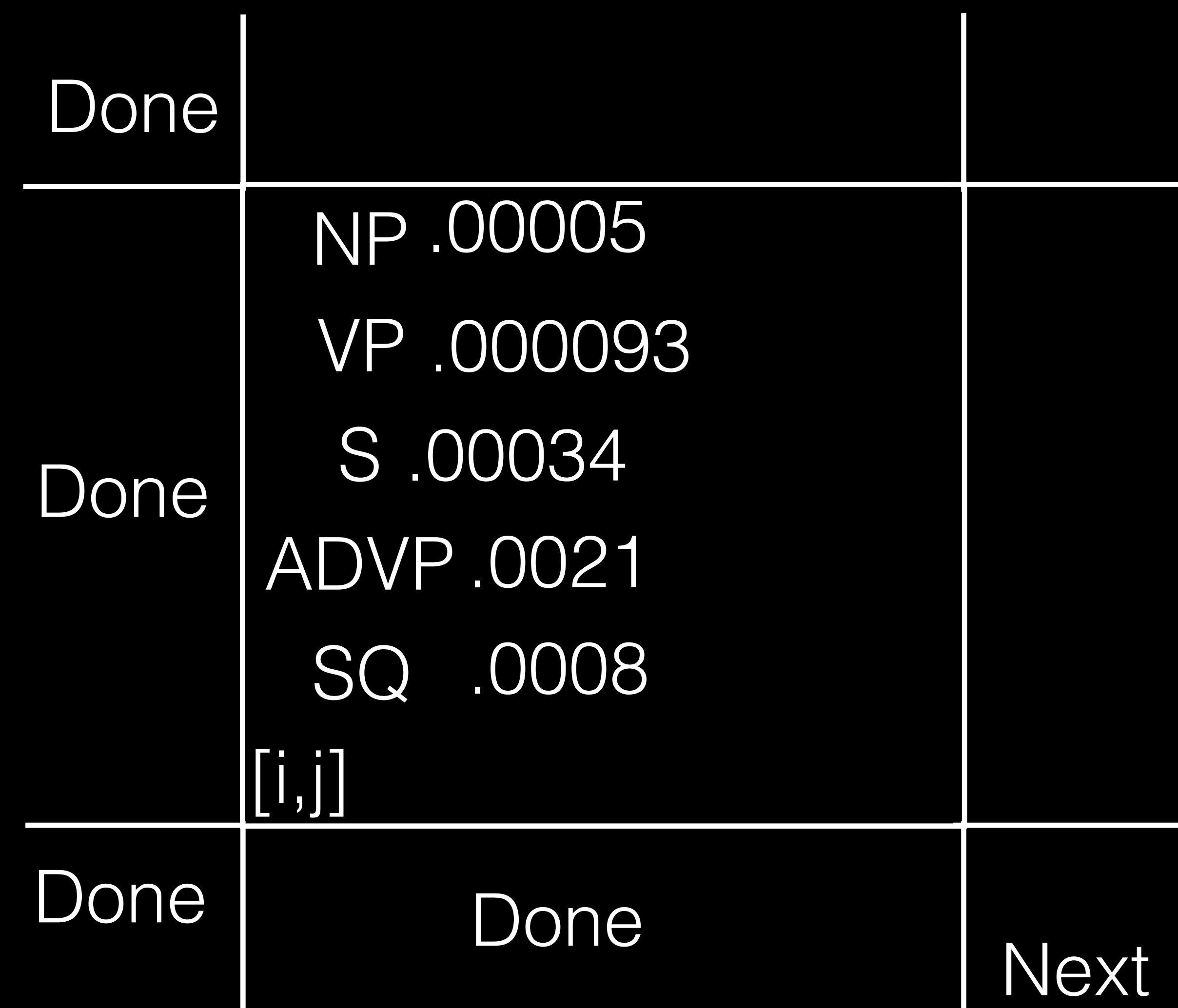
- Beam search eliminates part of the chart as it is constructed
- Can cause search errors = best parse found is suboptimal
- Basic idea: Using heuristic score of partial parse, eliminate states

Beaming


Done
Done
NP .00005
VP .000093
S .00034
ADVP .0021
SQ .0008
[i,j]
Done
Done
Next

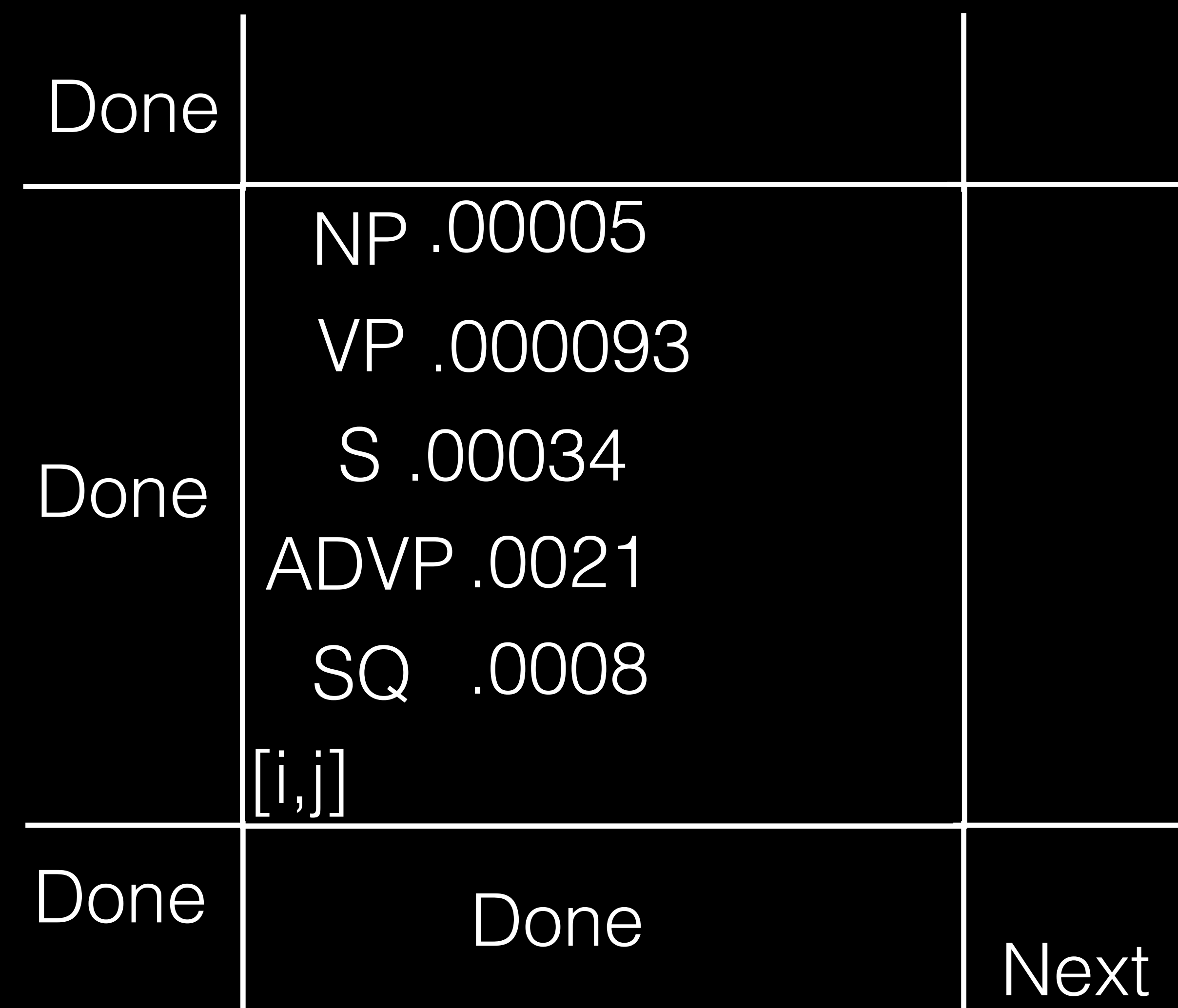
Beaming

- Before moving to [i+1, j+1], throw out some states



Beaming

- Before moving to [i+1, j+1], throw out some states
- Scores are *inside costs* = probability of subtree rooted in X



Beaming

- Before moving to [i+1, j+1], throw out some states

- Scores are *inside costs* = probability of subtree rooted in X

- We want the state most likely to be used in a *successful* parse

Done		
Done	NP .00005 VP .000093 S .00034 ADVP .0021 SQ .0008 [i,j]	
Done	Done	Next

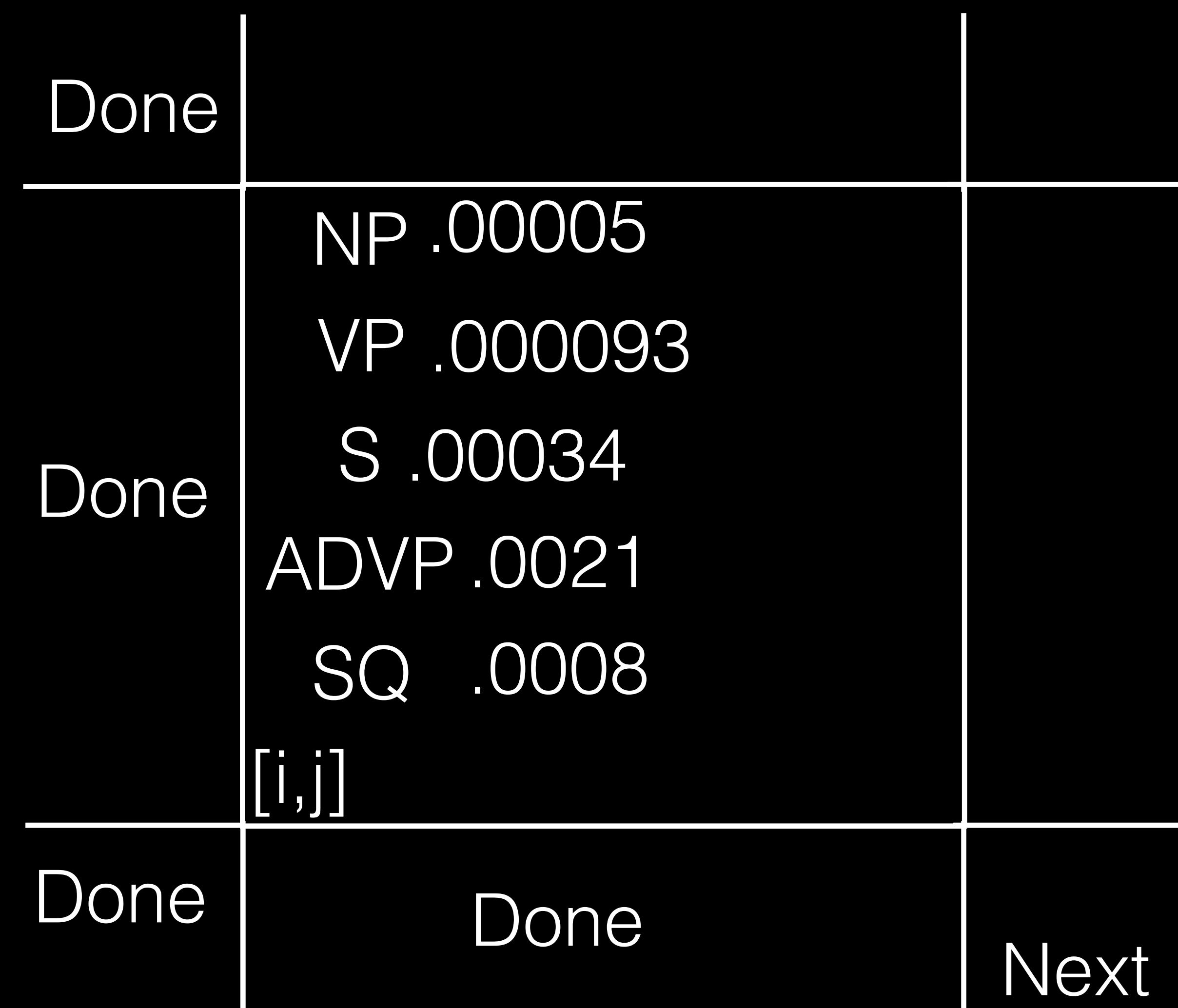
Beaming

- Before moving to [i+1, j+1], throw out some states

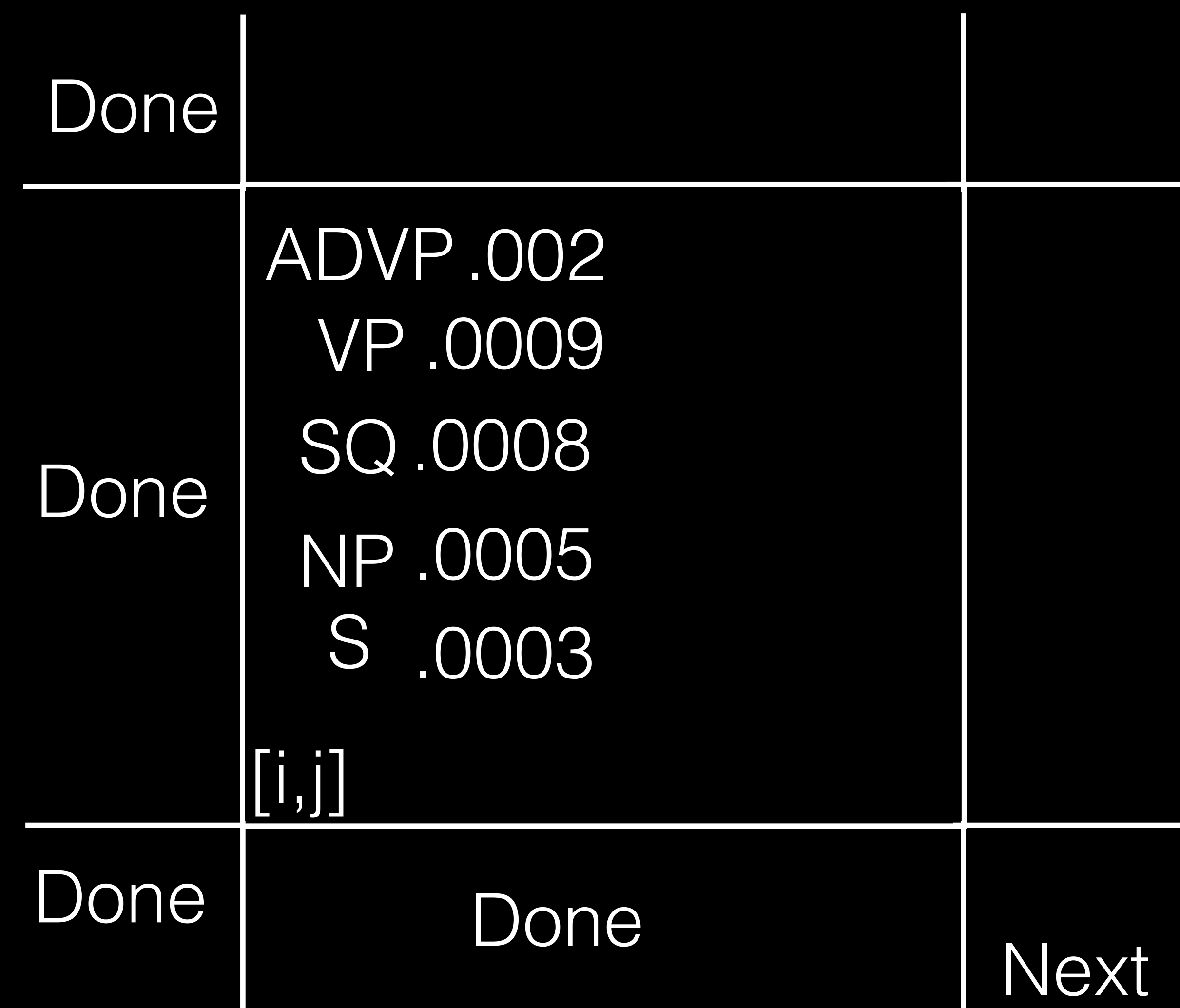
- Scores are *inside costs* = probability of subtree rooted in X

- We want the state most likely to be used in a *successful* parse

- What makes the state likely?

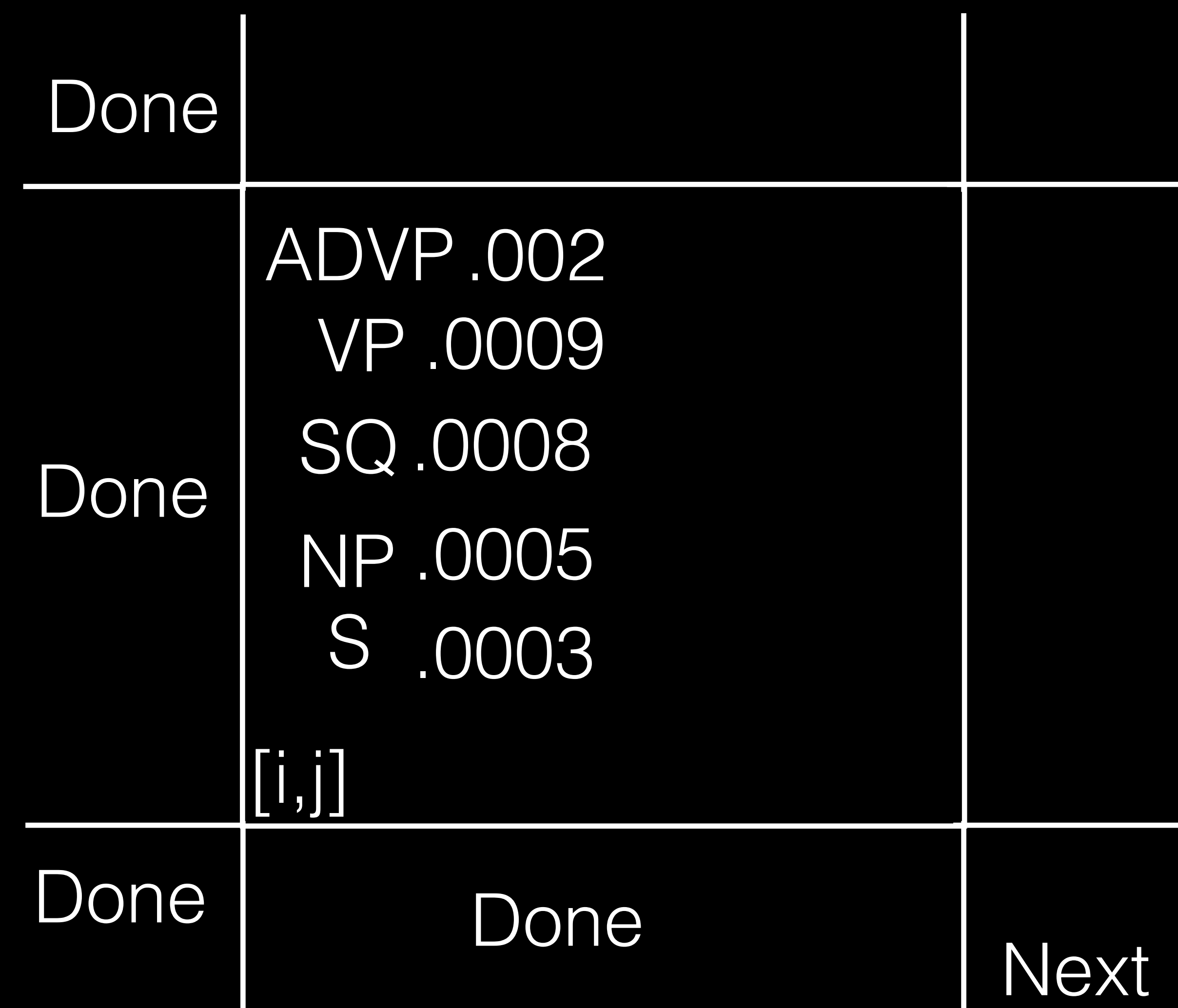


Beaming


Done
ADVP .002
VP .0009
SQ .0008
Done
NP .0005
S .0003
[i,j]
Done
Done
Next

Beaming

- Incorporate *heuristic* of completion (note: A* search!)



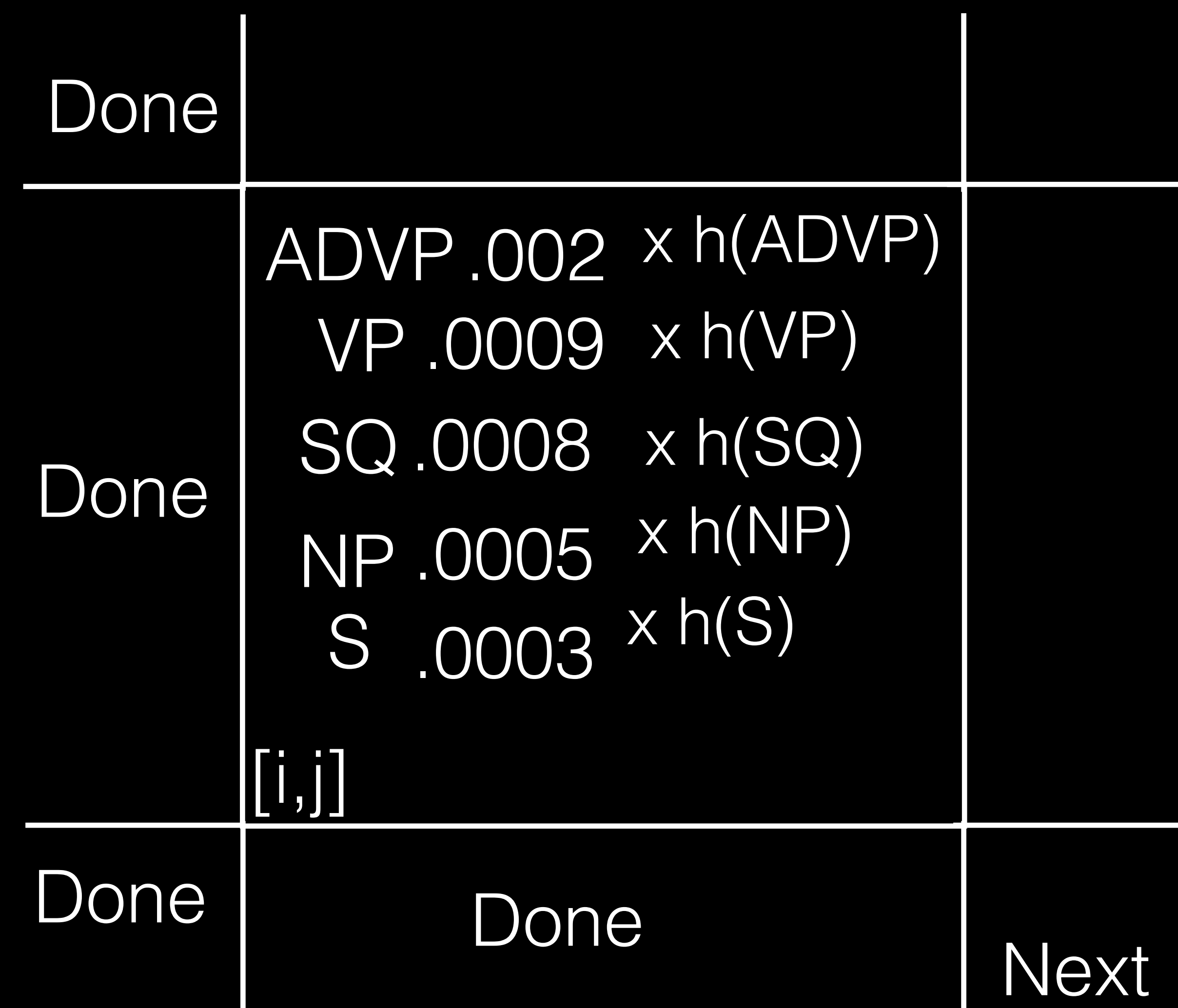
Beaming

- Incorporate *heuristic* of completion (note: A* search!)

Done		
Done	ADVP .002 x h(ADVP) VP .0009 x h(VP) SQ .0008 x h(SQ) NP .0005 x h(NP) S .0003 x h(S) [i,j]	
Done	Done	Next

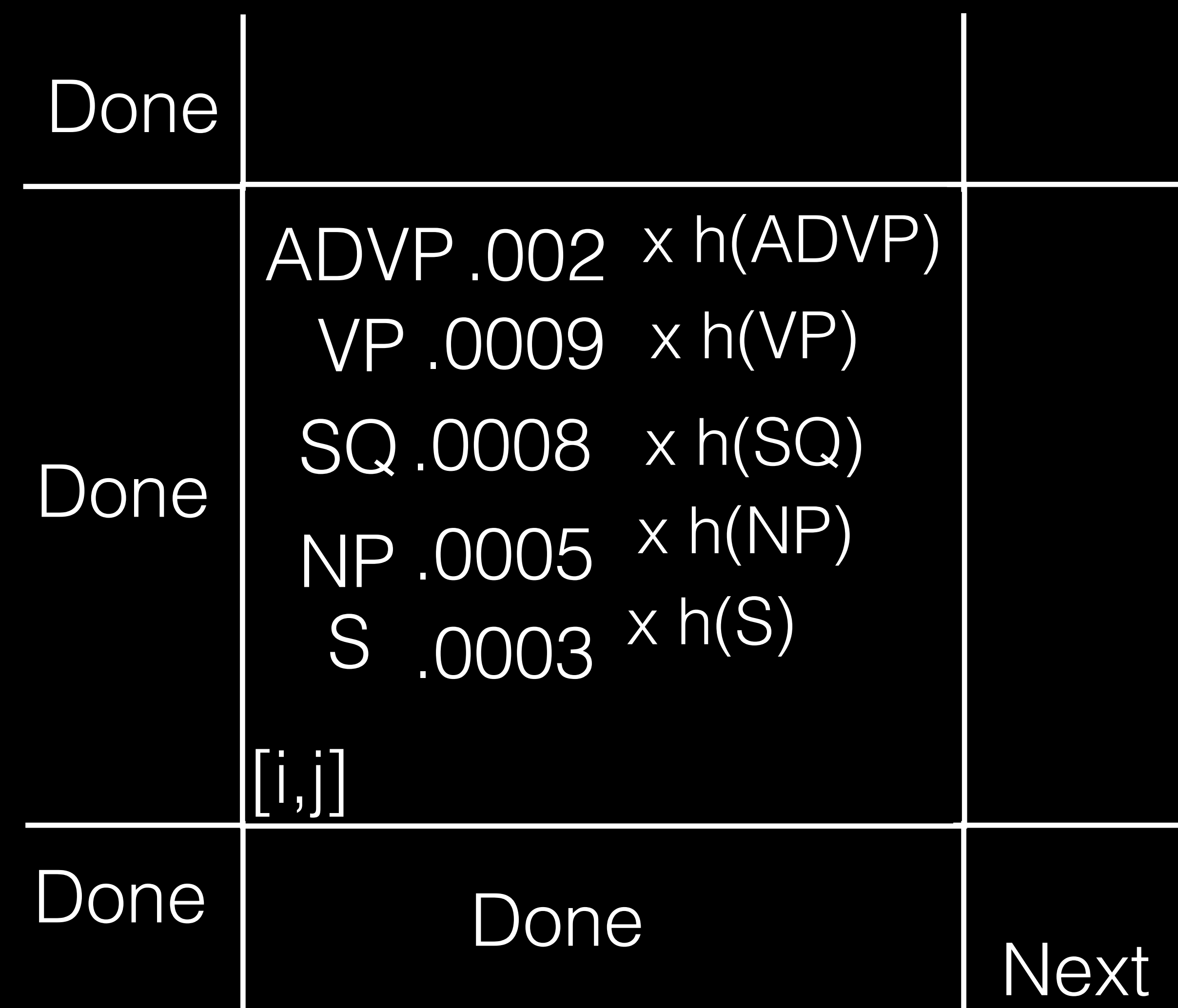
Beaming

- Incorporate *heuristic* of completion (note: A* search!)
- p(X) = prior probability of seeing X (count nonterminals in corpus)



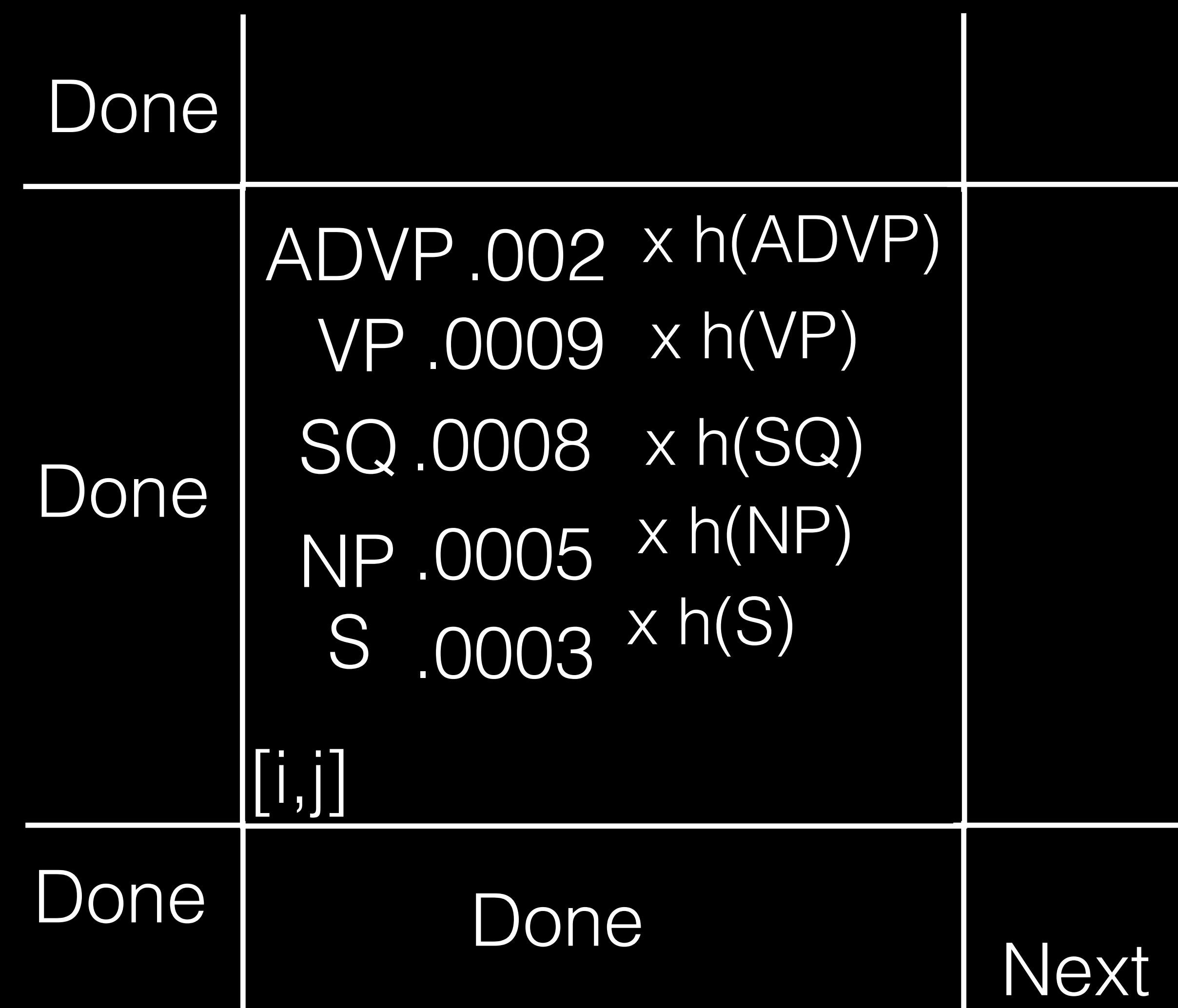
Beaming

- Incorporate *heuristic* of completion (note: A* search!)
- p(X) = prior probability of seeing X (count nonterminals in corpus)
- could subdivide by span size (p(X|j-i))



Beaming

- Incorporate *heuristic* of completion (note: A* search!)
- $p(X)$ = prior probability of seeing X (count nonterminals in corpus)
- could subdivide by span size ($p(X|j-i)$)
- could incorporate edge words ($p(X|w_{i-1}, w_j)$)



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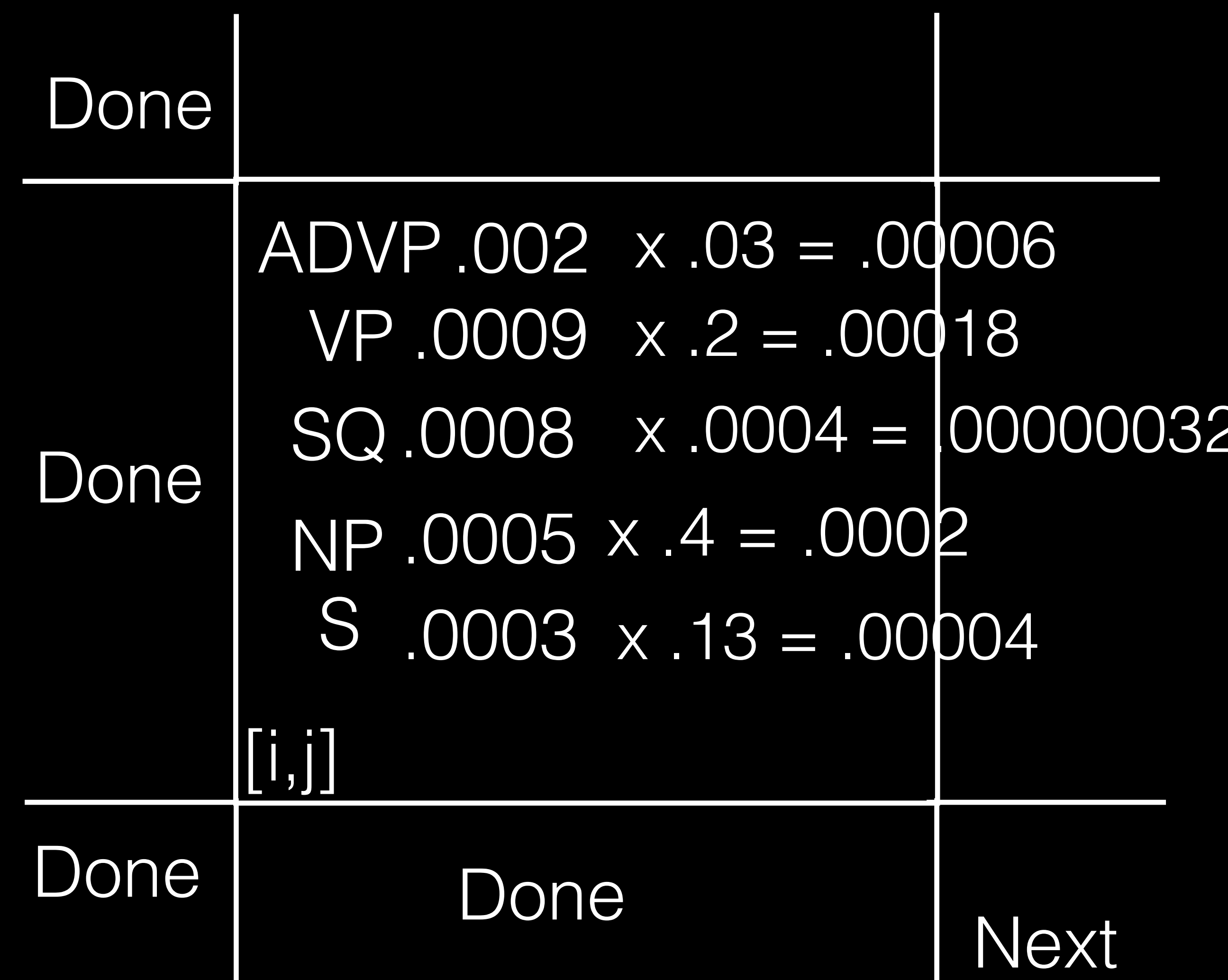

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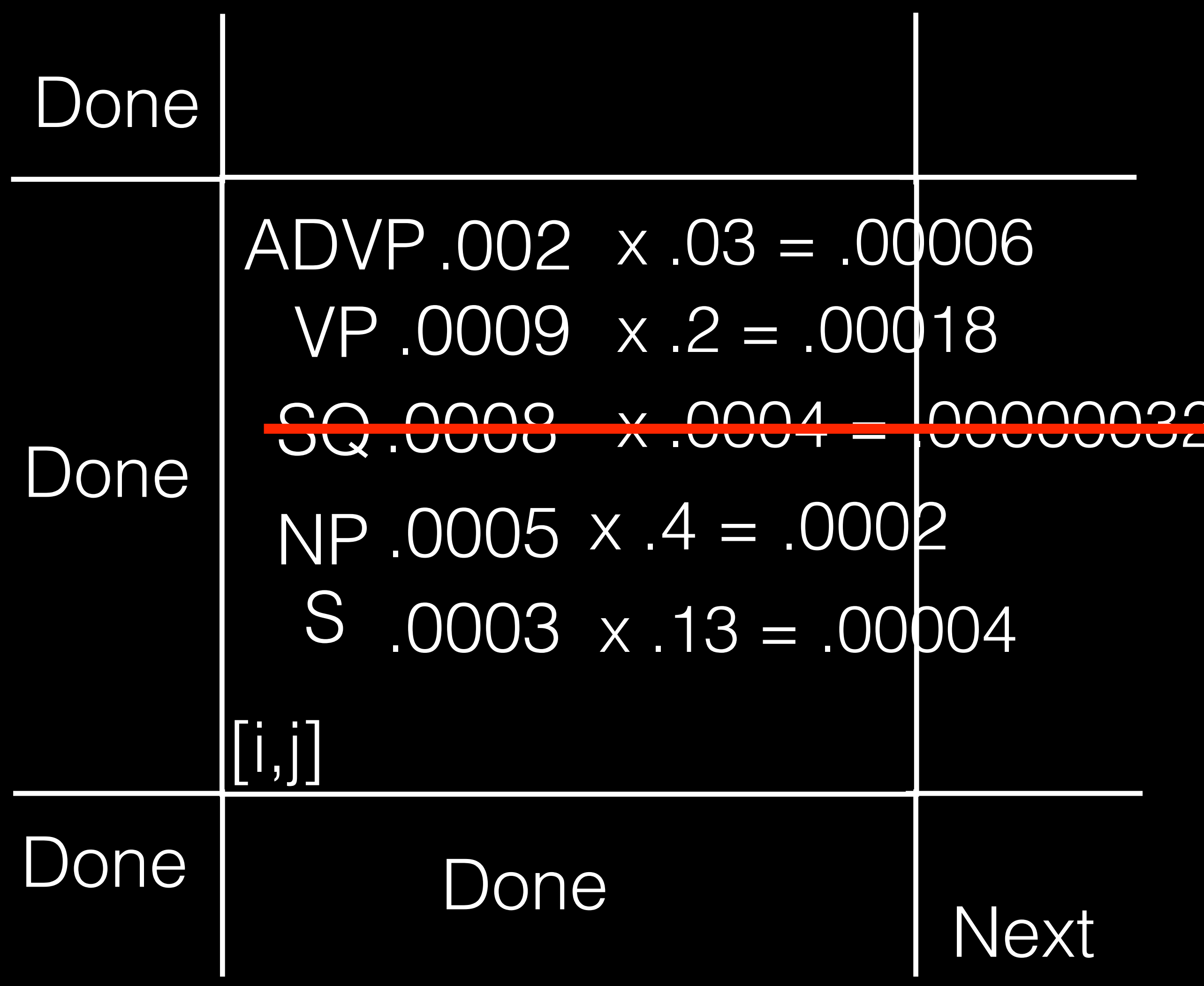

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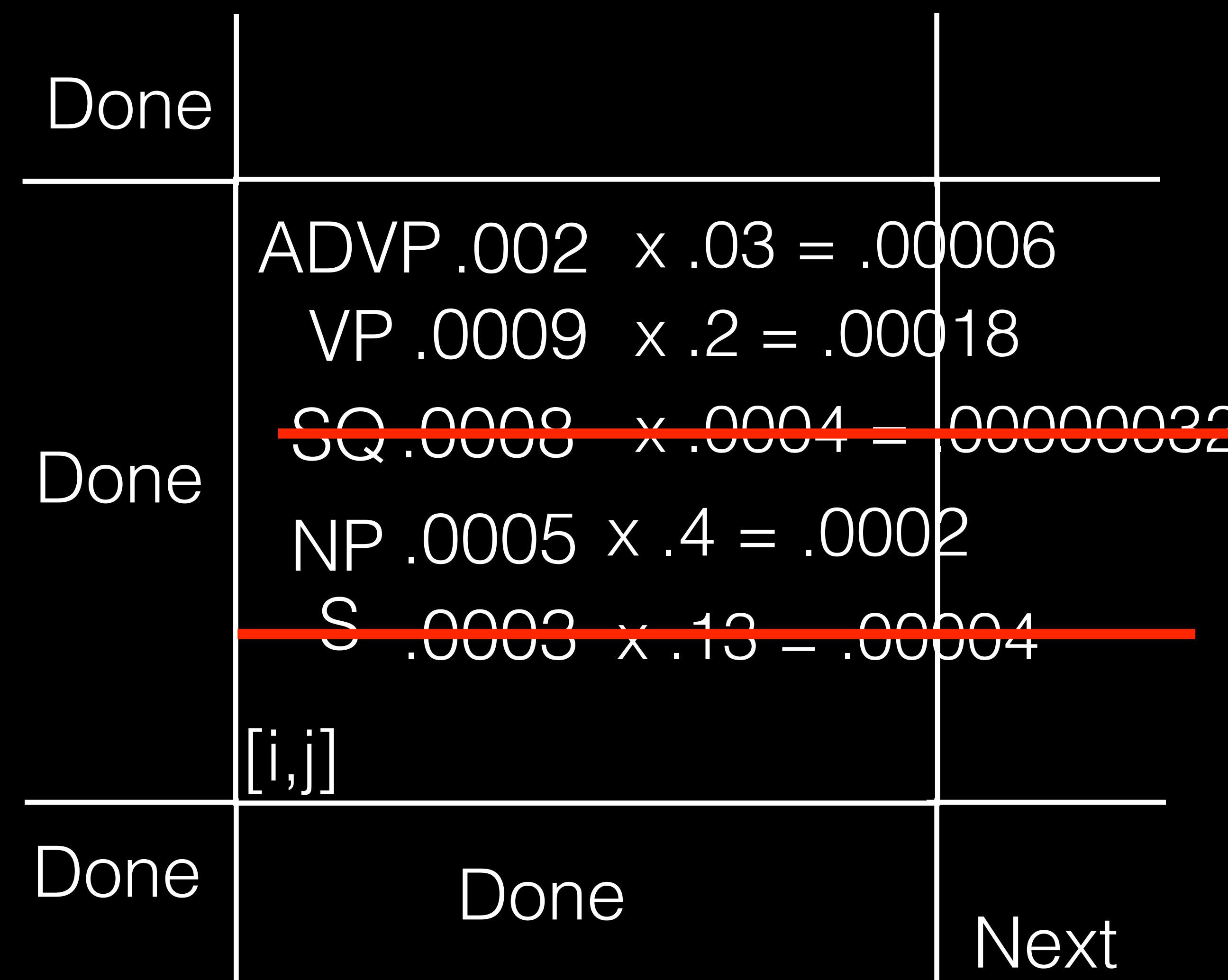

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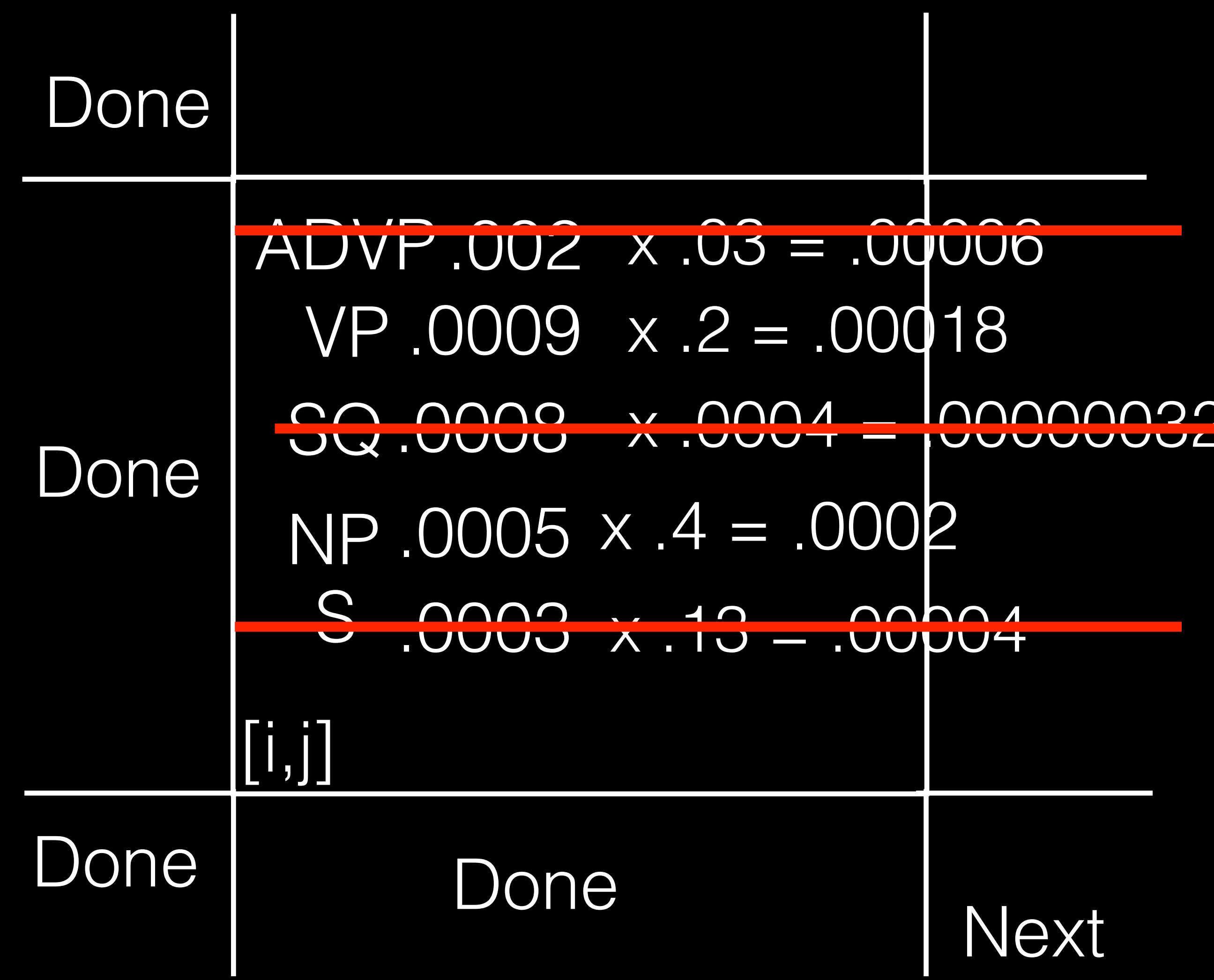

Summary

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- PCFG parsing

Summary

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- Estimating Vanilla PCFGs

Summary

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- Markovization

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Summary

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- Smoothing rich models

Summary

- PCFG parsing
- Estimating Vanilla PCFGs
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- Smoothing rich models
- Beaming the search