

Probabilistic Parsing: Issues & Improvement

LING 571 — Deep Processing Techniques for NLP
October 15th, 2018

Notes on HW #3

- Subtrees in cells
 - ...cells *are* subtrees, just represented differently!
 - You could use NLTK's Tree objects as backpointers efficiently *iff*:
 - each left or right child is defined by reference to another subtree.
 - ...this isn't more efficient than:

```
for tree_l in left_subtrees:
    for tree_r in right_subtrees:
        trees.append('({} {} {})'.format(nonterminal.symbol(),
                                           tree_l, tree_r))
```

A new type of vaccine? (0 parses)

0	Det -> "A"	NP -> 0•Det•1 1•Nom•3	NP -> 0•Det•1 1•Nom•5	_X_7 -> 0•NP•3 3•PP•5
1	Adj -> "new" ADJP -> "new"	NP -> 1•ADJP•2 2•Nom•3 Nom -> 1•ADJP•2 2•Nom•3	NP -> 1•ADJP•2 2•Nom•5 Nom -> 1•Nom•3 3•PP•5 _X_7 -> 1•NP•3 3•PP•5 NP -> 1•Nom•3 3•PP•5 Nom -> 1•ADJP•2 2•Nom•5	
2		Nom -> "type" NP -> "type"	Nom -> 2•Nom•3 3•PP•5 NP -> 2•Nom•3 3•PP•5 _X_7 -> 2•NP•3 3•PP•5	
3			Prep -> "of"	PP -> 3•Prep•4 4•NP•5
4			NP -> "vaccine"	Nom -> "vaccine"
5				

Will this work in humans? (0 parses)

0	MD -> "Will"				
1	NP -> "this"			S -> 1•NP•2 2•VP•5	
				TOP -> 1•NP•2 2•VP•5	
2	VB -> "work"			VP -> 2•VB•3 3•PP•5	
3			Prep -> "in"	PP -> 3•Prep•4 4•NP•5	
4				NP -> "humans"	
				Nom -> "humans"	
					5

Will this work in *apes*? (0 parses)

```
-----  
0 | MD -> "Will" | | |  
-----  
  | NP -> "this" | | |  
1 -----  
  | VB -> "work" | | |  
2 -----  
    | Prep -> "in" | | |  
3 -----  
                        | | |  
                        4 ----  
                          5
```

They restored immunity in mice with a weak immune system. (8 parses)

0	NP -> "They"	TOP -> 0•NP•1 1•VP•3 S -> 0•NP•1 1•VP•3	TOP -> 0•NP•1 1•VP•5 S -> 0•NP•1 1•VP•5					TOP -> 0•NP•1 1•VP•10 S -> 0•NP•1 1•VP•10
1	VBD -> "restored"	VP -> 1•VBD•2 2•NP•3	VP -> 1•VBD•2 2•_X_7•5 VP -> 1•VBD•2 2•NP•5					VP -> 1•VBD•2 2•_X_7•10 VP -> 1•VBD•2 2•NP•10
2		Nom -> "immunity" NP -> "immunity"	Nom -> 2•Nom•3 3•PP•5 NP -> 2•Nom•3 3•PP•5 _X_7 -> 2•NP•3 3•PP•5					Nom -> 2•Nom•3 3•PP•10 _X_7 -> 2•NP•5 5•PP•10 NP -> 2•Nom•3 3•PP•10 _X_7 -> 2•NP•3 3•PP•10 Nom -> 2•Nom•5 5•PP•10 NP -> 2•Nom•5 5•PP•10
3		Prep -> "in"	PP -> 3•Prep•4 4•NP•5					PP -> 3•Prep•4 4•NP•10
4			Nom -> "mice" NP -> "mice"					_X_7 -> 4•NP•5 5•PP•10 NP -> 4•Nom•5 5•PP•10 Nom -> 4•Nom•5 5•PP•10
5				Prep -> "with"				PP -> 5•Prep•6 6•NP•10
6					Det -> "a"			NP -> 6•Det•7 7•Nom•10
7						Adj -> "weak" ADJP -> "weak"	ADJP -> 7•Adj•8 8•ADJP•9	Nom -> 7•ADJP•8 8•Nom•10 NP -> 7•ADJP•8 8•Nom•10 Nom -> 7•ADJP•9 9•Nom•10 NP -> 7•ADJP•9 9•Nom•10
8							Adj -> "immune" ADJP -> "immune"	Nom -> 8•ADJP•9 9•Nom•10 NP -> 8•ADJP•9 9•Nom•10
9								Nom -> "system" NP -> "system"
10								

Start Recording!

PCFG Induction

Learning Probabilities

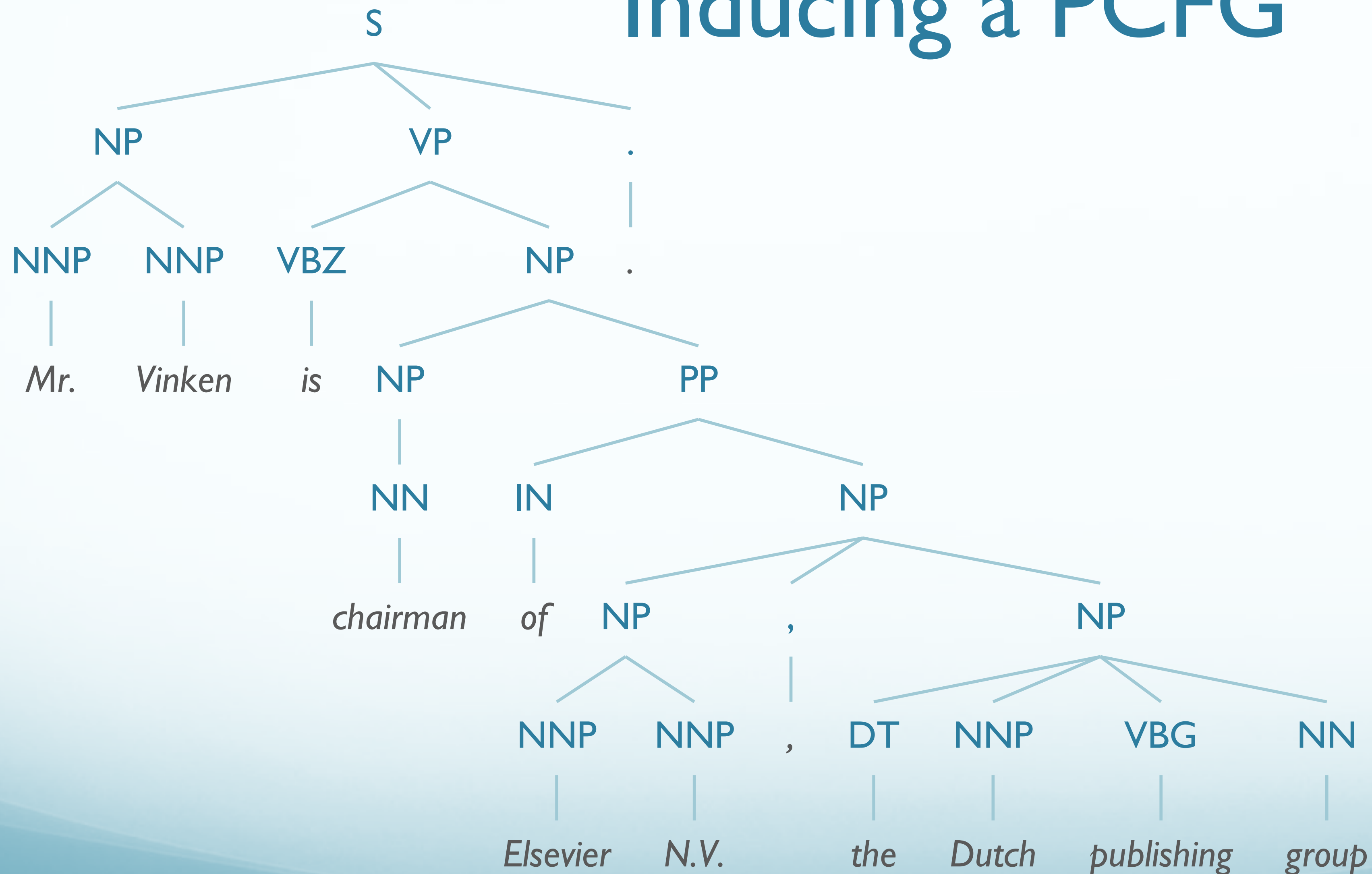
- Simplest way:
 - Use treebank of parsed sentences
 - To compute probability of a rule, count:
 - Number of times a nonterminal is expanded:
 - Number of times a nonterminal is expanded by a given rule:

$$\frac{\sum_{\gamma} \text{Count}(\alpha \rightarrow \gamma)}{\text{Count}(\alpha \rightarrow \beta)}$$

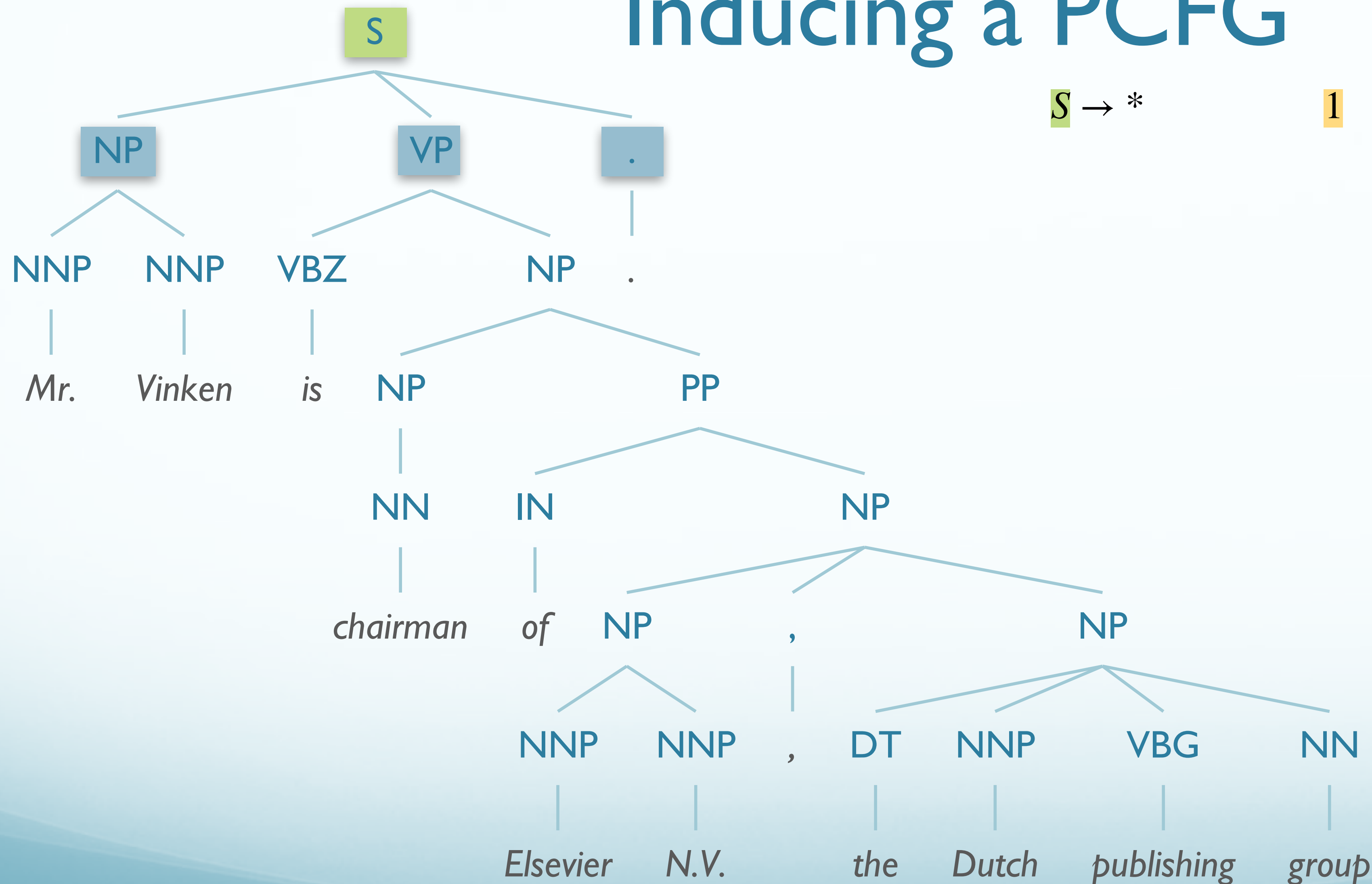
$$P(\alpha \rightarrow \beta \mid \alpha) = \frac{\text{Count}(\alpha \rightarrow \beta)}{\sum_{\gamma} \text{Count}(\alpha \rightarrow \gamma)} = \frac{\text{Count}(\alpha \rightarrow \beta)}{\text{Count}(\alpha)}$$

- Alternative: Learn probabilities by re-estimating
 - (Later)

Inducing a PCFG



Inducing a PCFG

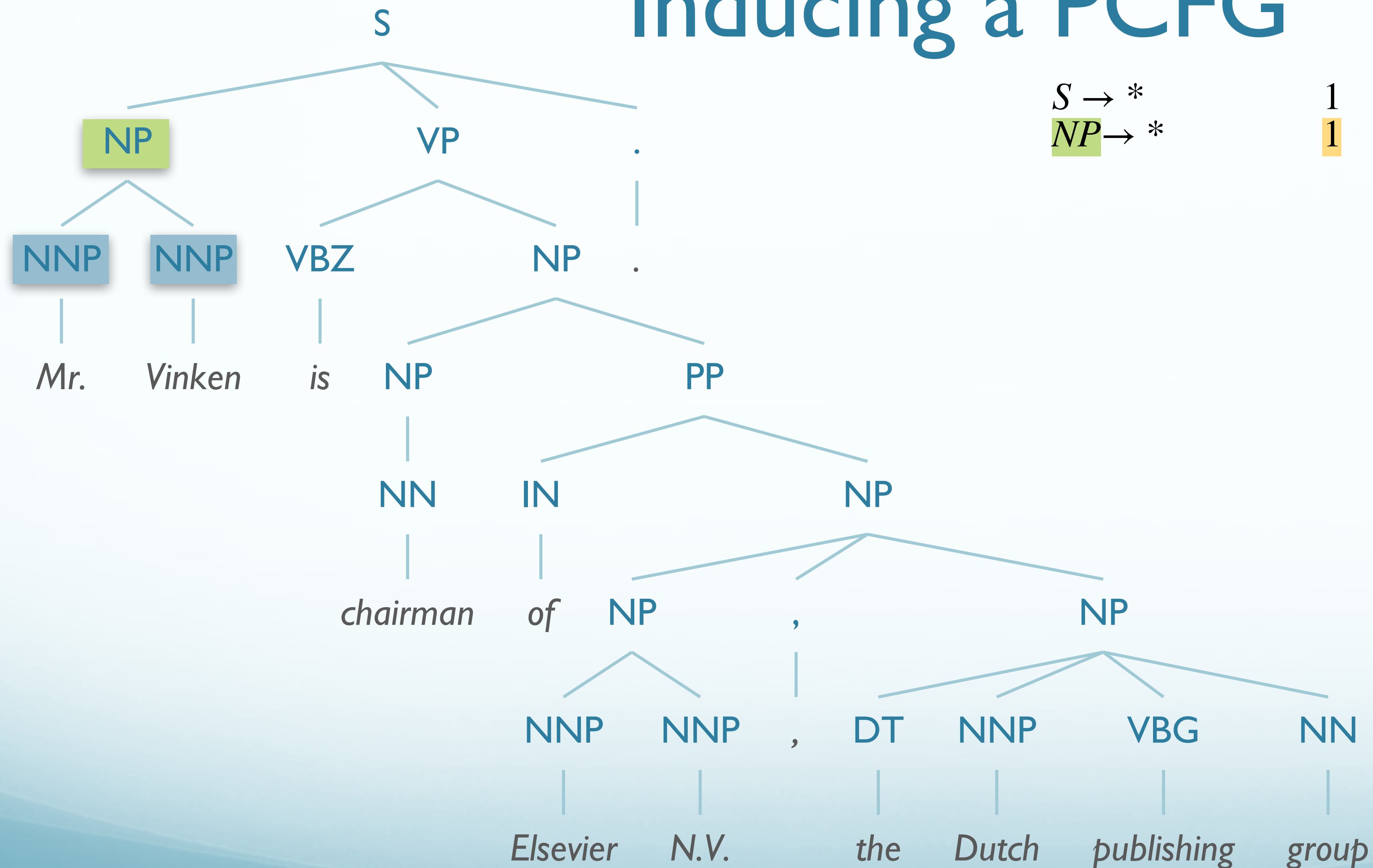


$S \rightarrow *$

1 $S \rightarrow NPVP.$

1

Inducing a PCFG

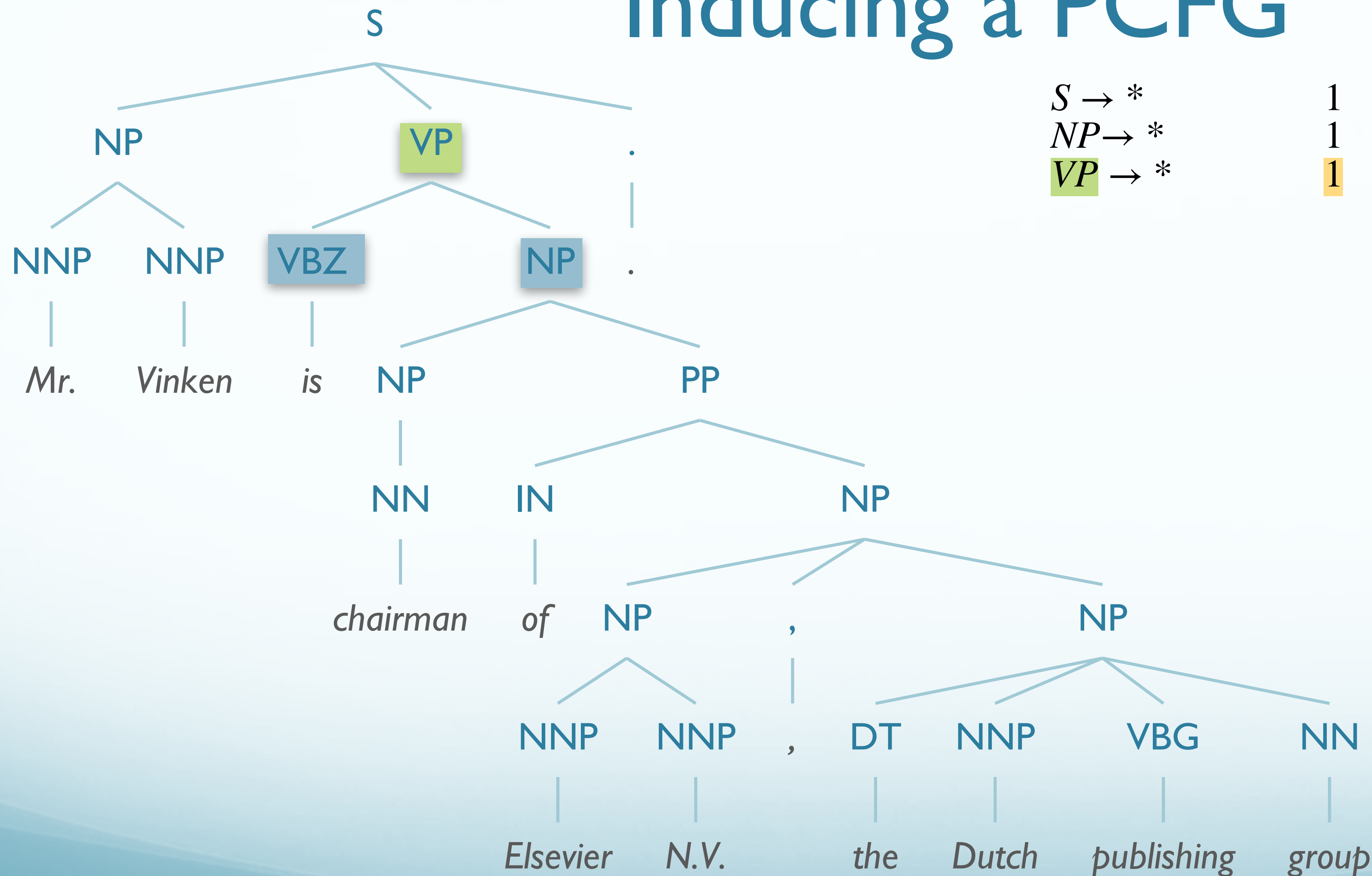


$S \rightarrow *$
 $\text{NP} \rightarrow *$

1 $S \rightarrow \text{NP VP} .$
 1 $\text{NP} \rightarrow \text{NNP NNP}$

1
 1

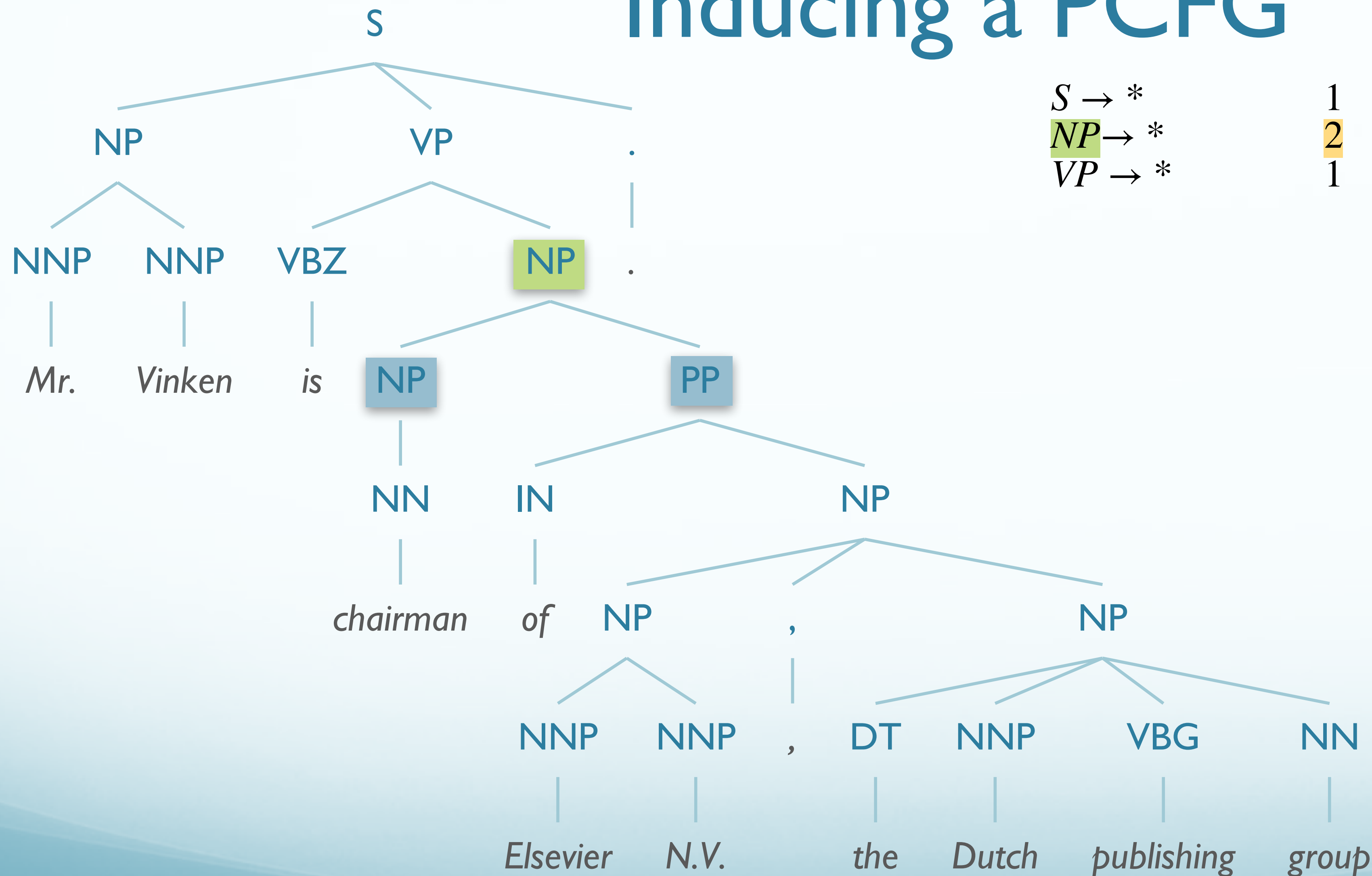
Inducing a PCFG



$S \rightarrow *$
 $NP \rightarrow *$
 $VP \rightarrow *$

1	$S \rightarrow NP VP .$	1
1	$NP \rightarrow NNP NNP$	1
1	$VP \rightarrow VBZ NP$	1

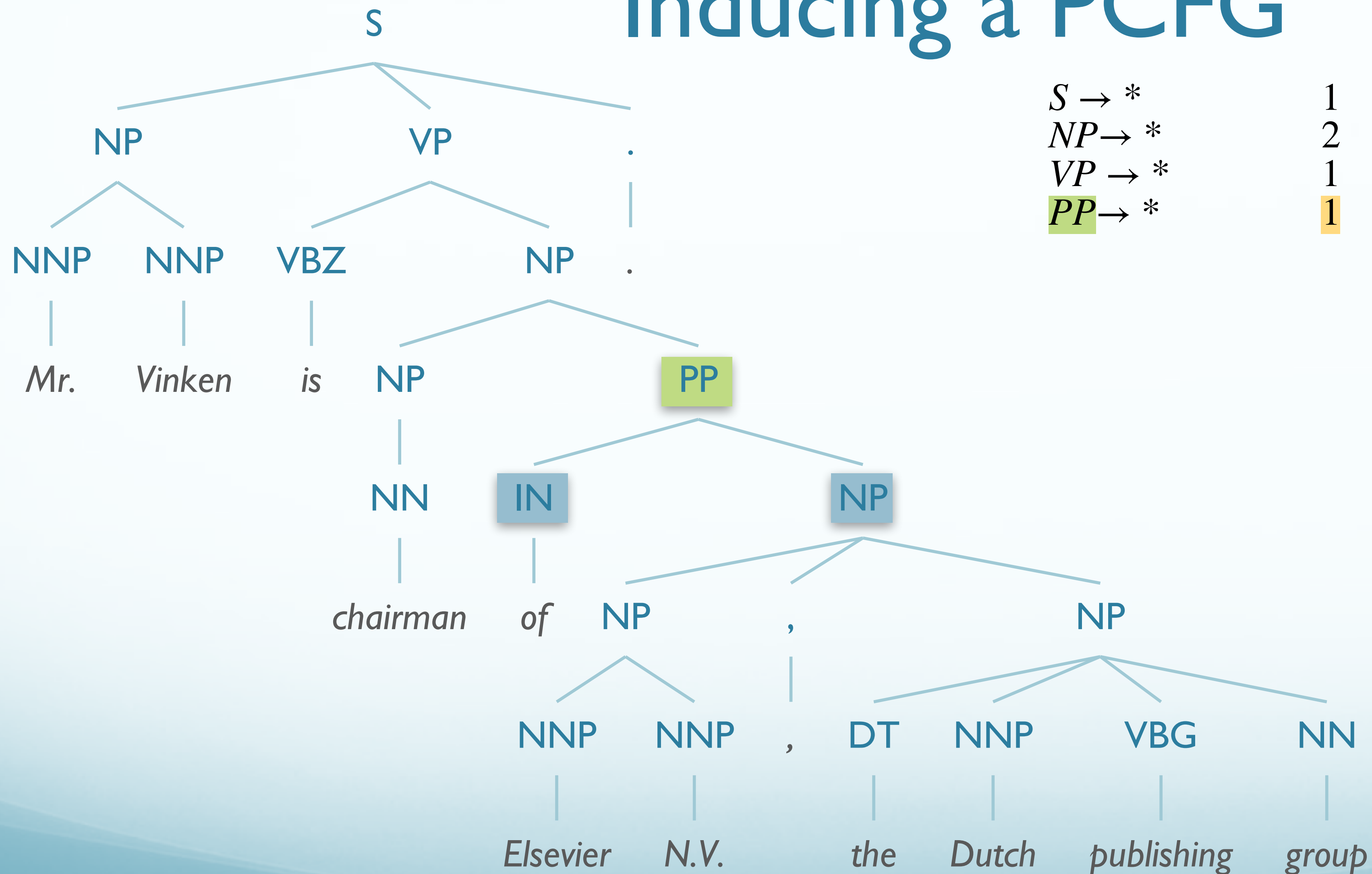
Inducing a PCFG



$S \rightarrow *$
 $\text{NP} \rightarrow *$
 $\text{VP} \rightarrow *$

1	$S \rightarrow \text{NP VP} .$	1
2	$\text{NP} \rightarrow \text{NNP NNP}$	1
1	$\text{VP} \rightarrow \text{VBZ NP}$	1
	$\text{NP} \rightarrow \text{NP PP}$	1

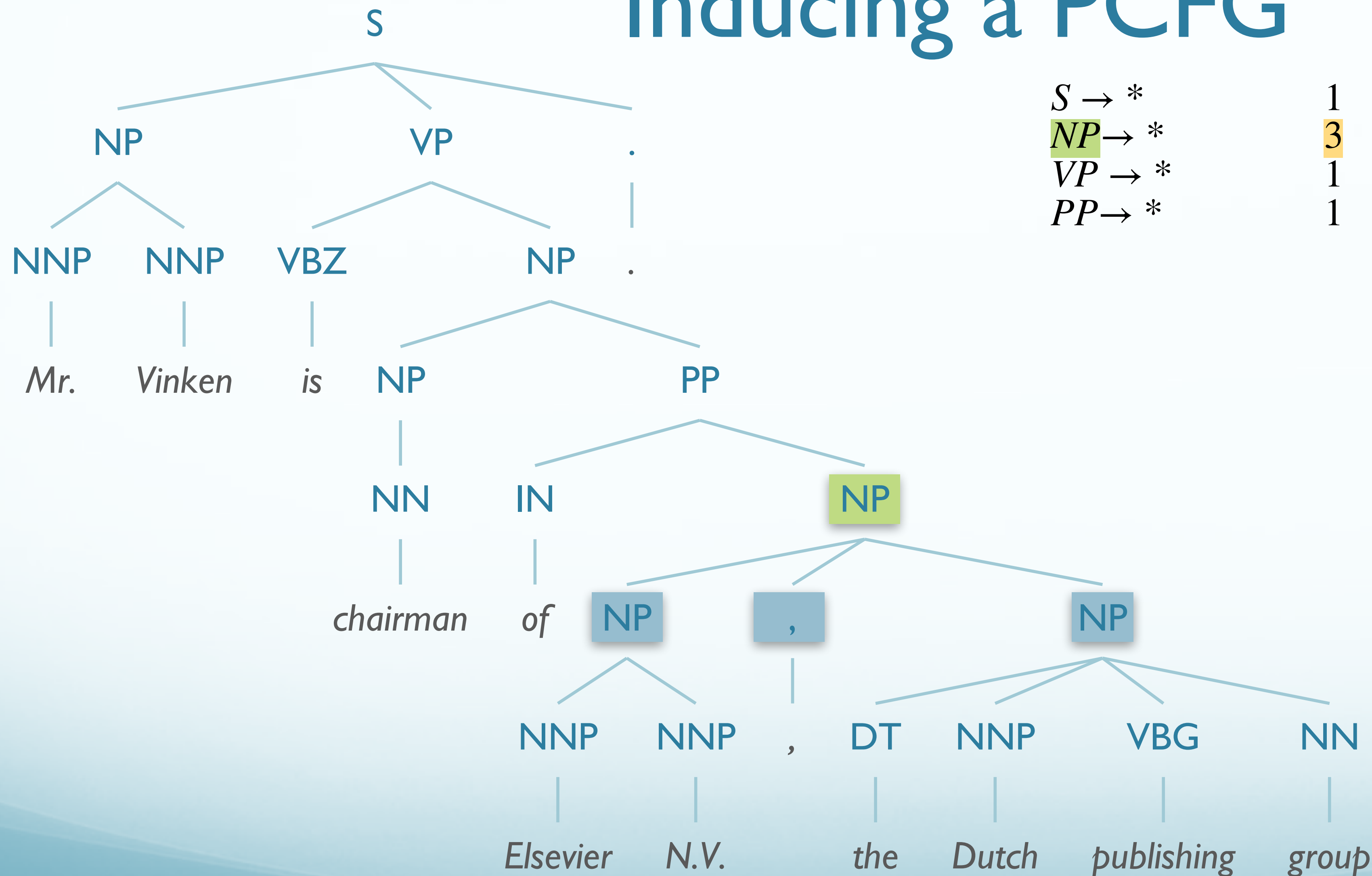
Inducing a PCFG



$S \rightarrow *$
 $NP \rightarrow *$
 $VP \rightarrow *$
 $PP \rightarrow *$

1	$S \rightarrow NP VP .$	1
2	$NP \rightarrow NNP NNP$	1
1	$VP \rightarrow VBZ NP$	1
1	$NP \rightarrow NP PP$	1
1	$PP \rightarrow IN NP$	1

Inducing a PCFG



$S \rightarrow *$

$NP \rightarrow *$

$VP \rightarrow *$

$PP \rightarrow *$

1 $S \rightarrow NP VP .$

3 $NP \rightarrow NNP NNP$

1 $VP \rightarrow VBZ NP$

1 $NP \rightarrow NP PP$

$PP \rightarrow IN NP$

$NP \rightarrow NP , NP$

1

1

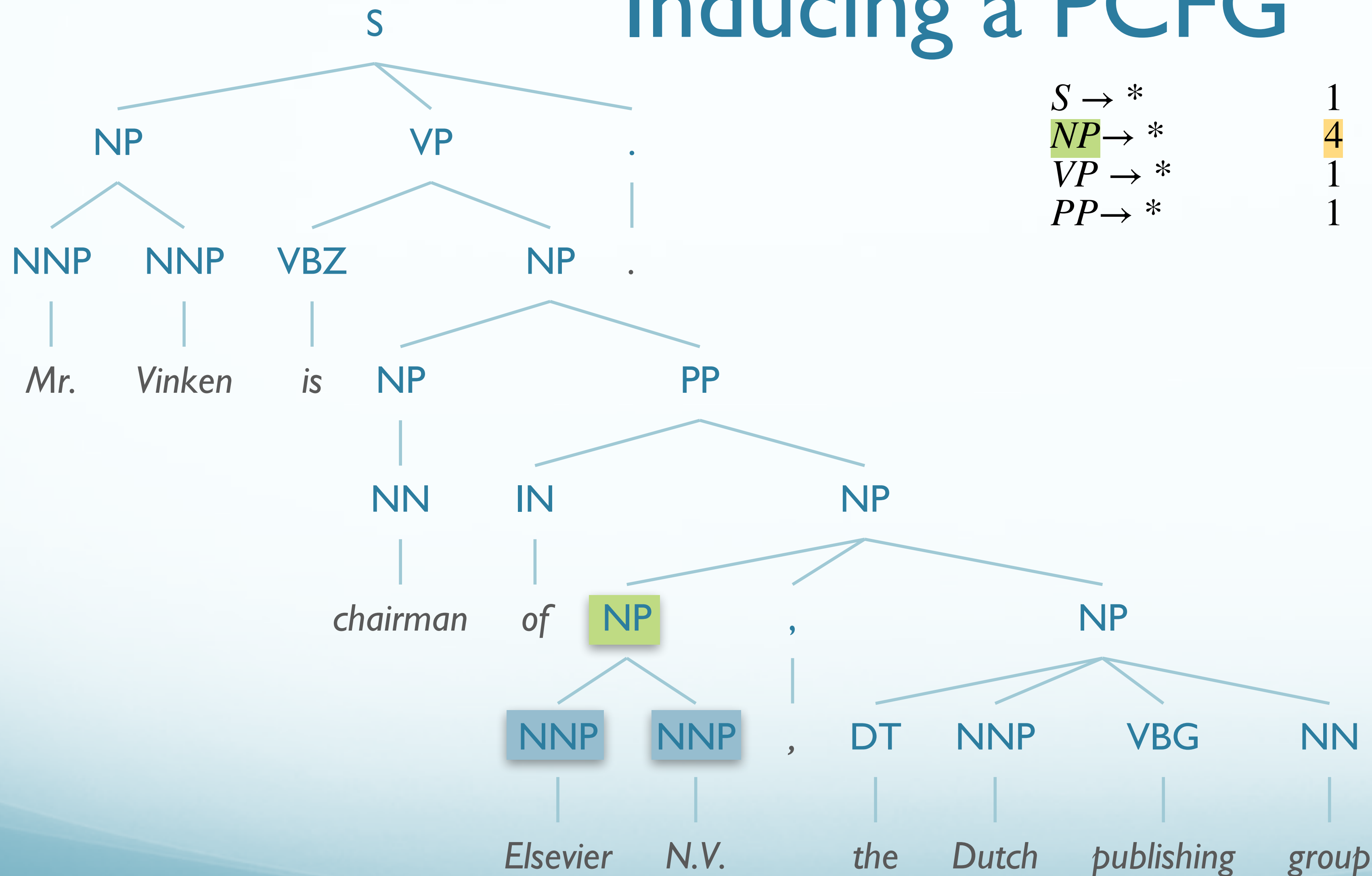
1

1

1

1

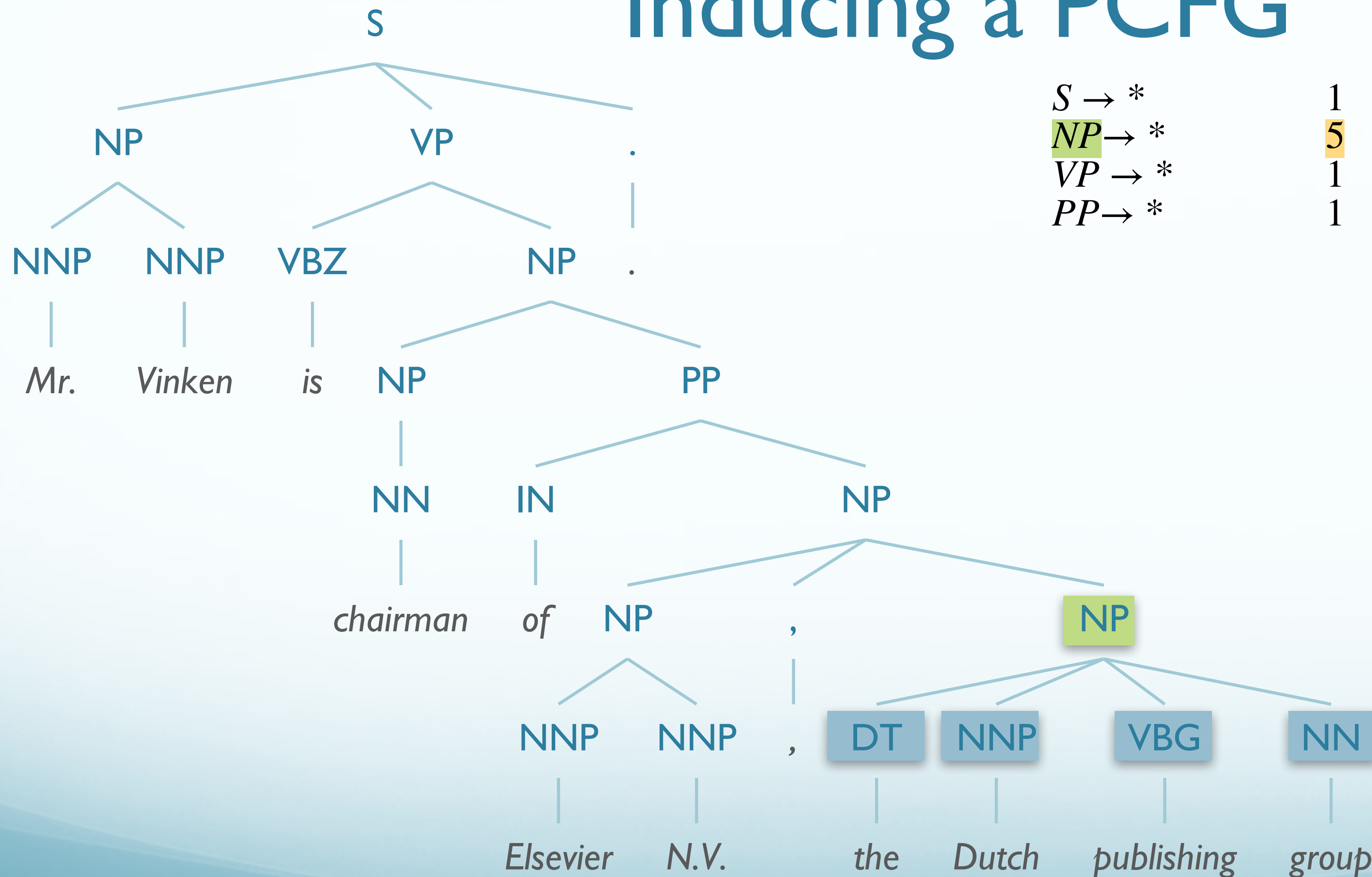
Inducing a PCFG



$S \rightarrow *$
 $NP \rightarrow *$
 $VP \rightarrow *$
 $PP \rightarrow *$

1	$S \rightarrow NP VP .$	1
4	$NP \rightarrow NNP NNP$	2
1	$VP \rightarrow VBZ NP$	1
1	$NP \rightarrow NP PP$	1
	$PP \rightarrow IN NP$	1
	$NP \rightarrow NP , NP$	1

Inducing a PCFG



$S \rightarrow *$

$NP \rightarrow *$

$VP \rightarrow *$

$PP \rightarrow *$

1 $S \rightarrow NP VP .$ 1

5 $NP \rightarrow NNP NNP$ 2

1 $VP \rightarrow VBZ NP$ 1

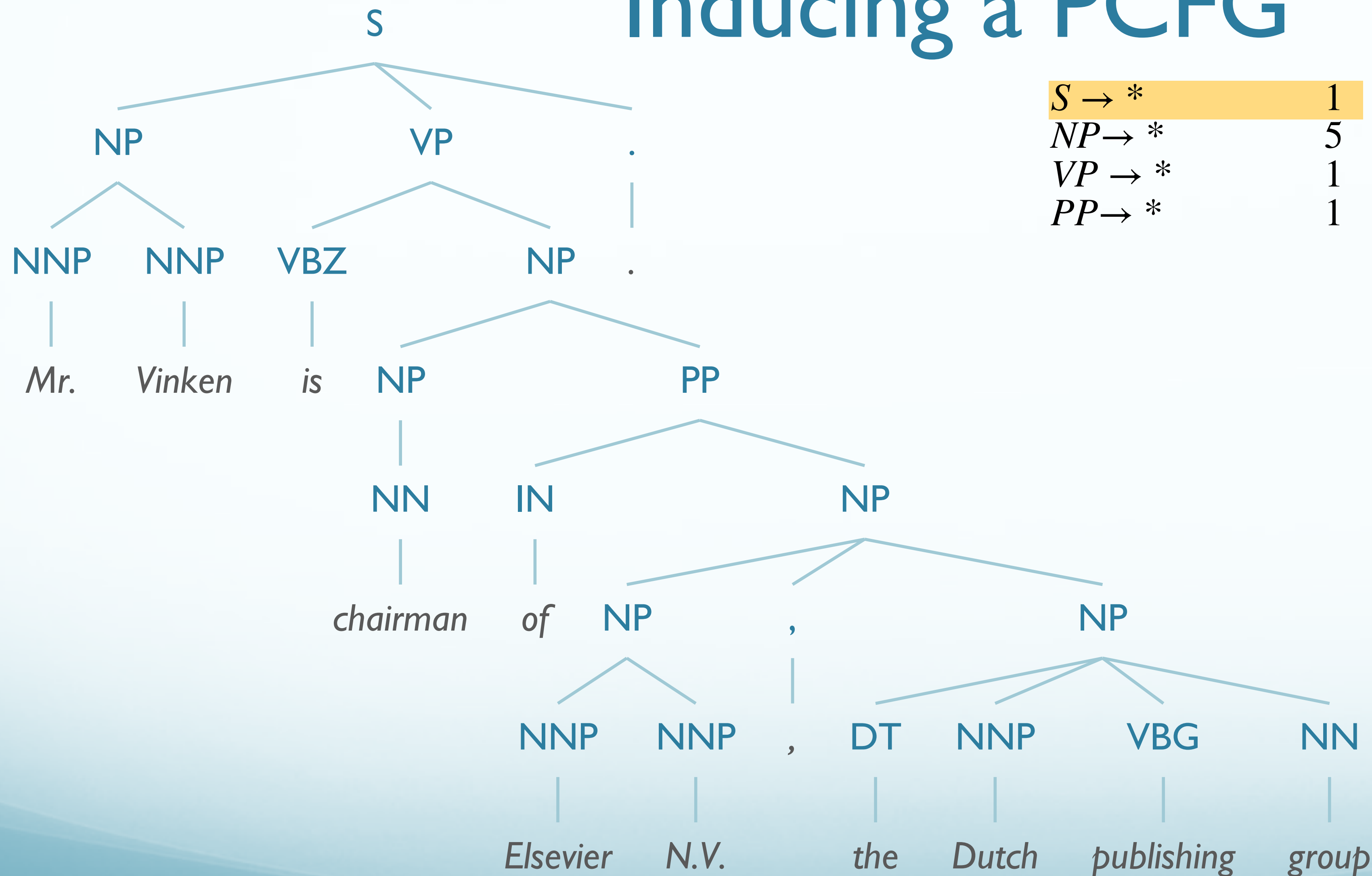
1 $NP \rightarrow NP PP$ 1

$PP \rightarrow IN NP$ 1

$NP \rightarrow NP , NP$ 1

$NP \rightarrow DT NNP VBG NN$ 1

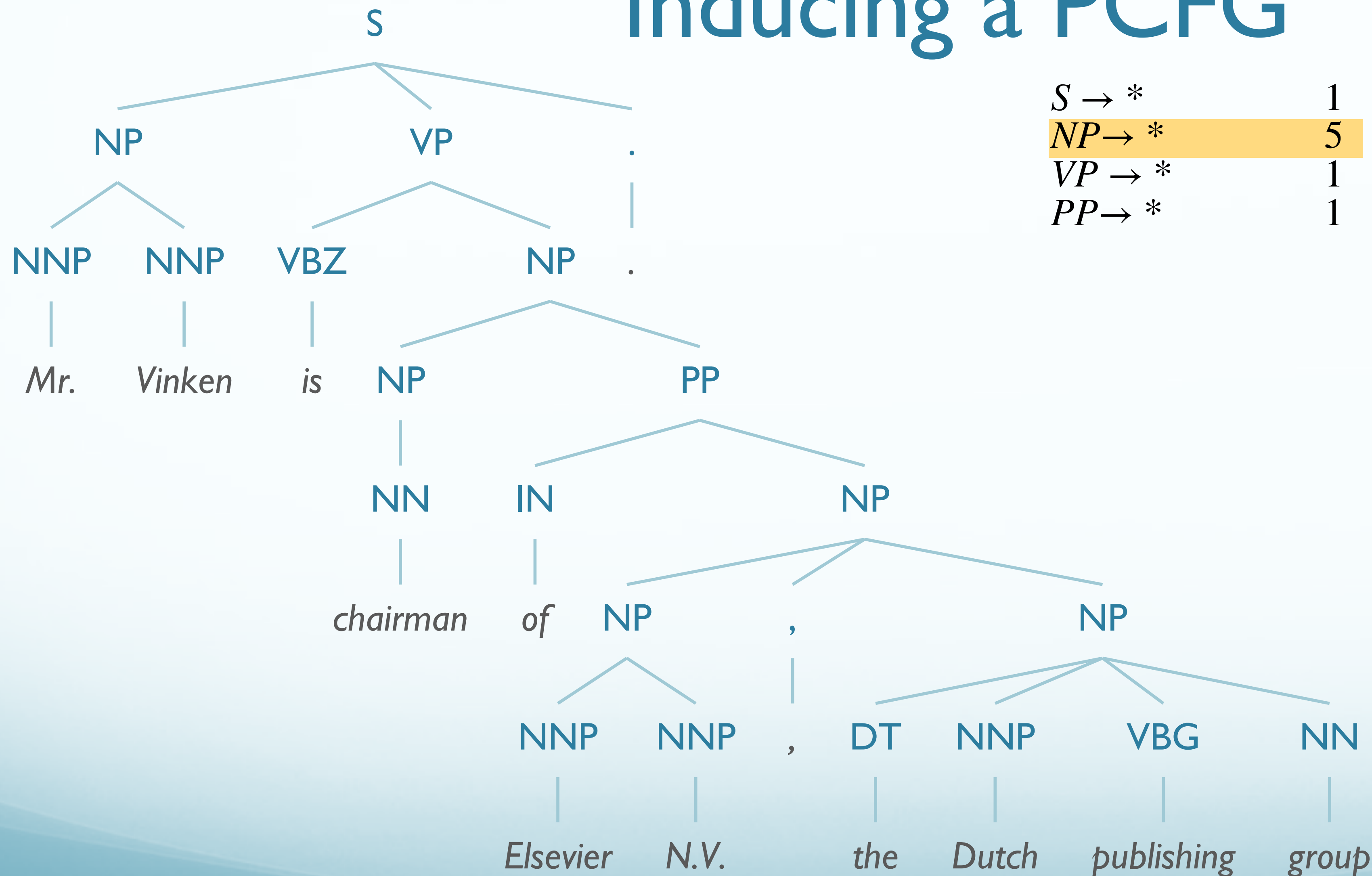
Inducing a PCFG



$S \rightarrow *$ 1
 $NP \rightarrow *$ 5
 $VP \rightarrow *$ 1
 $PP \rightarrow *$ 1

$S \rightarrow NP VP .$ 1
 $NP \rightarrow NNP NNP$ 2
 $VP \rightarrow VBZ NP$ 1
 $NP \rightarrow NP PP$ 1
 $PP \rightarrow IN NP$ 1
 $NP \rightarrow NP , NP$ 1
 $NP \rightarrow DT NNP VBG NN$ 1

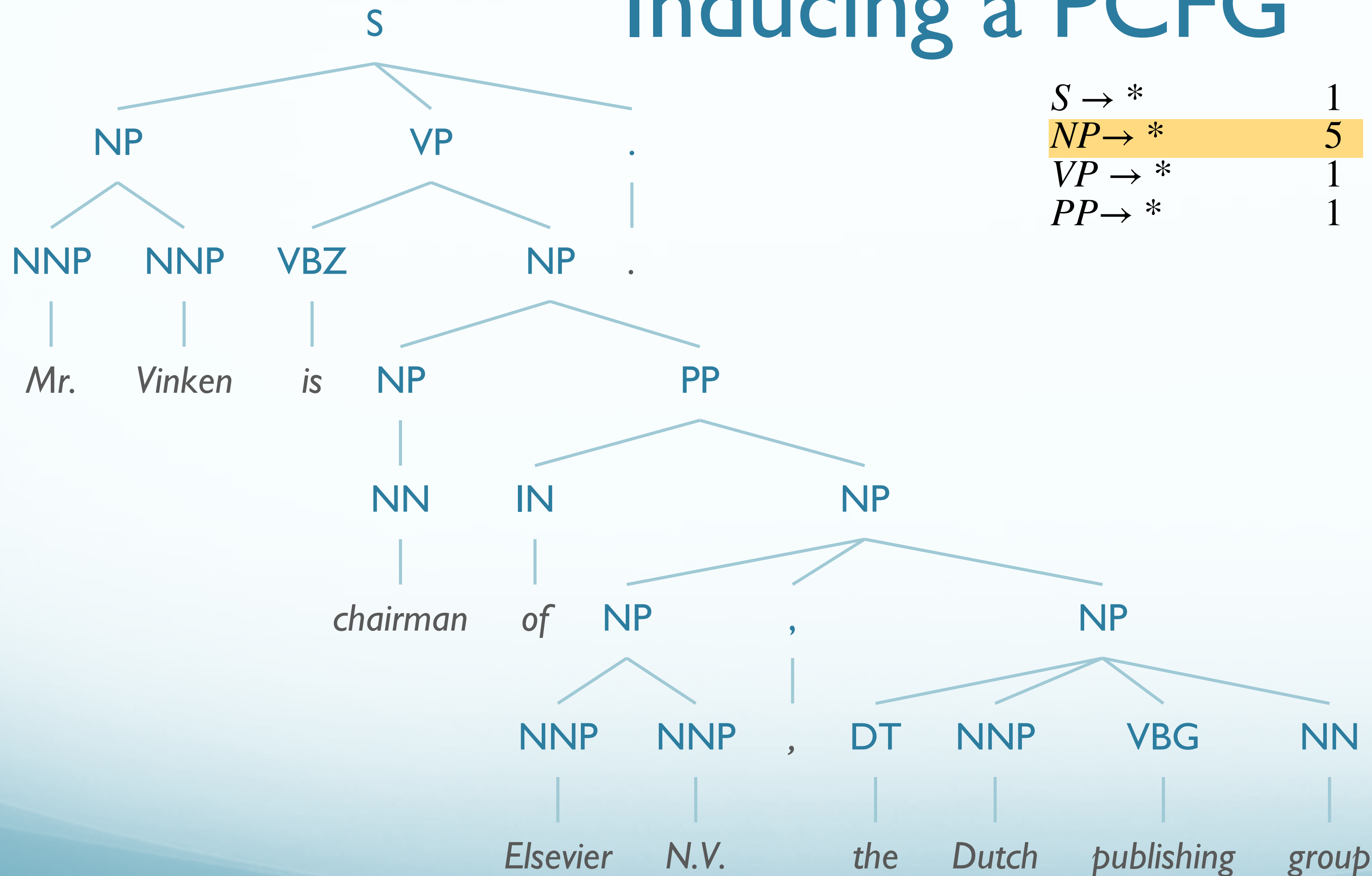
Inducing a PCFG



$S \rightarrow *$ 1
 $NP \rightarrow *$ 5
 $VP \rightarrow *$ 1
 $PP \rightarrow *$ 1

$S \rightarrow NP VP .$ 1
 $NP \rightarrow NNP NNP$ 2/5
 $VP \rightarrow VBZ NP$ 1
 $NP \rightarrow NP PP$ 1/5
 $PP \rightarrow IN NP$ 1
 $NP \rightarrow NP , NP$ 1/5
 $NP \rightarrow DT NNP VBG NN$ 1/5

Inducing a PCFG



$S \rightarrow *$	1	$S \rightarrow NP VP .$	1
$NP \rightarrow *$	5	$NP \rightarrow NNP NNP$	0.4
$VP \rightarrow *$	1	$VP \rightarrow VBZ NP$	1
$PP \rightarrow *$	1	$NP \rightarrow NP PP$	0.2
		$PP \rightarrow IN NP$	1
		$NP \rightarrow NP , NP$	0.2
		$NP \rightarrow DT NNP VBG NN$	0.2

Problems with PCFGs

Problems with PCFGs

- Independence Assumption
 - Assume that rule probabilities are independent
- Lack of Lexical Conditioning
 - Lexical items should influence the choice of analysis

Issues with PCFGs: Independence Assumption

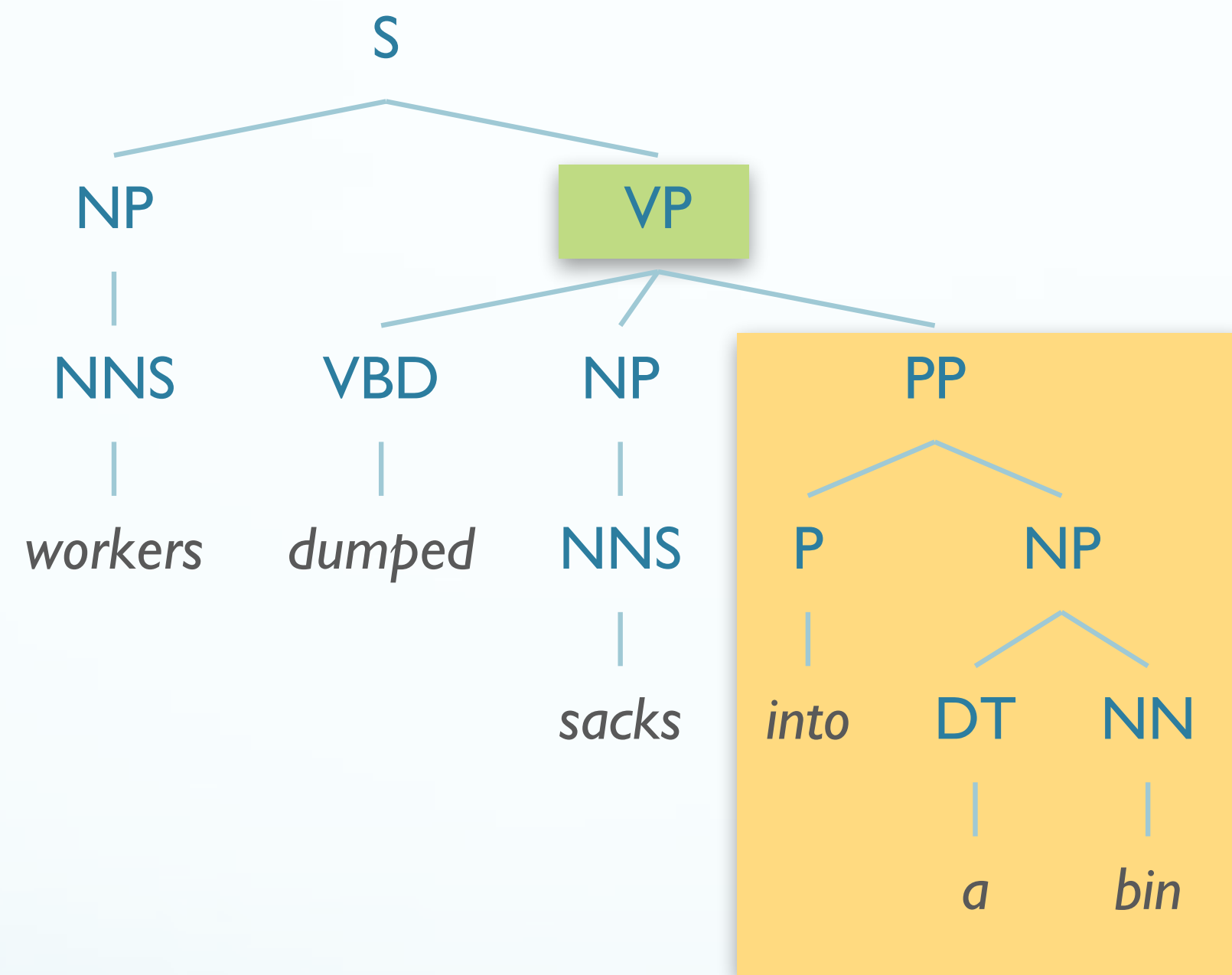
- *Context Free* \Rightarrow *Independence Assumption*
 - Rule expansion is context-independent
 - Allows us to multiply probabilities
- If we have two rules:
 - $NP \rightarrow DT\ NN$ [0.28]
 - $NP \rightarrow PRP$ [0.25]
- What does this new data tell us?
 - $NP \rightarrow DT\ NN$ [0.09 if $NP_{\Theta=subject}$ else 0.66]
 - $NP \rightarrow PRP$ [0.91 if $NP_{\Theta=subject}$ else 0.34]

Semantic Role of **NPs** in Switchboard Corpus

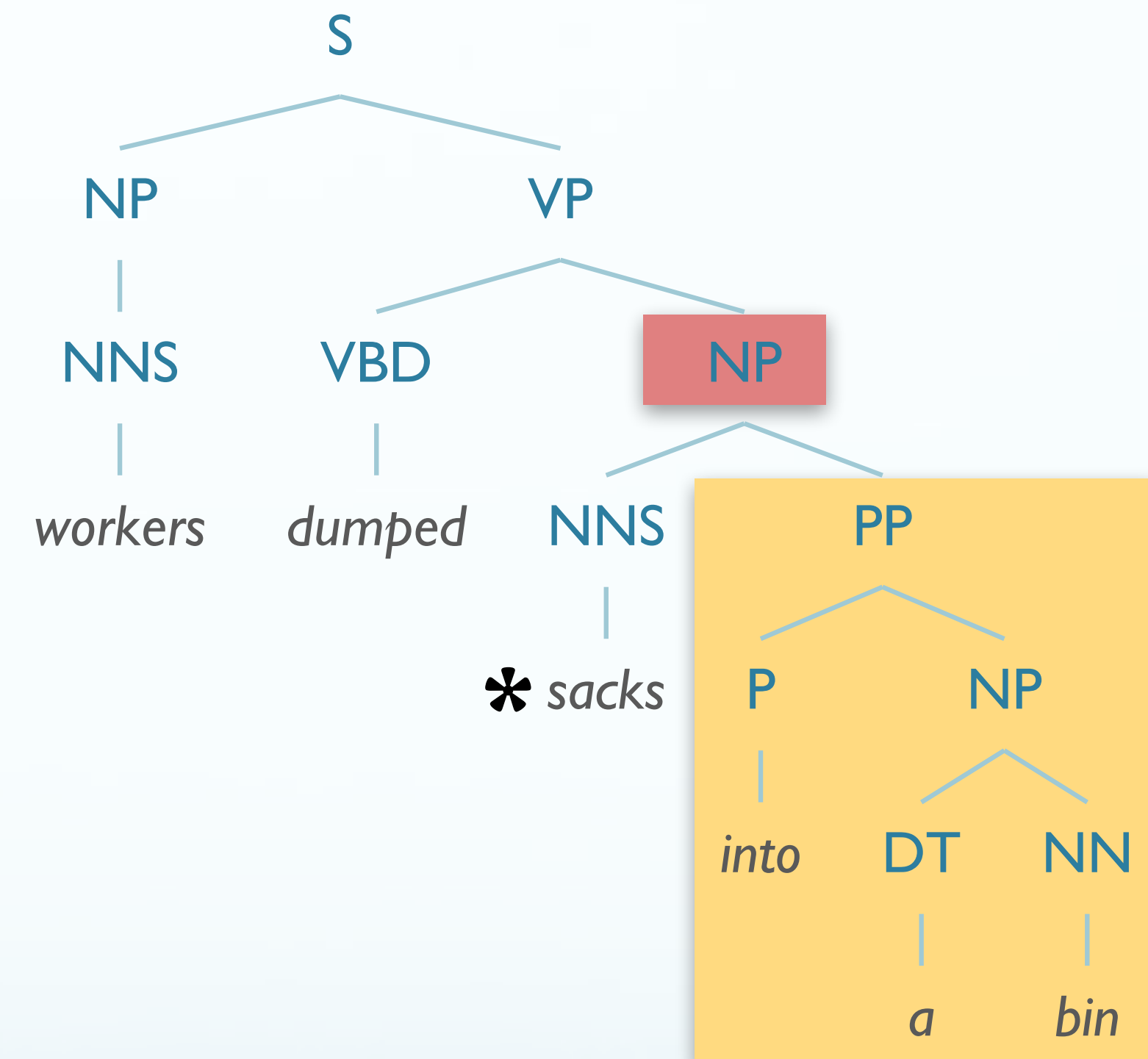
	Pronominal	Non-Pronominal
Subject	91%	9%
Object	34%	66%

...Can try **parent annotation**

Issues with PCFGs: Lexical Conditioning

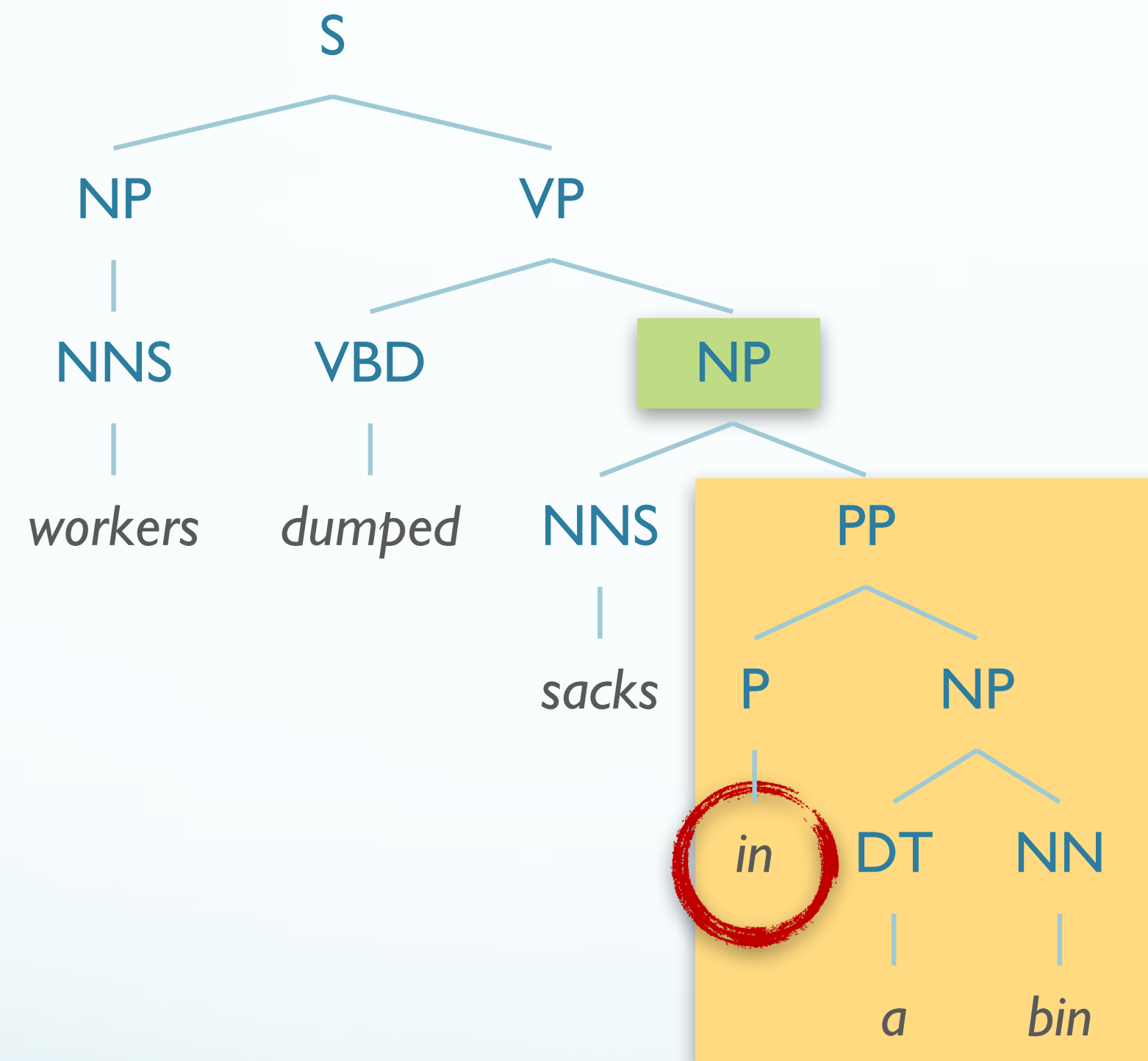


("into a bin" = location of sacks after dumping)
OK!

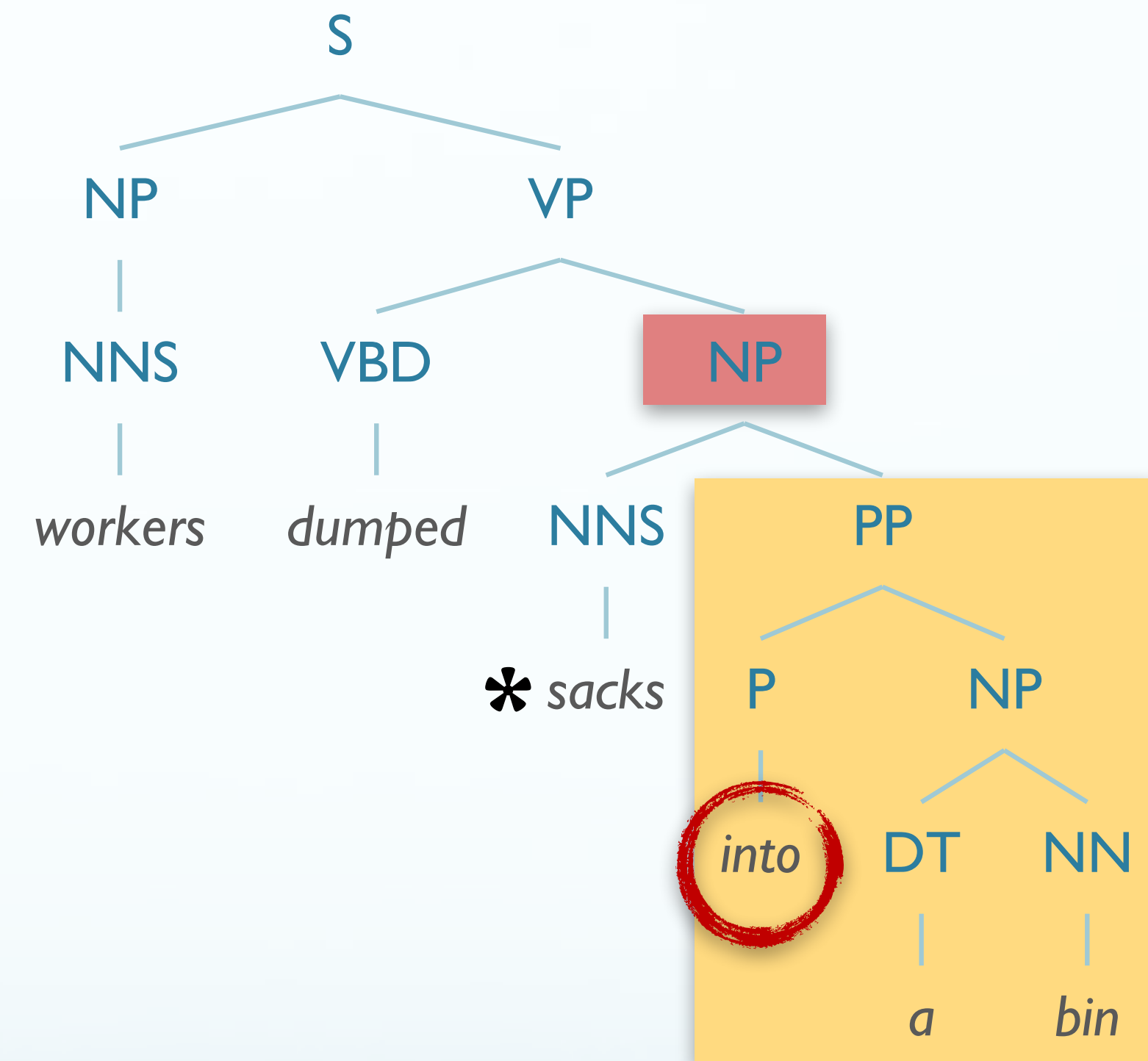


("into a bin" = *the sacks which were located **in PP**)
not OK

Issues with PCFGs: Lexical Conditioning



(“**in** a bin” = location of sacks **before** dumping)
OK!

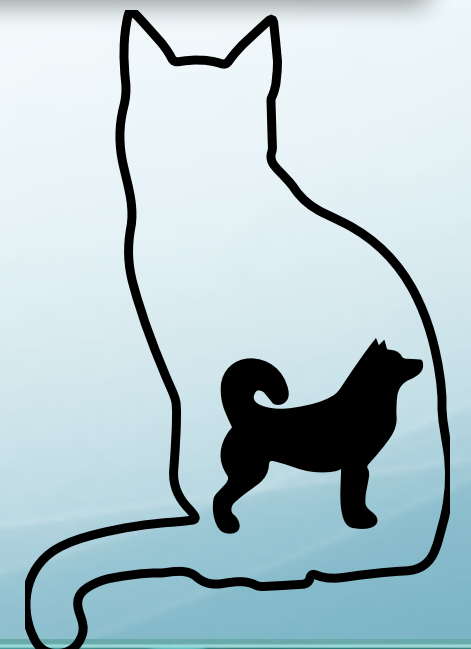
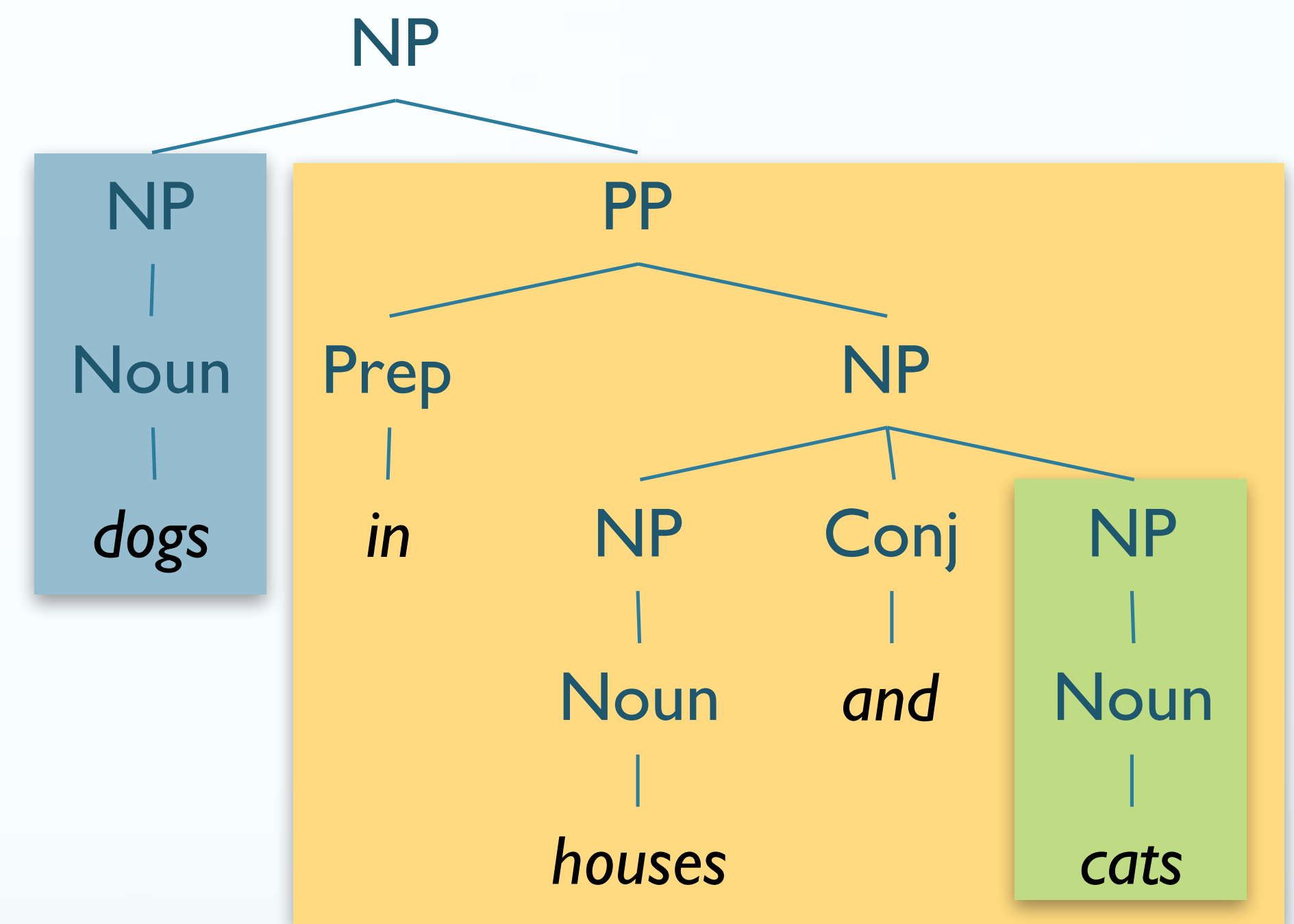
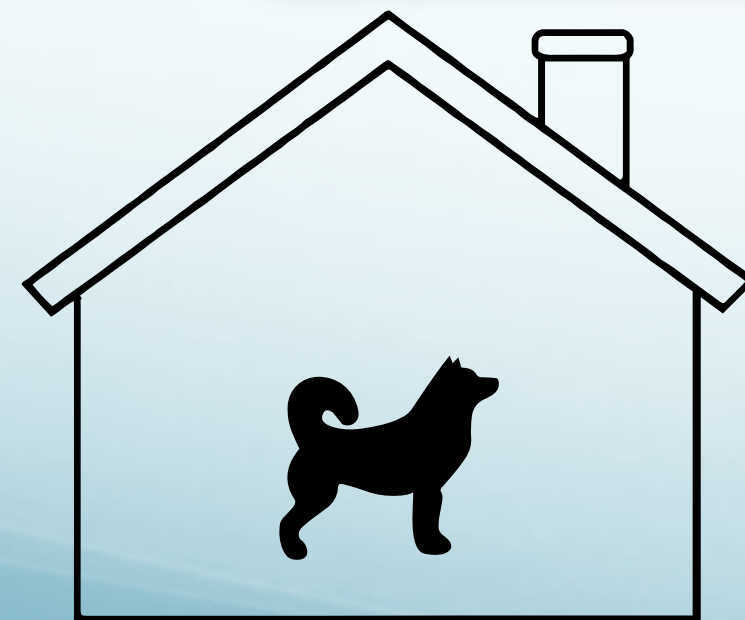
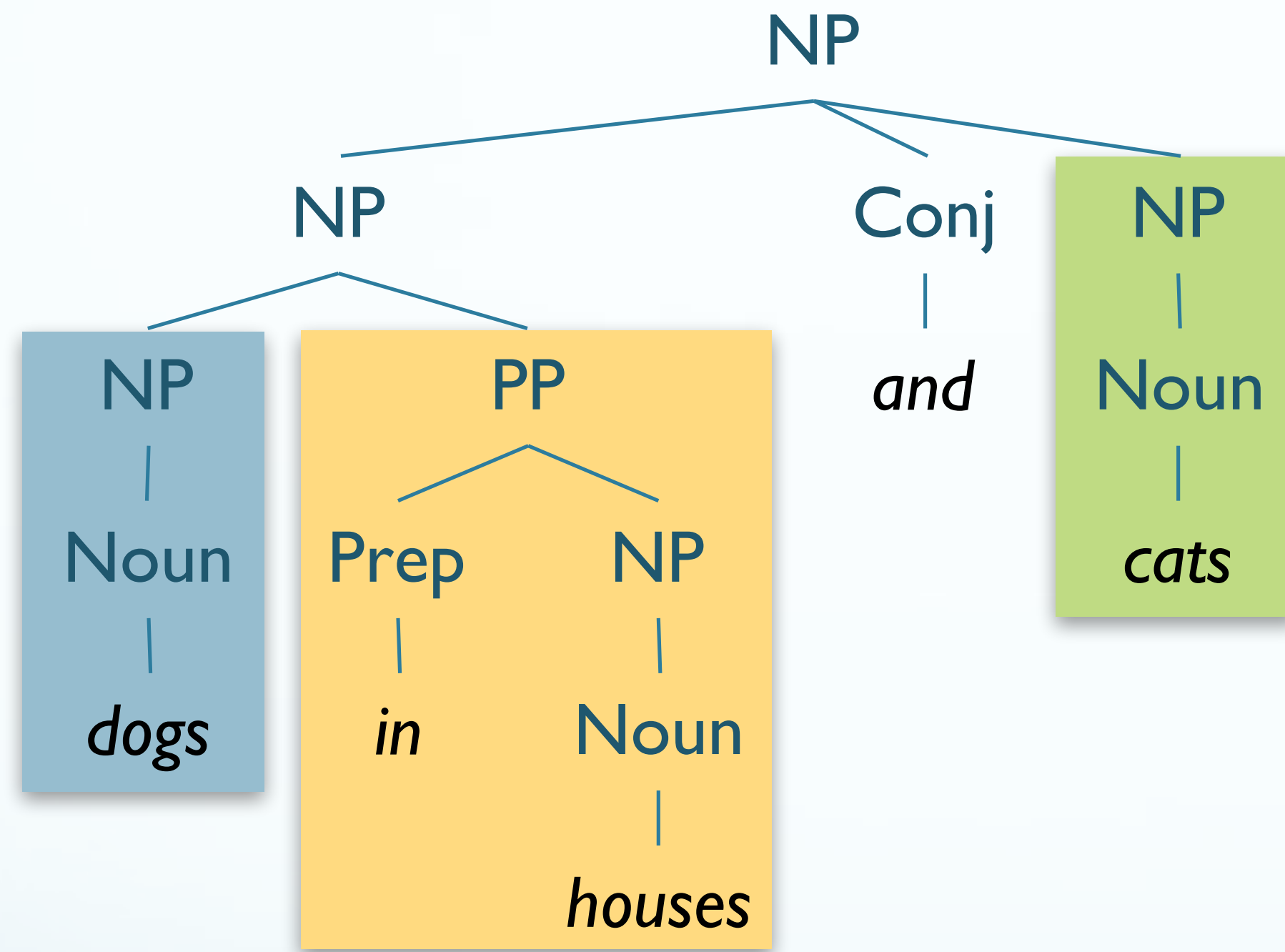


(“**into** a bin” = *the sacks which were located **in PP**)
not OK

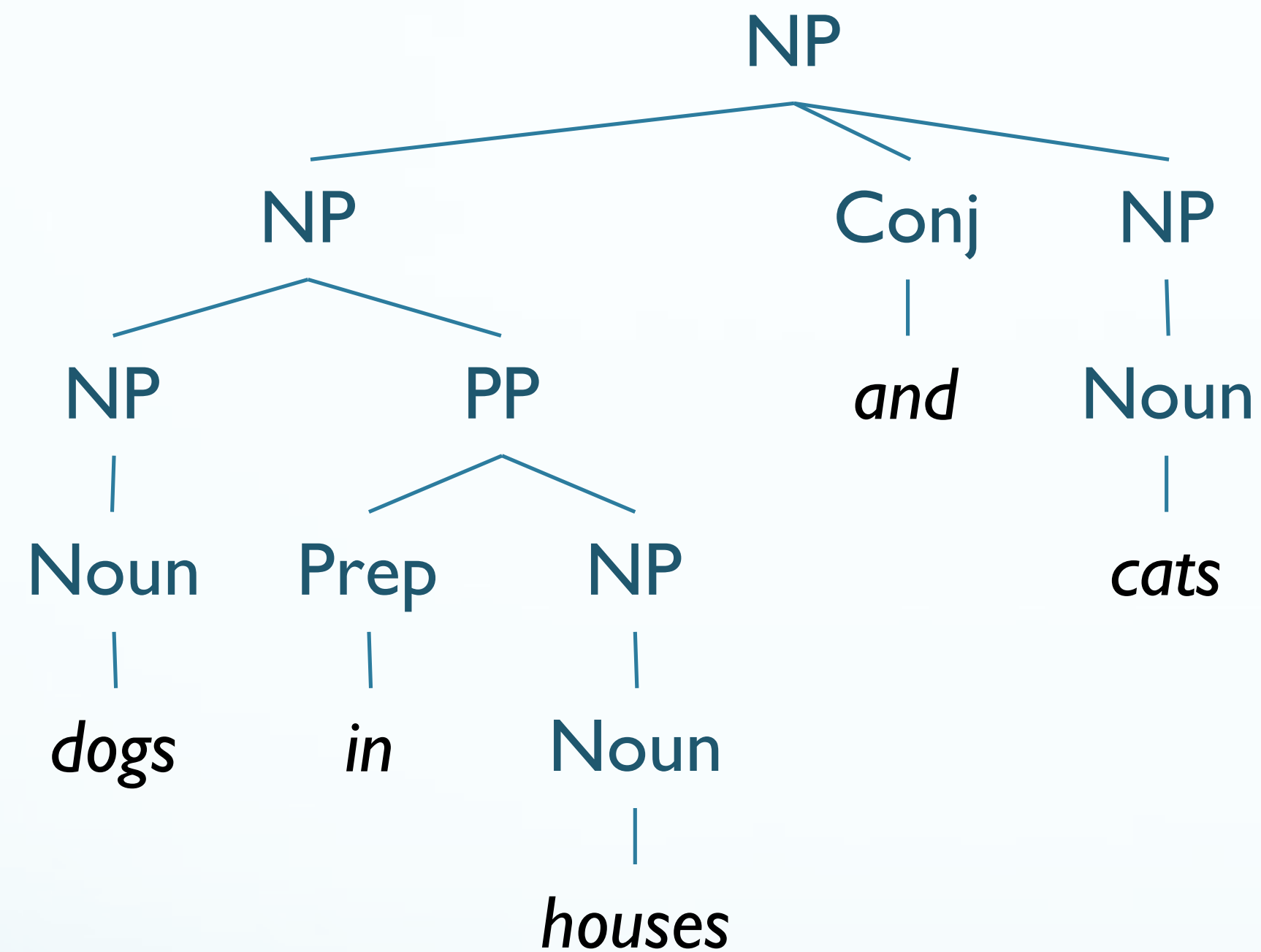
Issues with PCFGs: Lexical Conditioning

- *workers dumped sacks into a bin*
 - **into** should **prefer** modifying **dumped**
 - **into** should **disprefer** modifying **sacks**
- *fishermen caught tons of herring*
 - **of** should **prefer** modifying **tons**
 - **of** should **disprefer** modifying **caught**

Issues with PCFGs: Coordination Ambiguity

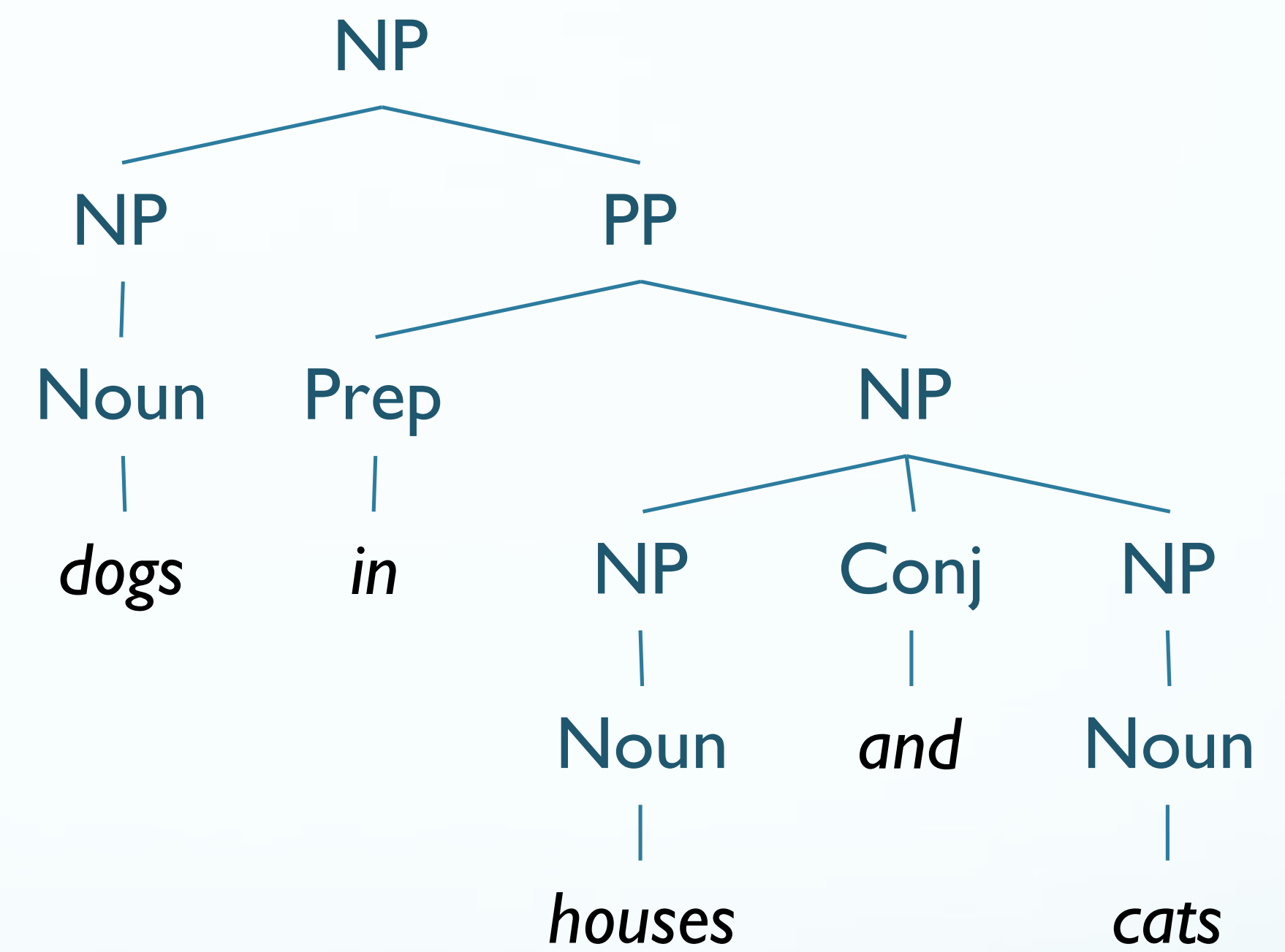


Issues with PCFGs: Coordination Ambiguity



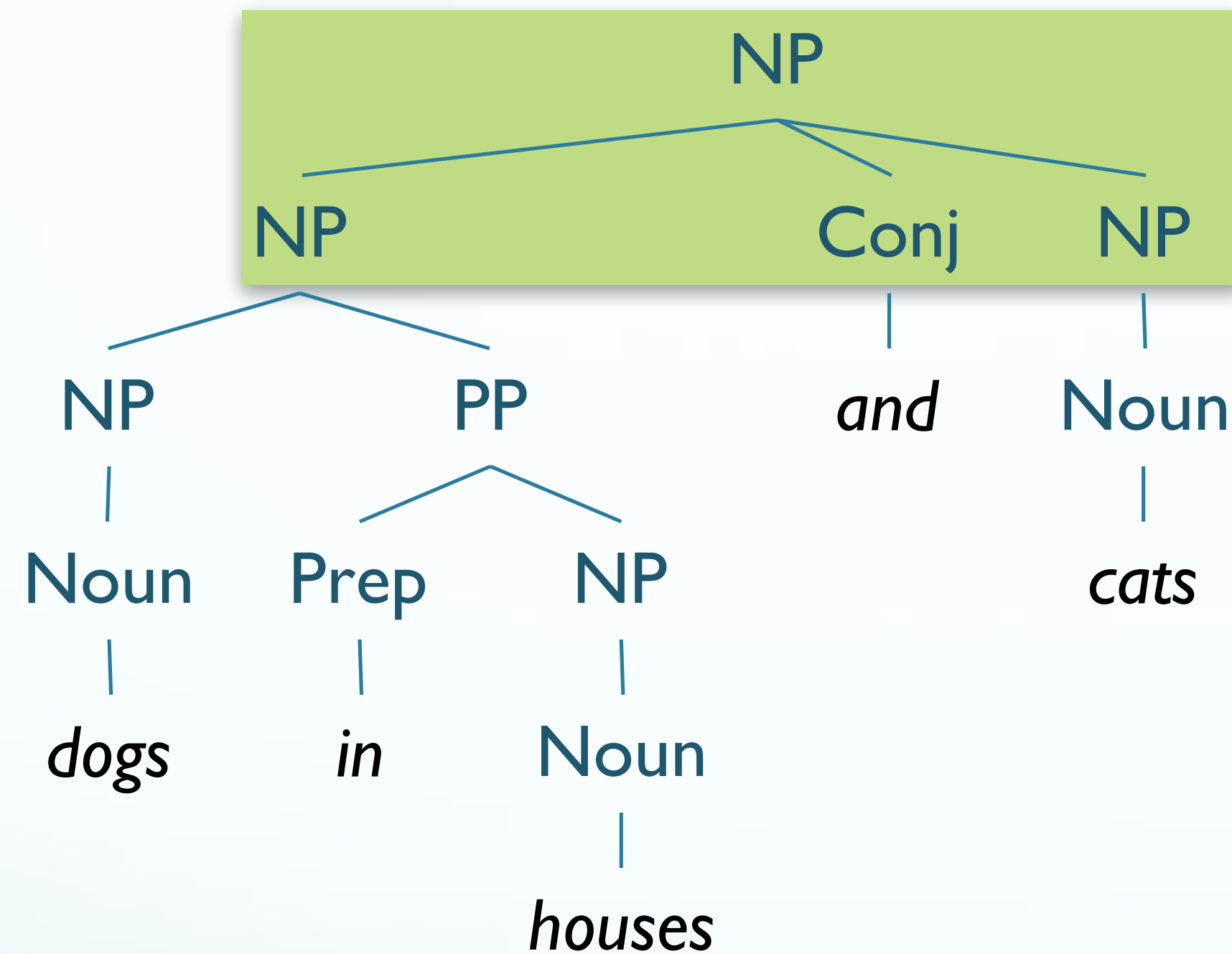
$NP \rightarrow NP \text{ Conj } NP$
 $NP \rightarrow NP \text{ PP}$
 $Noun \rightarrow \text{"dogs"}$
 $PP \rightarrow \text{Prep } NP$
 $\text{Prep} \rightarrow \text{"in"}$
 $NP \rightarrow Noun$
 $Noun \rightarrow \text{"houses"}$
 $\text{Conj} \rightarrow \text{"and"}$
 $NP \rightarrow Noun$
 $Noun \rightarrow \text{"cats"}$

Same Rules!



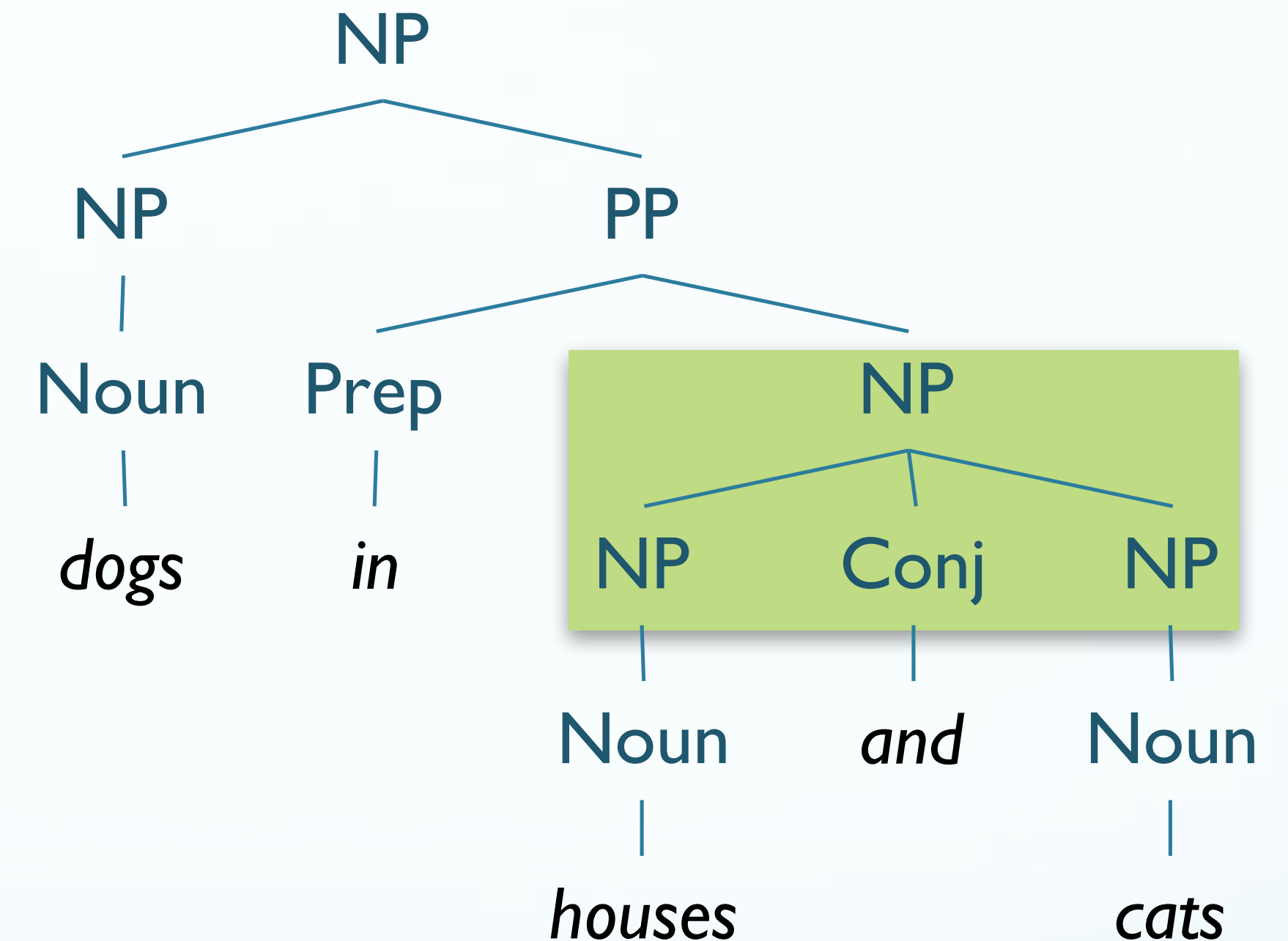
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 $Noun \rightarrow \text{"dogs"}$
 $PP \rightarrow \text{Prep } NP$
 $\text{Prep} \rightarrow \text{"in"}$
 $NP \rightarrow NP \text{ Conj } NP$
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Issues with PCFGs: Coordination Ambiguity



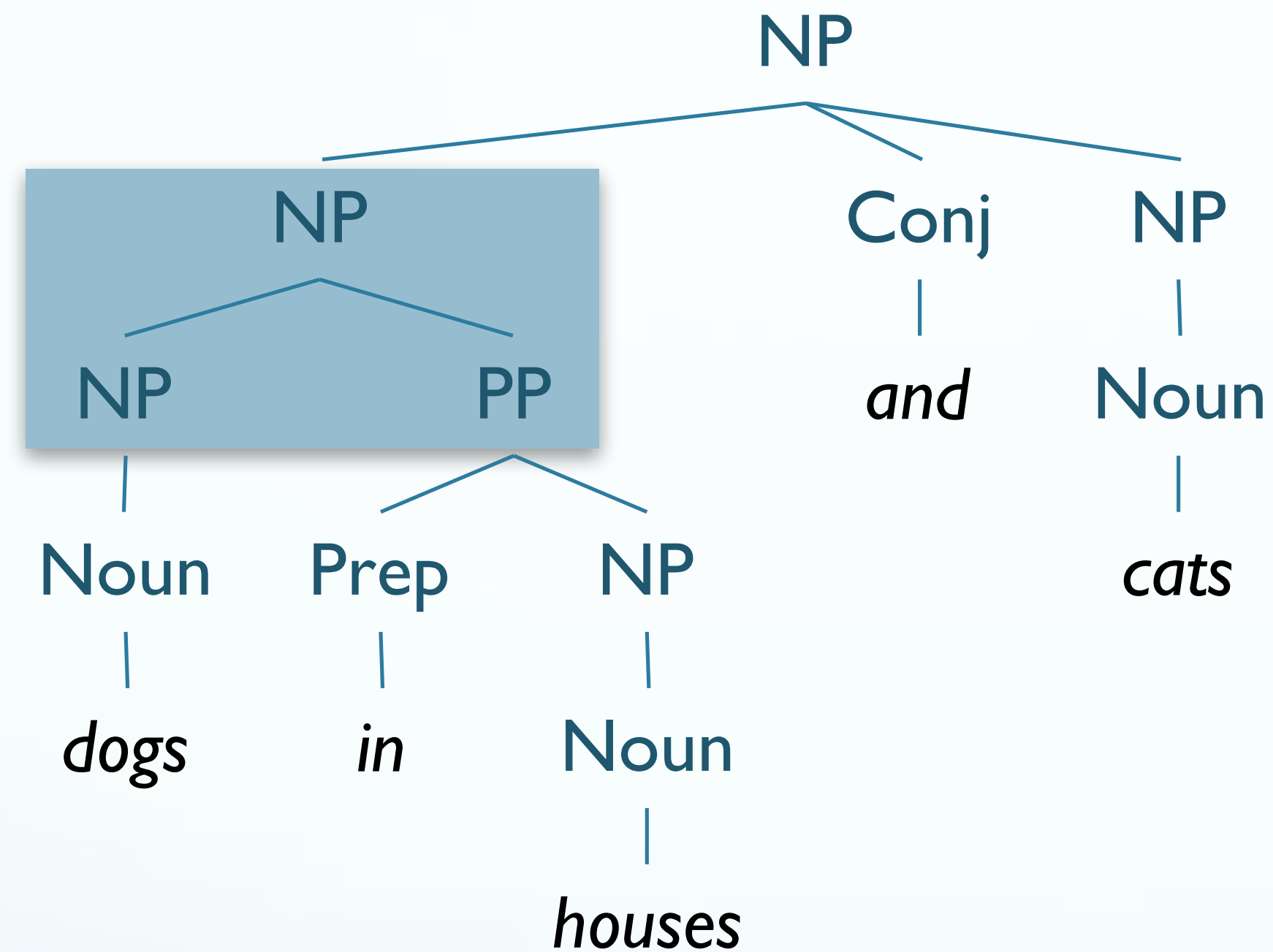
$NP \rightarrow NP \text{ Conj } NP$
 $NP \rightarrow NP \text{ PP}$
 $Noun \rightarrow \text{"dogs"}$
 $PP \rightarrow Prep \text{ NP}$
 $Prep \rightarrow \text{"in"}$
 $NP \rightarrow Noun$
 $Noun \rightarrow \text{"houses"}$
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 $NP \rightarrow Noun$
 $Noun \rightarrow \text{"cats"}$

Same Rules!



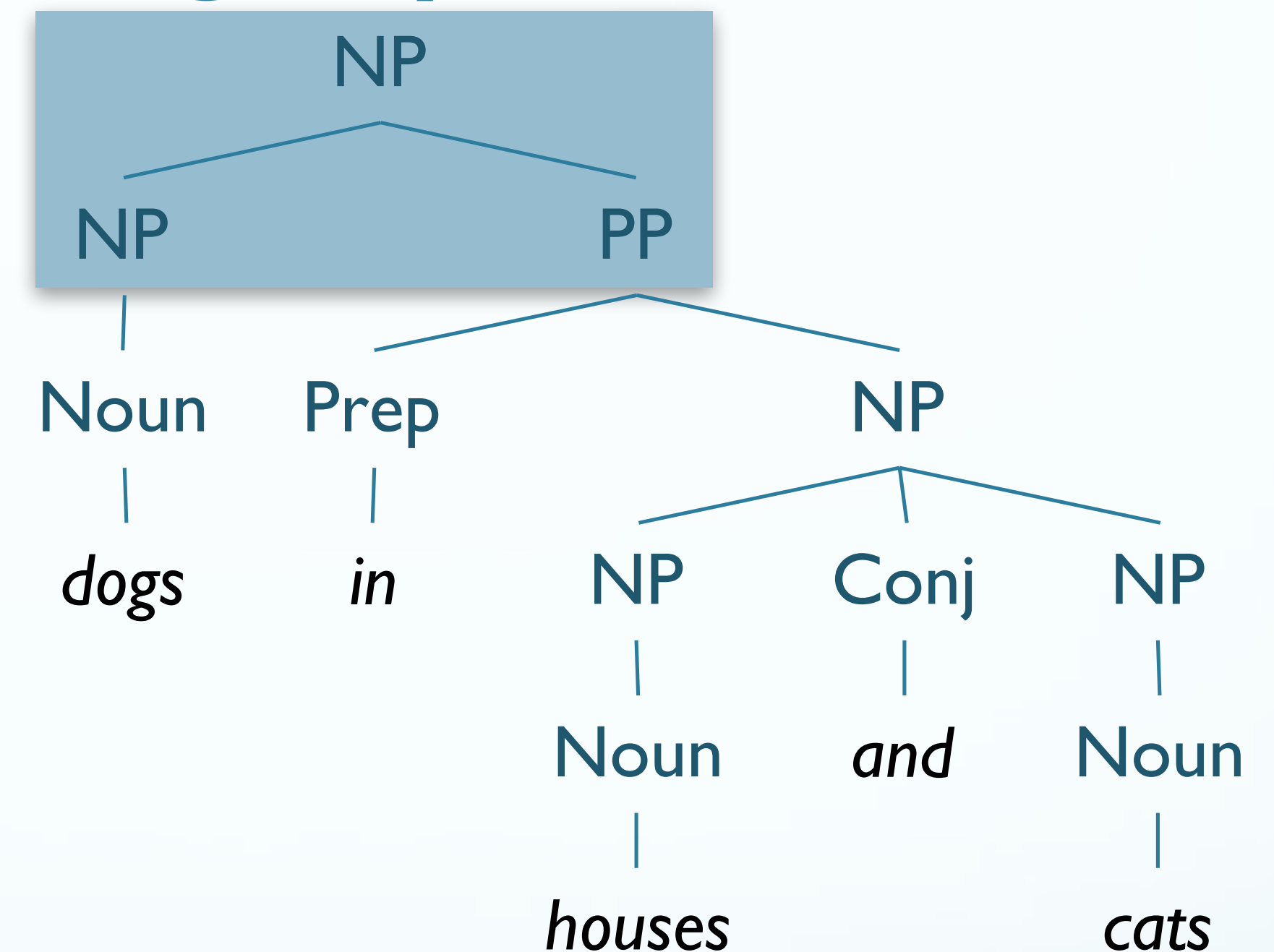
$NP \rightarrow NP \text{ PP}$
 $Noun \rightarrow \text{"dogs"}$
 $PP \rightarrow Prep \text{ NP}$
 $Prep \rightarrow \text{"in"}$
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Issues with PCFGs: Coordination Ambiguity



$NP \rightarrow NP \text{ Conj } NP$
 $NP \rightarrow NP \text{ PP}$
 $Noun \rightarrow \text{"dogs"}$
 $PP \rightarrow Prep \text{ NP}$
 $Prep \rightarrow \text{"in"}$
 $NP \rightarrow Noun$
 $Noun \rightarrow \text{"houses"}$
 $Conj \rightarrow \text{"and"}$
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 $Noun \rightarrow \text{"cats"}$

Same Rules!



$NP \rightarrow NP \text{ PP}$
 $Noun \rightarrow \text{"dogs"}$
 $PP \rightarrow Prep \text{ NP}$
 $Prep \rightarrow \text{"in"}$
 $NP \rightarrow NP \text{ Conj } NP$
 $NP \rightarrow Noun$
 $Noun \rightarrow \text{"houses"}$
 $Conj \rightarrow \text{"and"}$
 $NP \rightarrow Noun$
 $Noun \rightarrow \text{"cats"}$

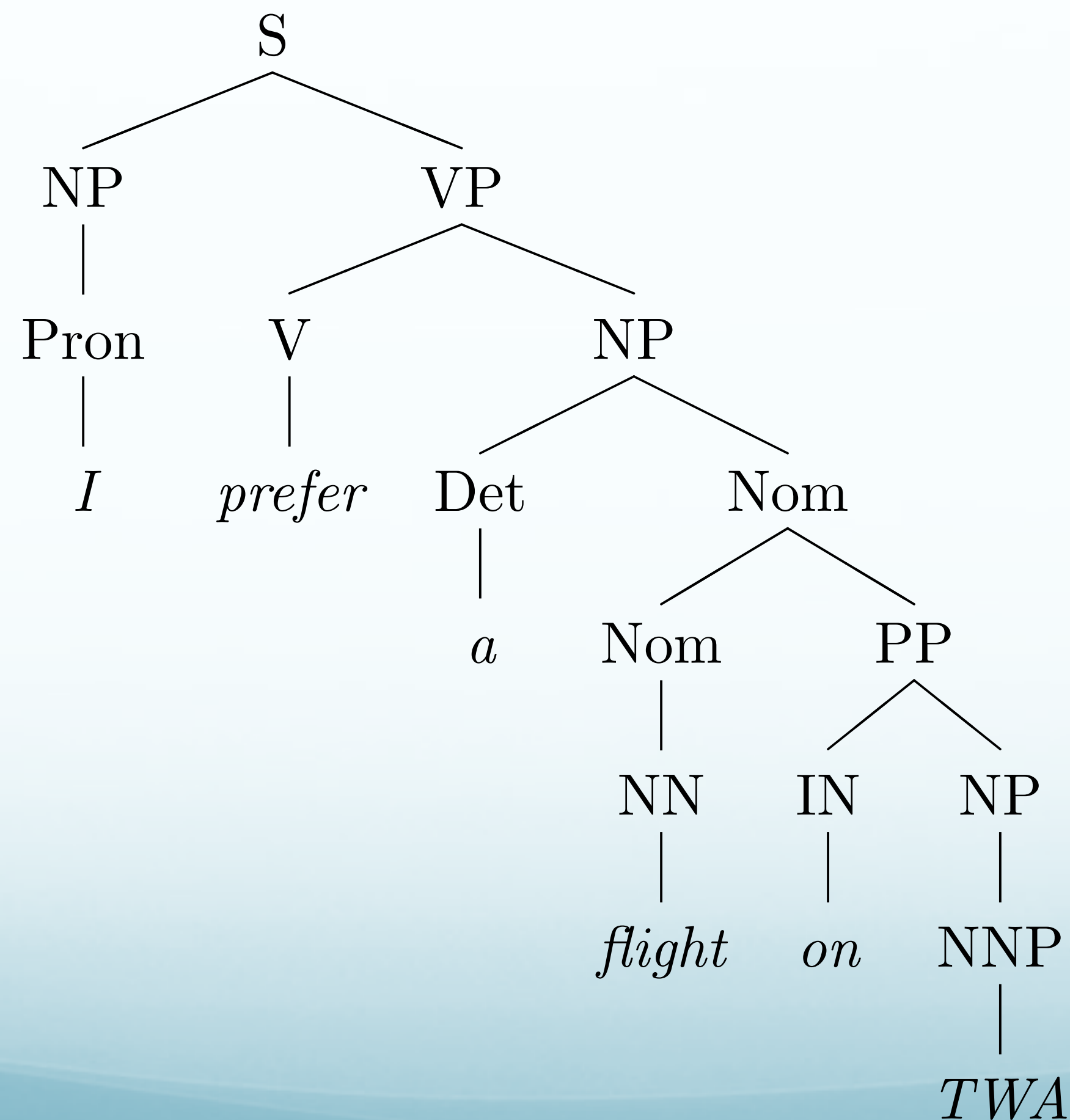
Improving PCFGs

Improving PCFGs

- **Parent Annotation**
- Lexicalization
- Markovization
- Reranking

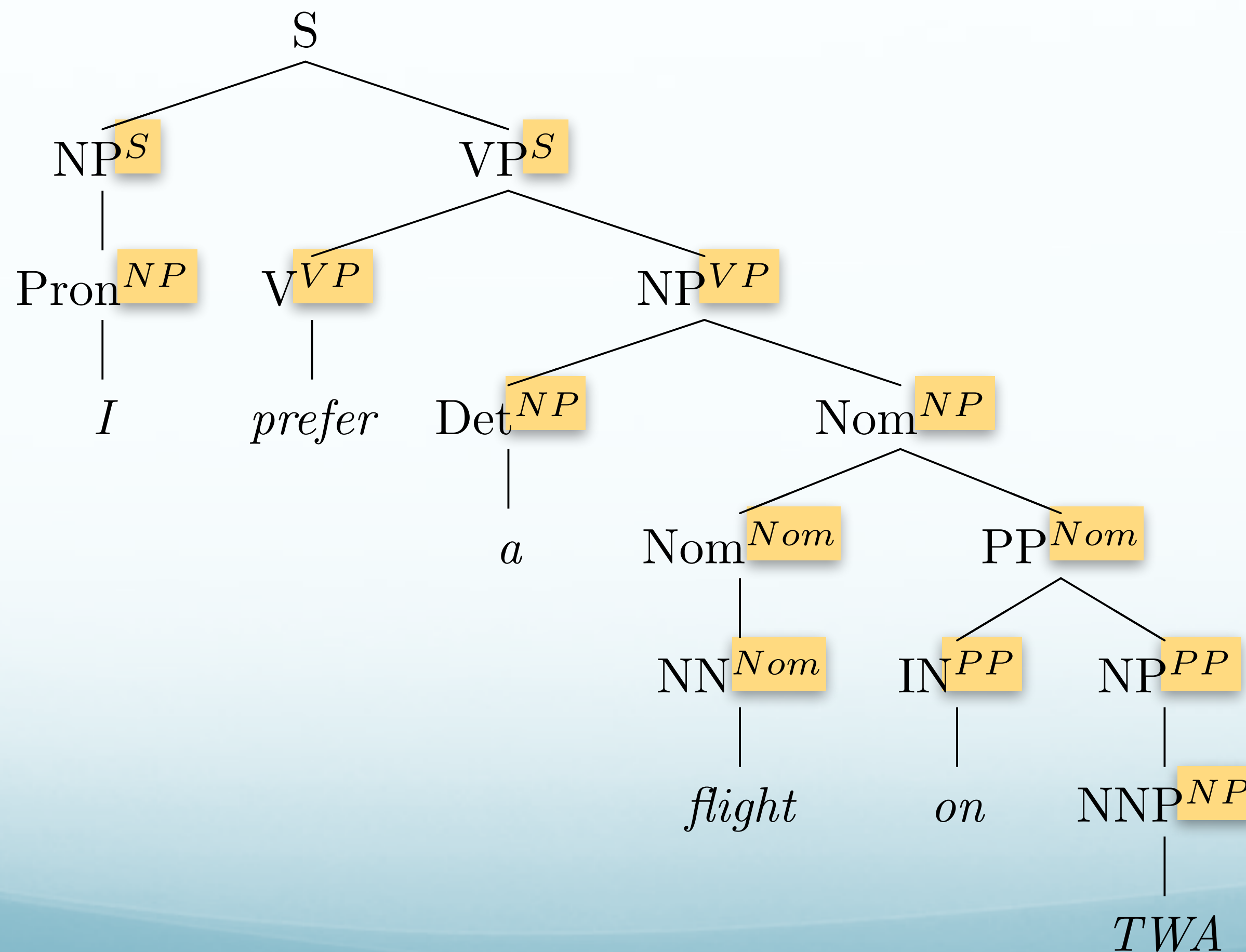
Improving PCFGs: Parent Annotation

- To handle the $NP \rightarrow PRP$ [0.91 if $NP_{\Theta=subject}$ else 0.34]
- Can annotate each node with its parent



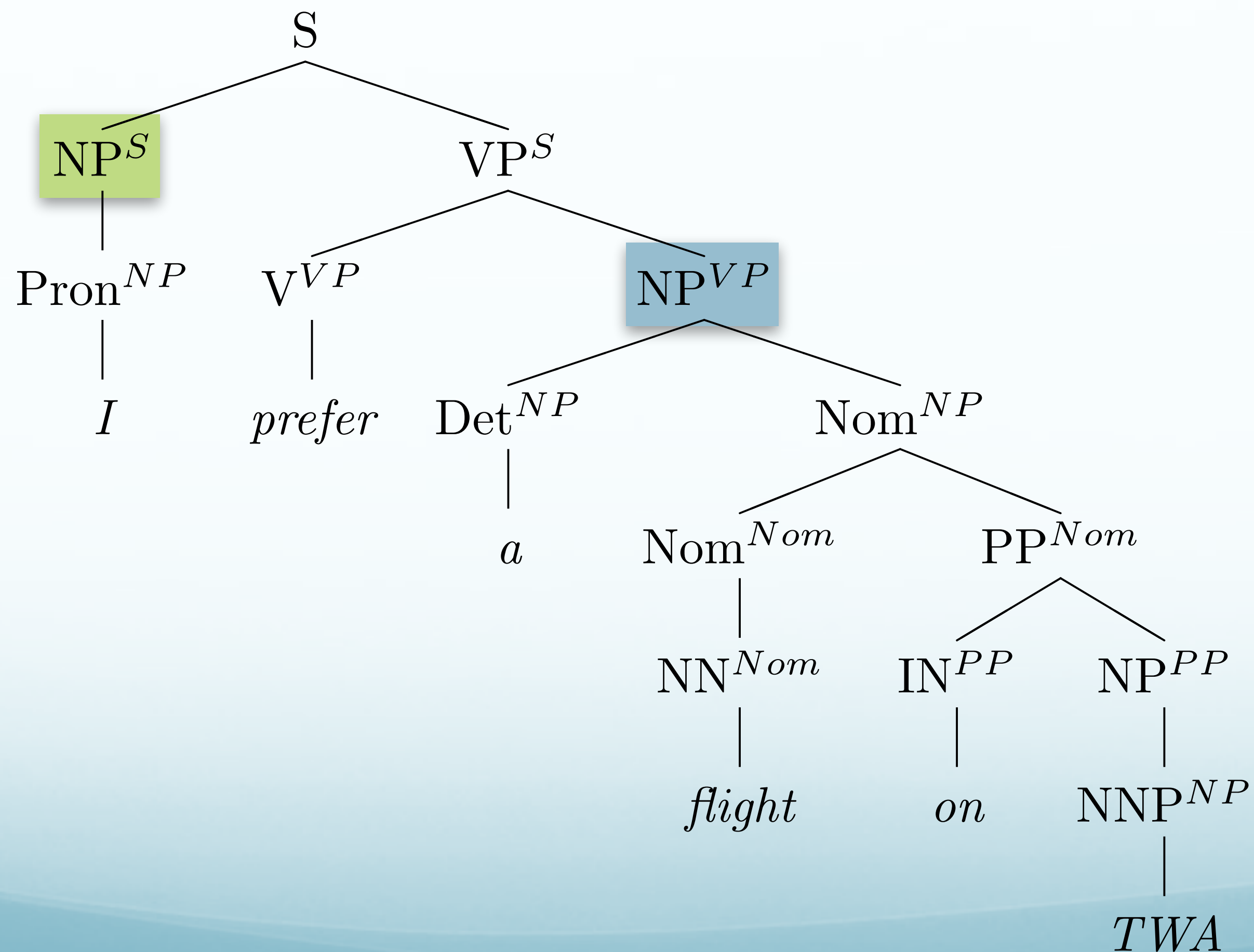
Improving PCFGs: Parent Annotation

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Improving PCFGs: Parent Annotation

- To handle the $NP \rightarrow PRP$ [0.91 if $NP_{\Theta=subject}$ else 0.34]
- Can annotate each node with its parent



Improving PCFGs: Parent Annotation

- Advantages:
 - Captures structural dependencies in grammar
- Disadvantages:
 - Explodes number of rules in grammar
 - Same problem with subcategorization
 - Results in sparsity problems
- Strategies to find an optimal number of splits
 - [Petrov et al \(2006\)](#)

Improving PCFGs

- Parent Annotation
- **Lexicalization**
- Markovization
- Reranking

Improving PCFGs: Lexical “Heads”

- Remember back to syntax intro (Lecture #1)
 - Phrases are “headed” by key words
 - **VP** are headed by **V**
 - **NP** by **NN, NNS, PRON**
 - **PP** by **PREP**
- We can take advantage of this in our grammar!

Improving PCFGs: Lexical Dependencies

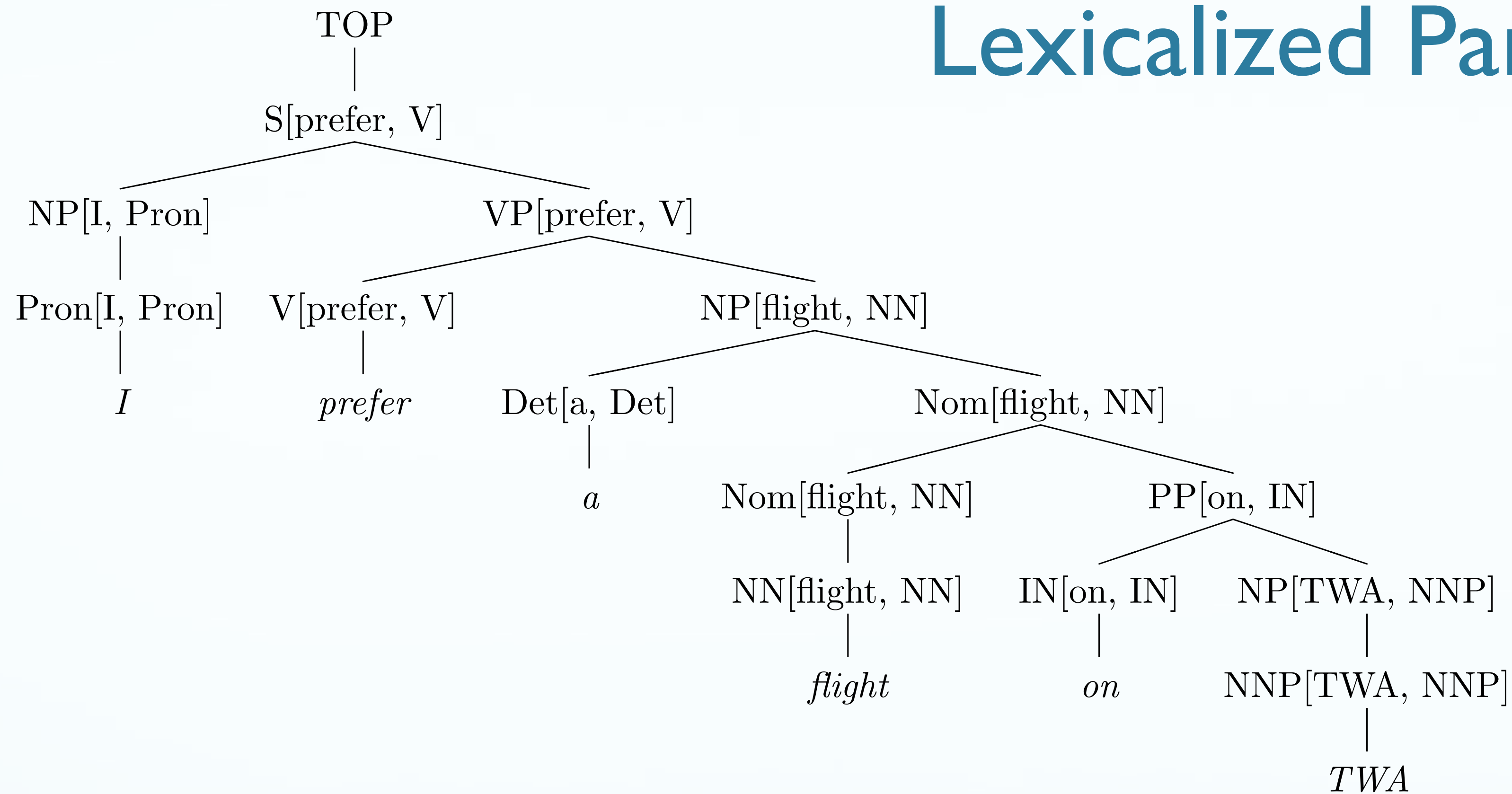
- As we've seen, some rules should be conditioned on certain words
- **Proposal:** annotate nonterminals with lexical head

$$VP \rightarrow VBD\ NP\ PP$$
$$VP(dumped) \rightarrow VBD(dumped)\ NP(sacks)\ PP(into)$$

- **Additionally:** annotate with lexical head + POS

$$VP(dumped, \mathbf{VBD}) \rightarrow VBD(dumped, \mathbf{VBD})\ NP(sacks, \mathbf{NNS})\ PP(into, \mathbf{IN})$$

Lexicalized Parse Tree



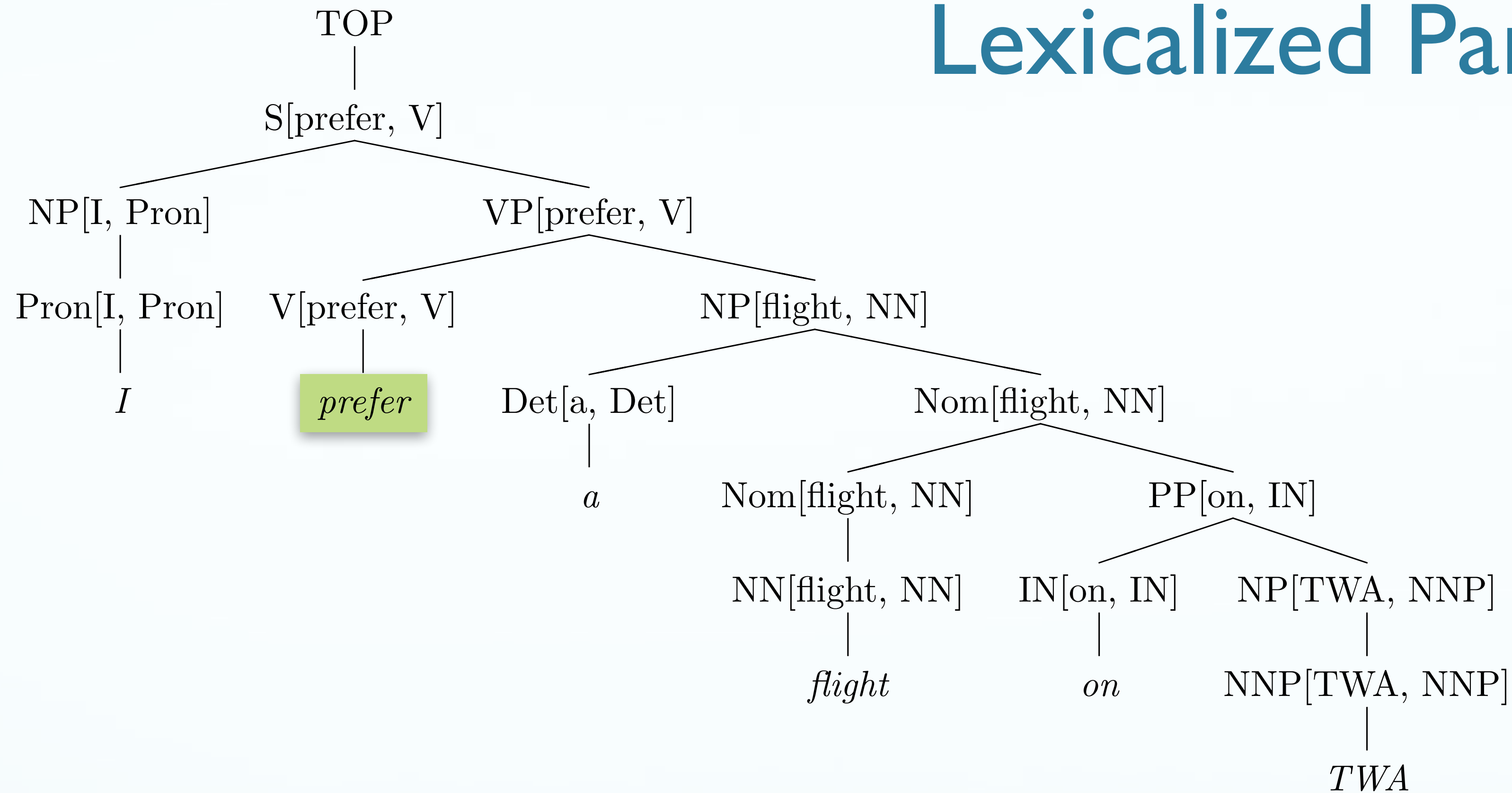
Internal Rules

<i>TOP</i>	→	<i>S(prefer, V)</i>
<i>S(prefer, V)</i>	→	<i>NP(I, Pron) VP(prefer, V)</i>
<i>NP(I, Pron)</i>	→	<i>Pron(I, Pron)</i>
<i>VP(prefer, V)</i>	→	<i>V(prefer, V) NP(flight, NN)</i>
<i>NP(flight, NN)</i>	→	<i>Det(a, Det) Nom(flight, NN)</i>
<i>PP(on, IN)</i>	→	<i>IN(on, IN) NP(TWA, NNP)</i>

Lexical Rules

<i>Pron(I, Pron)</i>	→	<i>I</i>
<i>V(prefer, V)</i>	→	<i>prefer</i>
<i>Det(a, Det)</i>	→	<i>a</i>
<i>NN(flight, NN)</i>	→	<i>flight</i>
<i>IN(on, IN)</i>	→	<i>on</i>
<i>NNP(TWA, NNP)</i>	→	<i>TWA</i>

Lexicalized Parse Tree



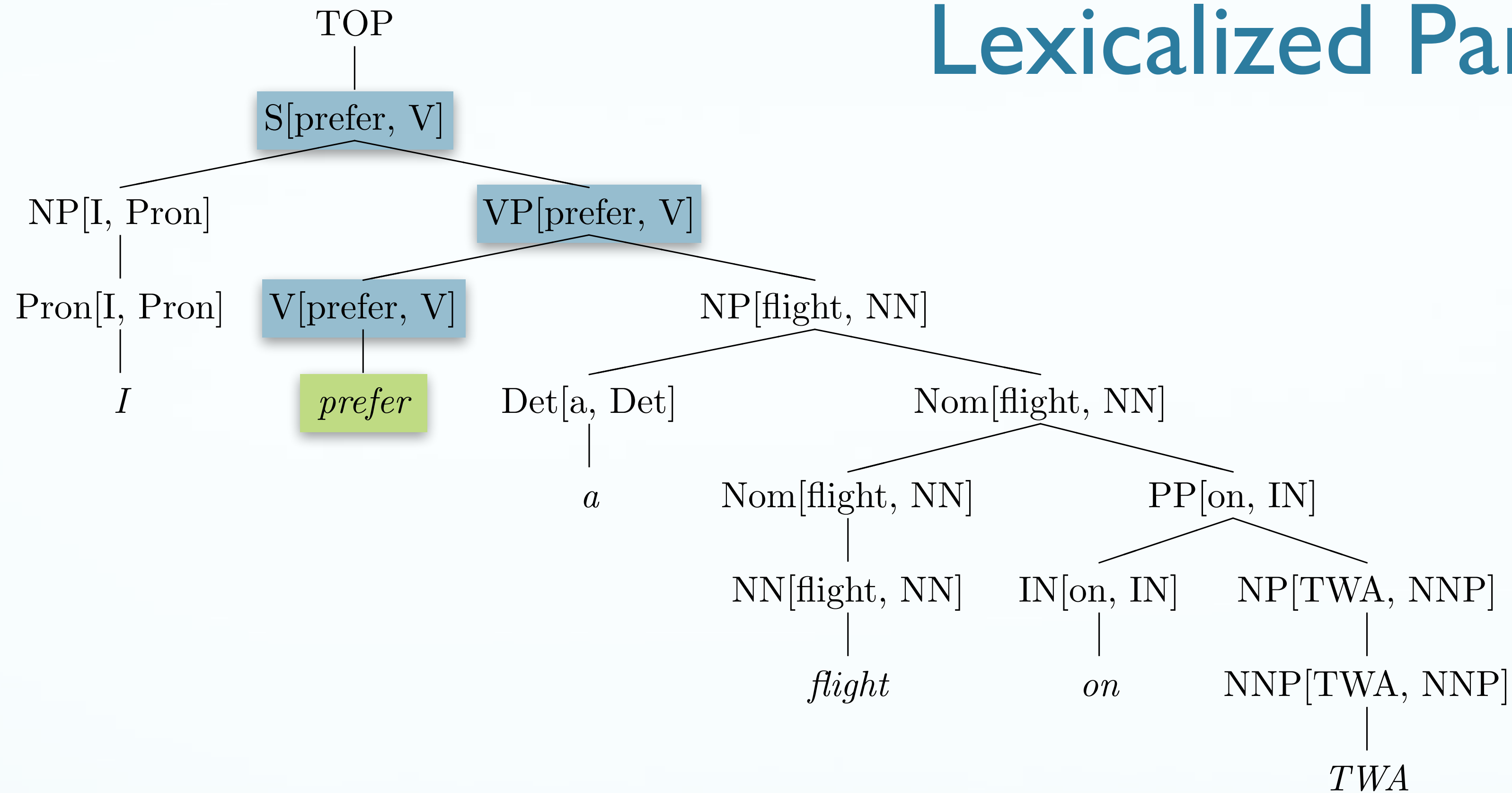
Internal Rules

<i>TOP</i>	→	<i>S(prefer, V)</i>
<i>S(prefer, V)</i>	→	<i>NP(I, Pron) VP(prefer, V)</i>
<i>NP(I, Pron)</i>	→	<i>Pron(I, Pron)</i>
<i>VP(prefer, V)</i>	→	<i>V(prefer, V) NP(flight, NN)</i>
<i>NP(flight, NN)</i>	→	<i>Det(a, Det) Nom(flight, NN)</i>
<i>PP(on, IN)</i>	→	<i>IN(on, IN) NP(TWA, NNP)</i>

Lexical Rules

<i>Pron(I, Pron)</i>	→	<i>I</i>
<i>V(prefer, V)</i>	→	<i>prefer</i>
<i>Det(a, Det)</i>	→	<i>a</i>
<i>NN(flight, NN)</i>	→	<i>flight</i>
<i>IN(on, IN)</i>	→	<i>on</i>
<i>NNP(TWA, NNP)</i>	→	<i>TWA</i>

Lexicalized Parse Tree



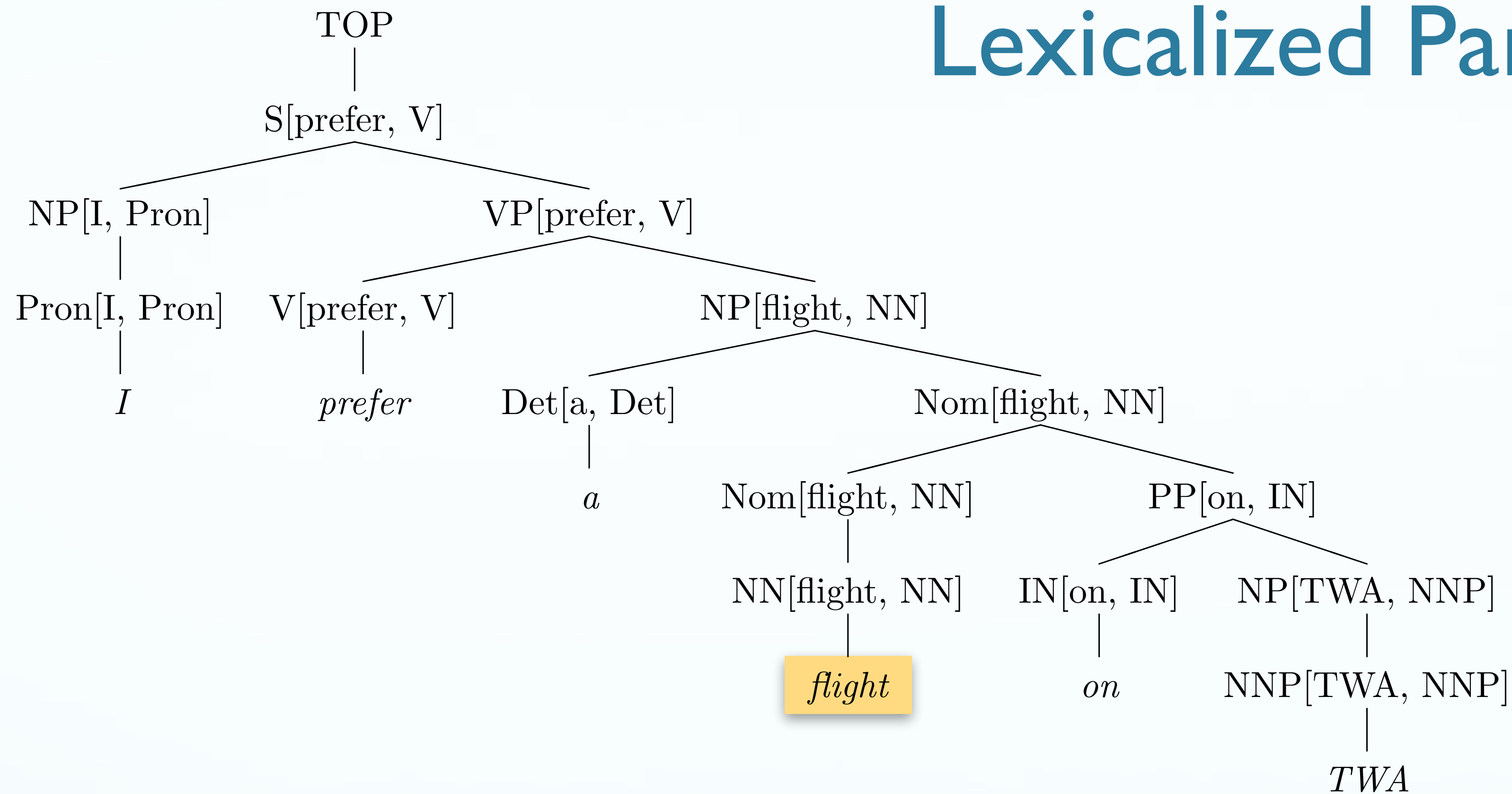
Internal Rules

<i>TOP</i>	→	<i>S(prefer, V)</i>
<i>S(prefer, V)</i>	→	<i>NP(I, Pron)</i> <i>VP(prefer, V)</i>
<i>NP(I, Pron)</i>	→	<i>Pron(I, Pron)</i>
<i>VP(prefer, V)</i>	→	<i>V(prefer, V)</i> <i>NP(flight, NN)</i>
<i>NP(flight, NN)</i>	→	<i>Det(a, Det)</i> <i>Nom(flight, NN)</i>
<i>PP(on, IN)</i>	→	<i>IN(on, IN)</i> <i>NP(TWA, NNP)</i>

Lexical Rules

<i>Pron(I, Pron)</i>	→	<i>I</i>
<i>V(prefer, V)</i>	→	<i>prefer</i>
<i>Det(a, Det)</i>	→	<i>a</i>
<i>NN(flight, NN)</i>	→	<i>flight</i>
<i>IN(on, IN)</i>	→	<i>on</i>
<i>NNP(TWA, NNP)</i>	→	<i>TWA</i>

Lexicalized Parse Tree



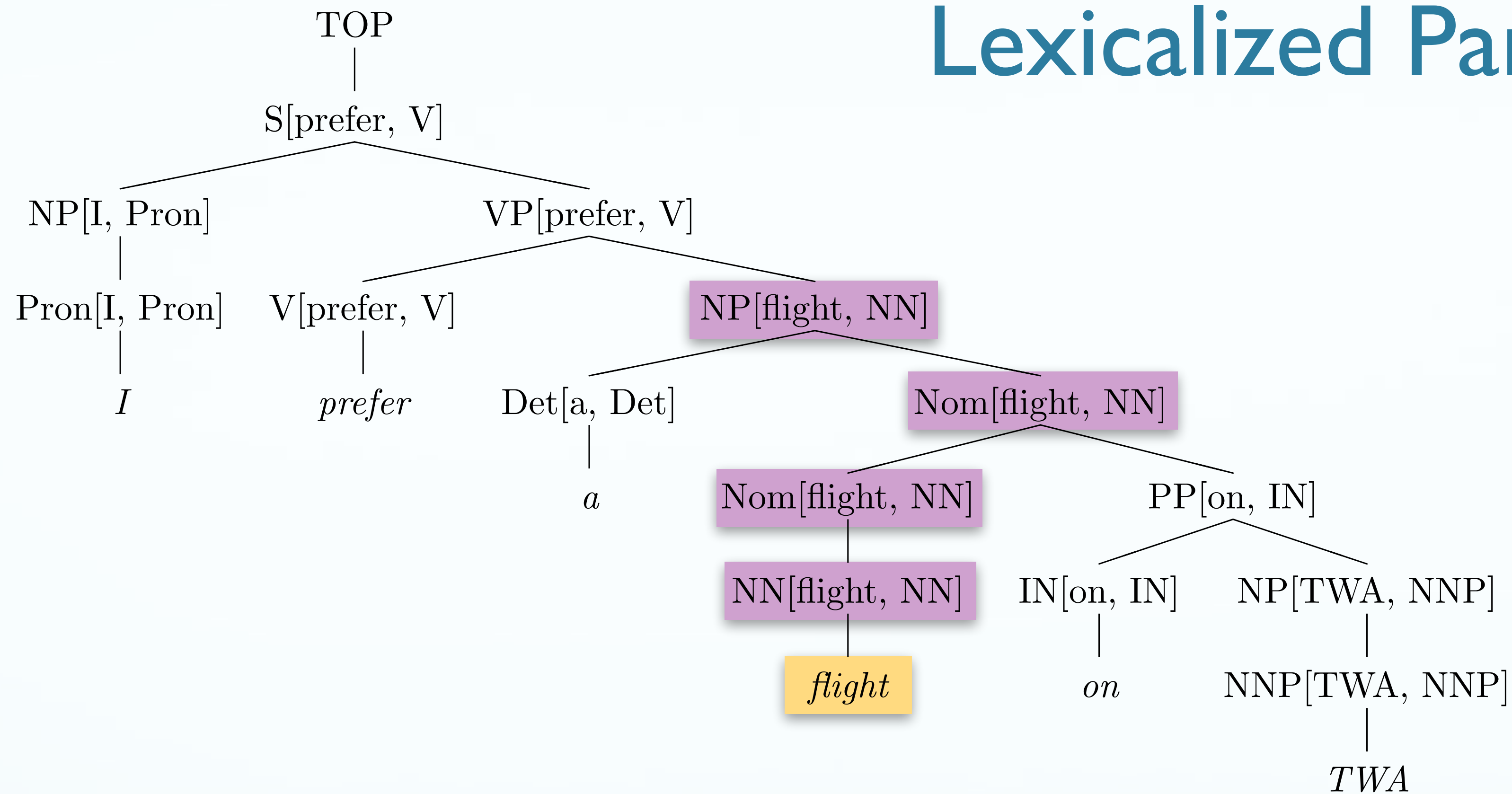
Internal Rules

<i>TOP</i>	→	<i>S(prefer, V)</i>
<i>S(prefer, V)</i>	→	<i>NP(I, Pron) VP(prefer, V)</i>
<i>NP(I, Pron)</i>	→	<i>Pron(I, Pron)</i>
<i>VP(prefer, V)</i>	→	<i>V(prefer, V) NP(flight, NN)</i>
<i>NP(flight, NN)</i>	→	<i>Det(a, Det) Nom(flight, NN)</i>
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Lexicalized Parse Tree



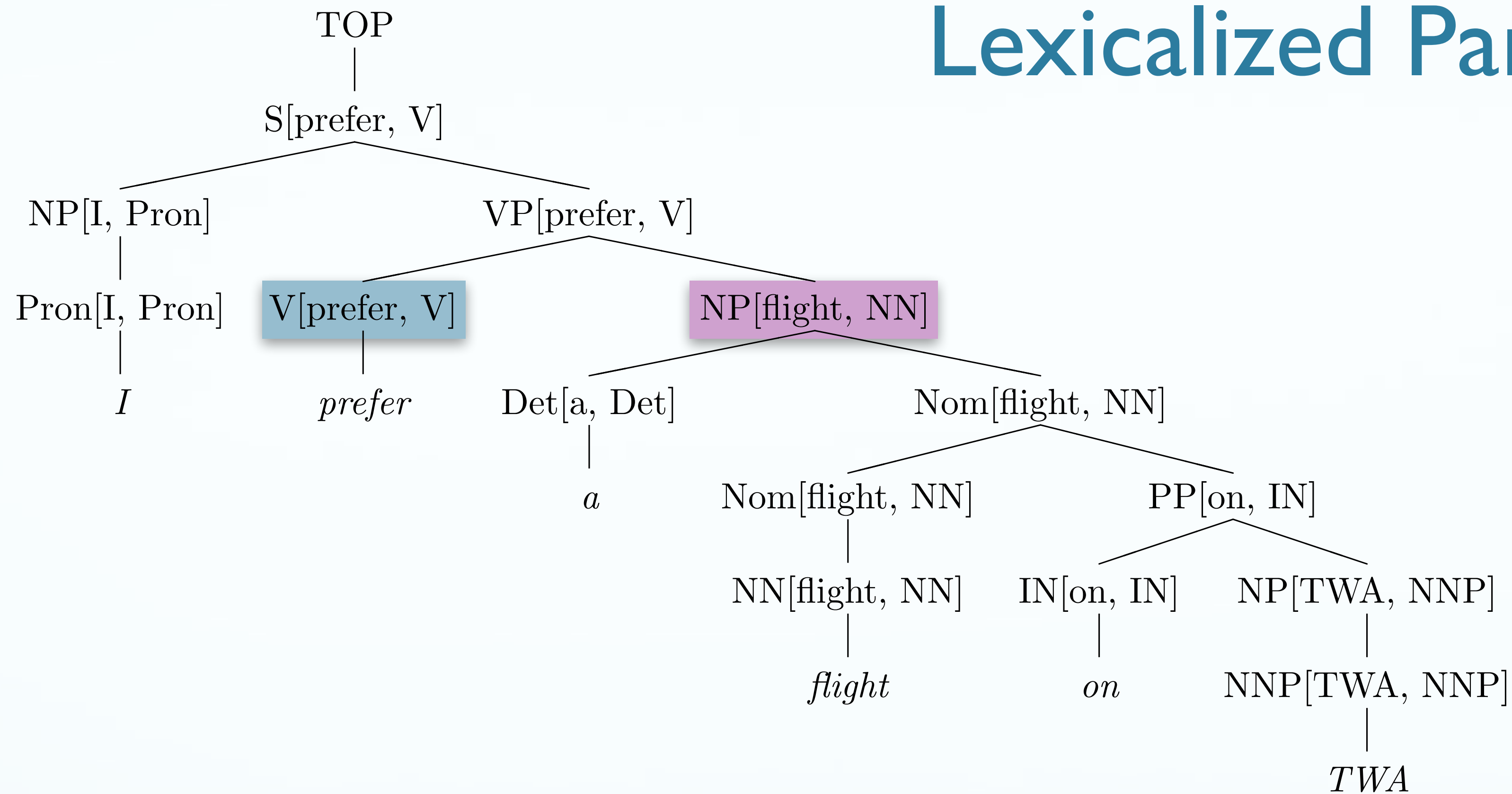
Internal Rules

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<i>S(prefer, V)</i>	→	<i>NP(I, Pron) VP(prefer, V)</i>
<i>NP(I, Pron)</i>	→	<i>Pron(I, Pron)</i>
<i>VP(prefer, V)</i>	→	<i>V(prefer, V) NP(flight, NN)</i>
<i>NP(flight, NN)</i>	→	<i>Det(a, Det) Nom(flight, NN)</i>
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Lexicalized Parse Tree



Internal Rules

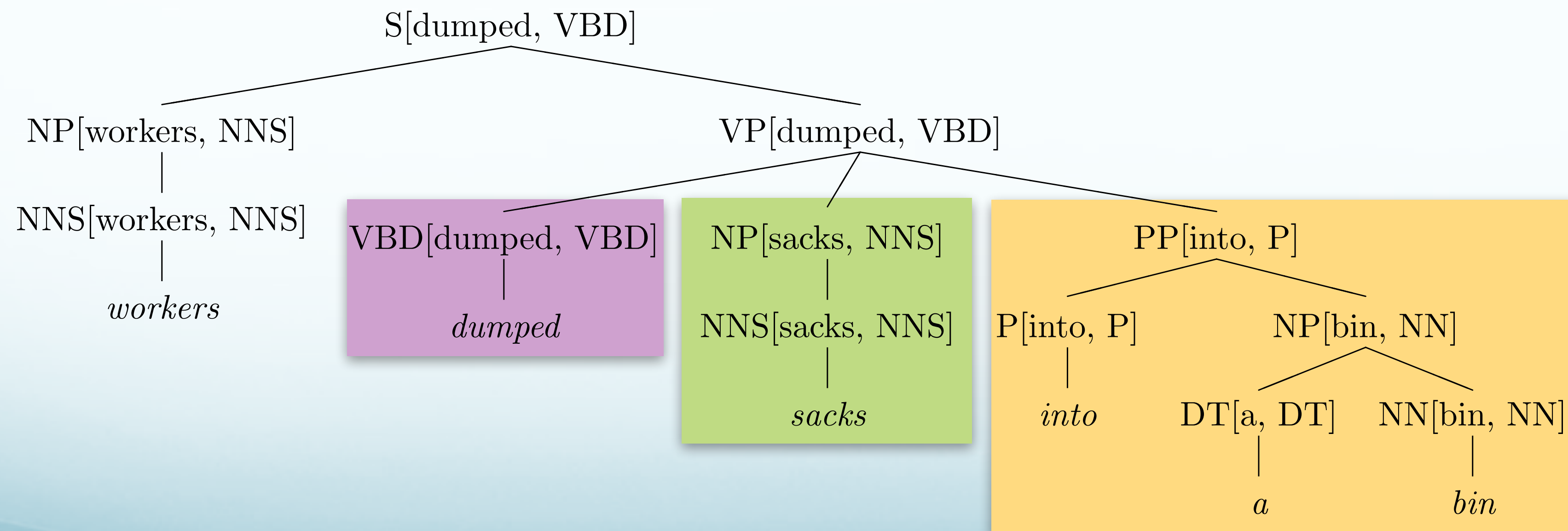
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<i>S(prefer, V)</i>	→	<i>NP(I, Pron) VP(prefer, V)</i>
<i>NP(I, Pron)</i>	→	<i>Pron(I, Pron)</i>
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<i>NNP(TWA, NNP)</i>	→	<i>TWA</i>

Improving PCFGs: Lexical Dependencies

- Upshot: heads propagate up tree:
 - $VP \rightarrow VBD(dumped, VBD) NP(sacks, NNS) PP(into, P)$ ✓
 - $NP \rightarrow NNS(sacks, NNS) PP(into, P)$ ✗



Improving PCFGs: Lexical Dependencies

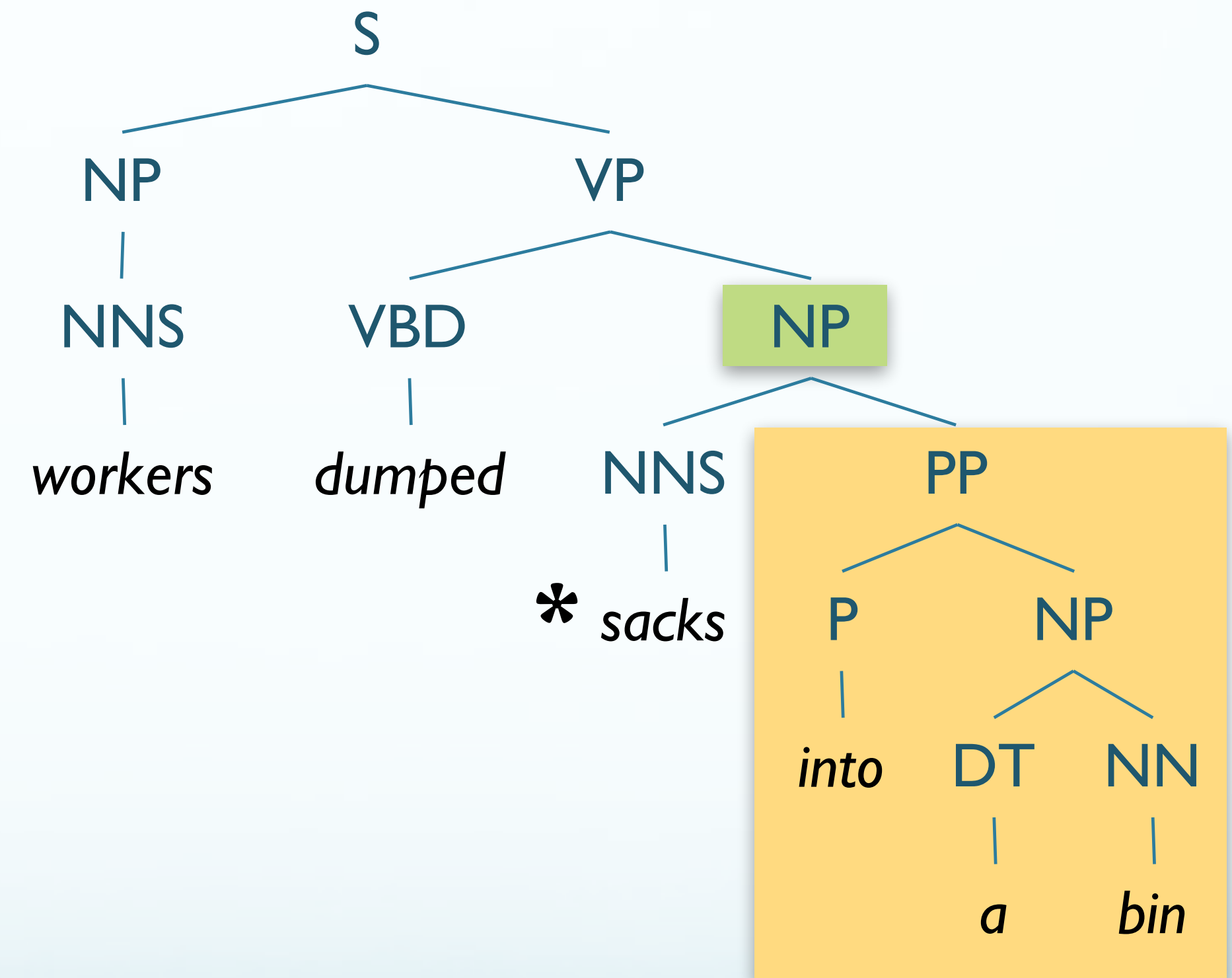
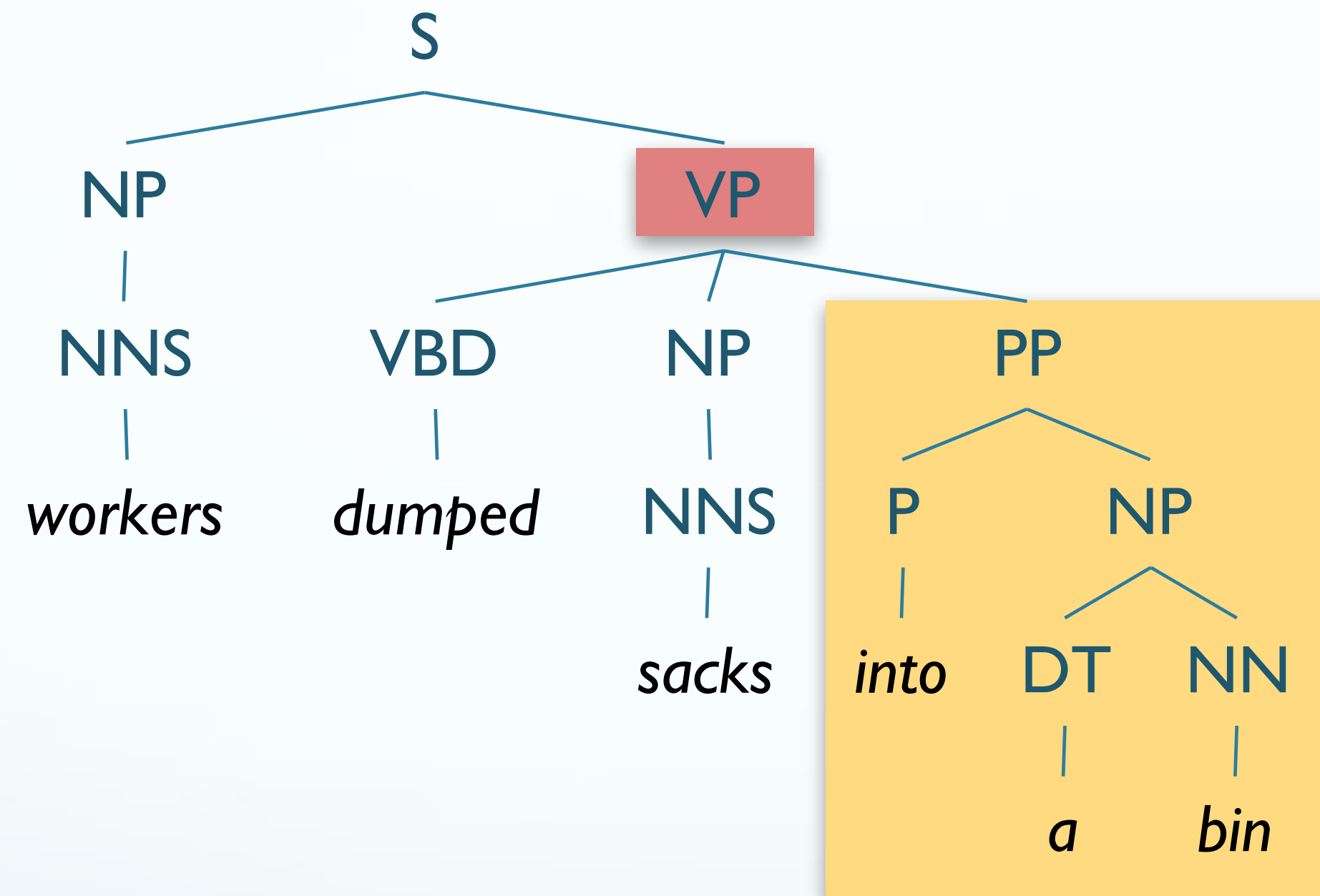
- Downside:
 - Rules far too specialized — will be sparse
- Solution:
 - Assume **conditional** independence
 - Create more rules

Improving PCFGs: Collins Parser

- Proposal:
 - $LHS \rightarrow \textit{LeftOfHead} \dots \textit{Head} \dots \textit{RightOfHead}$
 - Instead of calculating $P(\textit{EntireRule})$, which is sparse:
 - Calculate:
 - Probability that LHS has nonterminal phrase H given head-word $hw\dots$
 - \times Probability of modifiers to the **left** given head-word $hw\dots$
 - \times Probability of modifiers to the **right** given head-word $hw\dots$

$$P(T, S) = \prod_{n \in T} p(r(n) | n, h(n)) \cdot p(h(n) | n, h(m(n)))$$

Collins Parser Example



Collins Parser Example

$$P(VP \rightarrow VBD \ NP \ PP \mid VP, \textit{dumped})$$

$$= \frac{\text{Count}(VP(\textit{dumped}) \rightarrow VBD \ NP \ PP)}{\sum_{\beta} \text{Count}(VP(\textit{dumped}) \rightarrow \beta)}$$

$$= \frac{6}{9} = 0.67$$

$$P(VP \rightarrow VBD \ NP \mid VP, \textit{dumped})$$

$$= \frac{\text{Count}(VP(\textit{dumped}) \rightarrow VBD \ NP)}{\sum_{\beta} \text{Count}(VP(\textit{dumped}) \rightarrow \beta)}$$

$$= \frac{1}{9} = 0.11$$

$$P_R(\textit{into} \mid PP, \textit{dumped})$$

$$= \frac{\text{Count}(X(\textit{dumped}) \rightarrow \dots PP(\textit{into}) \dots)}{\sum_{\beta} \text{Count}(X(\textit{dumped}) \rightarrow \dots PP \dots)}$$

$$= \frac{2}{9} = 0.22$$

$$P_R(\textit{into} \mid PP, \textit{sacks})$$

$$= \frac{\text{Count}(X(\textit{sacks}) \rightarrow \dots PP(\textit{into}) \dots)}{\sum_{\beta} \text{Count}(X(\textit{sacks}) \rightarrow \dots PP \dots)}$$

$$= \frac{0}{0}$$

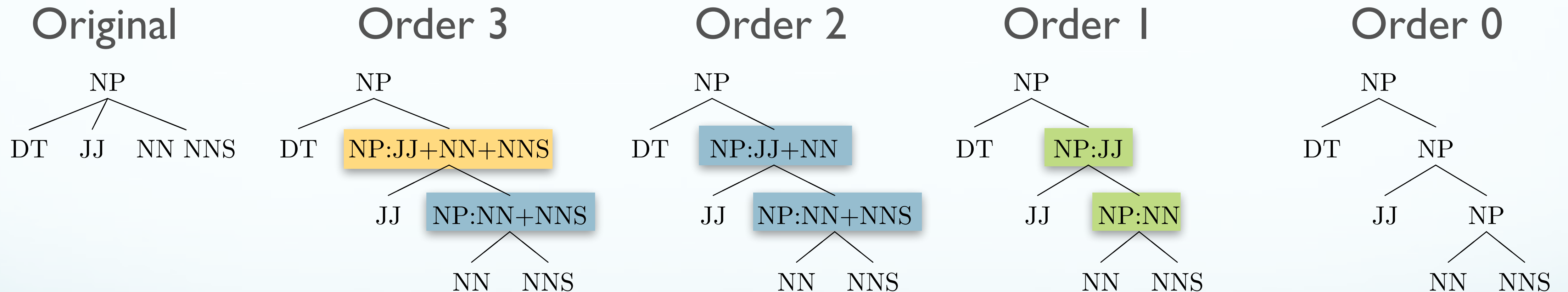
Improving PCFGs

- Parent Annotation
- Lexicalization
- **Markovization**
- Reranking

CNF Factorization & Markovization

- CNF Factorization:
 - Converts n-ary branching to binary branching
 - Can maintain information about original structure
 - Neighborhood history and parent

Different Markov Orders



Markovization and Costs

PCFG	Time(s)	Words/s	V	P	LR	LP	F ₁
Right-factored	4848	6.7	10105	23220	69.2	73.8	71.5
Right-factored, Markov order-2	1302	24.9	2492	11659	68.8	73.8	71.3
Right-factored, Markov order-1	445	72.7	564	6354	68.0	730	70.5
Right-factored, Markov order-0	206	157.1	99	3803	61.2	65.5	63.3
Parent-annotated, Right-factored, Markov order-2	7510	4.3	5876	22444	76.2	78.3	77.2

from [Mohri & Roark 2006](#)

Improving PCFGs

- Parent Annotation
- Lexicalization
- Markovization
- **Reranking**

Reranking

- Issue: Locality
 - PCFG probabilities associated with rewrite rules
 - Context-free grammars are, well, context-free
 - Previous approaches create new rules to incorporate context
- Need approach that incorporates broader, global info

Discriminative Parse Reranking

- General approach:
 - Parse using (L)PCFG
 - Obtain top-N parses
 - Re-rank top-N using better features
- Use discriminative model (e.g. MaxEnt) to rerank with features:
 - right-branching vs. left-branching
 - speaker identity
 - conjunctive parallelism
 - fragment frequency
 - ...

Reranking Effectiveness

- How can reranking improve?
 - ...assuming N-best includes the correct parse

- Results from [Collins \(2000\)](#), with 50-best

System	Accuracy
Baseline	0.897
Oracle	0.968
Discriminative	0.917

- “Oracle” is to automatically choose the correct parse if in N-best

Improving PCFGs: Tradeoffs

- **Pros:**
 - Increased accuracy/specificity
 - e.g. Lexicalization, Parent annotation, Markovization, etc
- **Cons:**
 - Explode grammar size
 - Increased processing time
 - Increased data requirements
- *How can we balance?*

Improving PCFGs: Efficiency

- **Beam thresholding**
- Heuristic Filtering

Efficiency

- PCKY is $|G| \cdot n^3$
 - Grammar can be huge
 - Grammar can be extremely ambiguous
 - Hundreds of analyses not unusual
- ...but only care about best parses
- Can we use this to improve efficiency?

Beam Thresholding

- Inspired by Beam Search
- Assume low probability parses unlikely to yield high probability overall
 - Keep only top k most probable partial parses
 - Retain only k choices per cell
 - For large grammars, maybe 50-100
 - For small grammars, 5 or 10

Heuristic Filtering

- **Intuition:** Some rules/partial parses unlikely to create best parse
- **Proposal:** Don't store these in table.
- **Exclude:**
 - Low frequency: (singletons)
 - Low probability: constituents X s.t. $P(X) < 10^{-200}$
 - Low relative probability:
 - Exclude X if there exists Y s.t. $P(Y) > 100 \times P(X)$

HW #4

Probabilistic Parsing

- Goals:
 - Learn about PCFGs
 - Implement PCKY
 - Analyze Parsing Evaluation
 - Assess improvements to PCFG Parsing

Tasks

1. Train a PCFG

- Estimate rule probabilities from treebank
- Treebank is already in CNF
- More ATIS data from Penn Treebank

2. Build CKY Parser

- Modify (your) existing CKY implementation

Tasks

3. Evaluation

- Evaluate your parser using standard metric
- We will provide **evalb** program and gold standard

4. Improvement

- Improve your parser in some way:
 - Coverage
 - Accuracy
 - Speed
- Evaluate new parser

Improvement Possibilities

- Coverage:
 - Some test sentences won't parse as is!
 - Lexical gaps (aka out-of-vocabulary [OOV] tokens)
 - ...remember to model the probabilities, too
- Better context modeling
 - e.g. — Parent Annotation
- Better Efficiency
 - e.g. — Heuristic Filtering, Beam Search
- No “cheating” improvements:
 - improvement can't change training by looking at test data