Probabilistic Parsing: Issues & Improvement

LING 571 — Deep Processing Techniques for NLP
October 18, 2021
Shane Steinert-Threlkeld

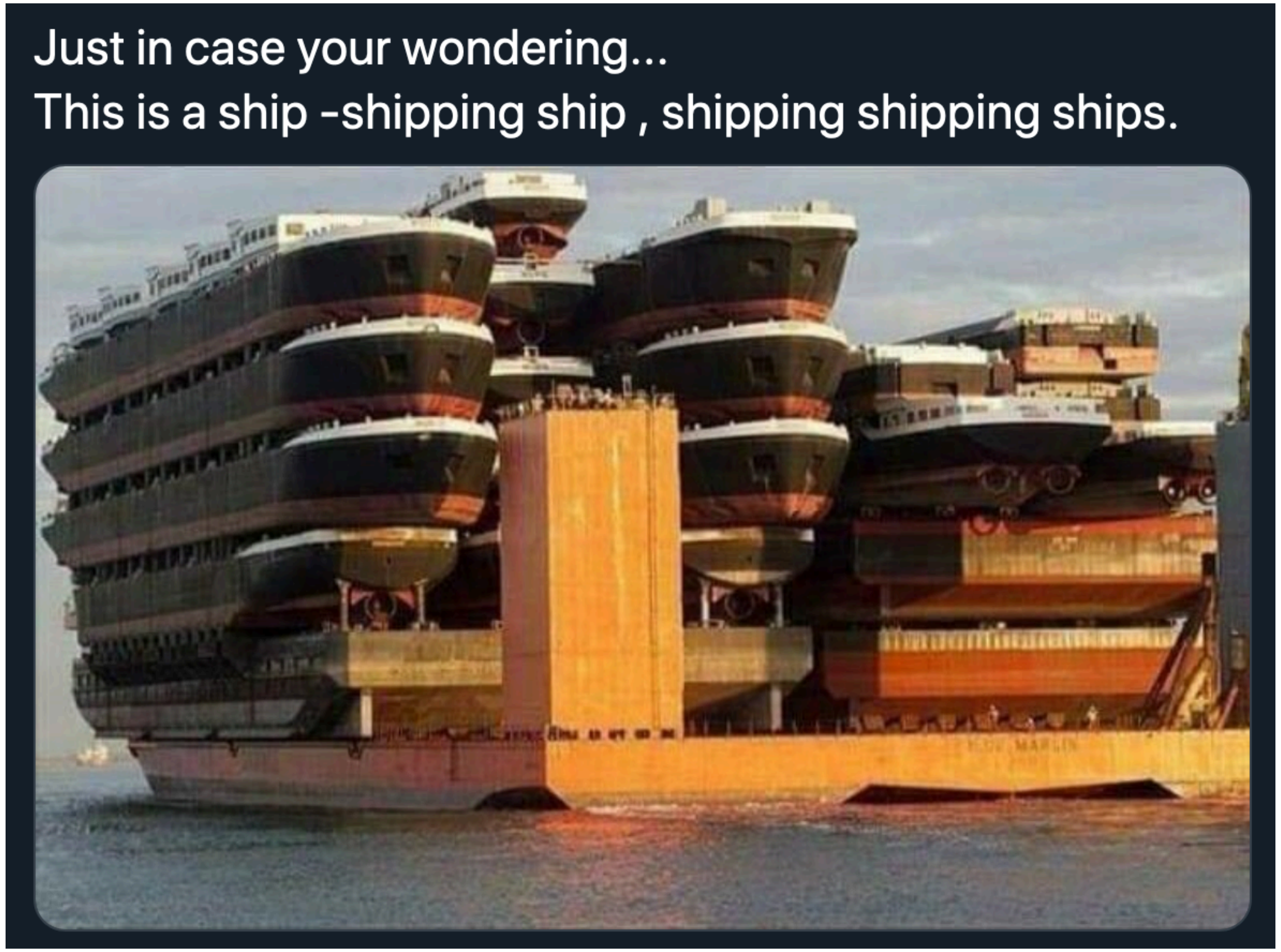
Announcements

- Patas update: *should* be back up by tomorrow afternoon/evening 🤞 🤞
  - All assignment deadlines moved back *one week* [see updated website]

Notes on HW #3

- Python's `range` has many use cases by manipulating start/end, and step
    - `range(n)` is equivalent to `range(0, n, 1)`
- Reminder: the `rhs=` argument in NLTK's `grammar.productions()` method only matches the *first* symbol, not an entire string
    - You'll want to implement an efficient look-up based on RHS
- HW3: compare your output to running HW1 parser on the same grammar/sentences
    - order of output in ambiguous sentences could differ
- We will provide grammars in CNF; don't need to use your HW2 for that

Language Does the Darnedest Things



https://twitter.com/ArrivedInGenX/status/1317879511795535872

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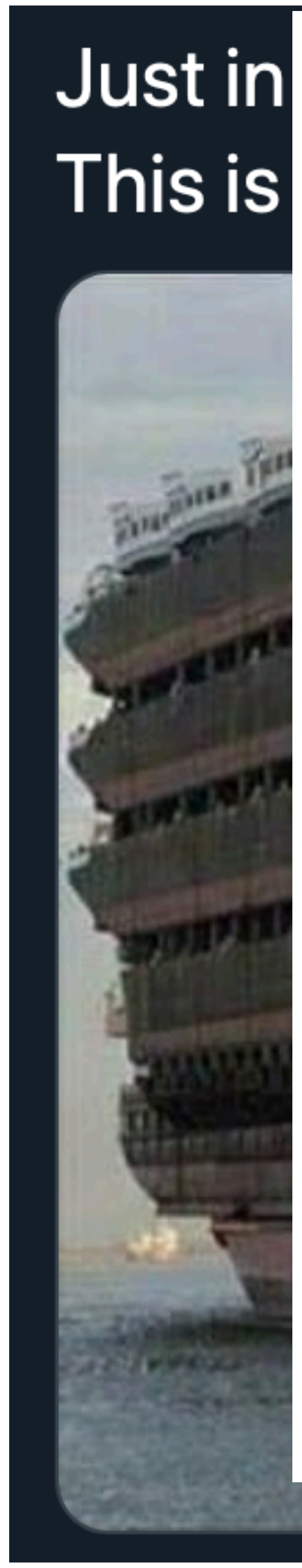


Buffalo buffalo Buffalo buffalo buffalo buffalo Buffalo buffalo

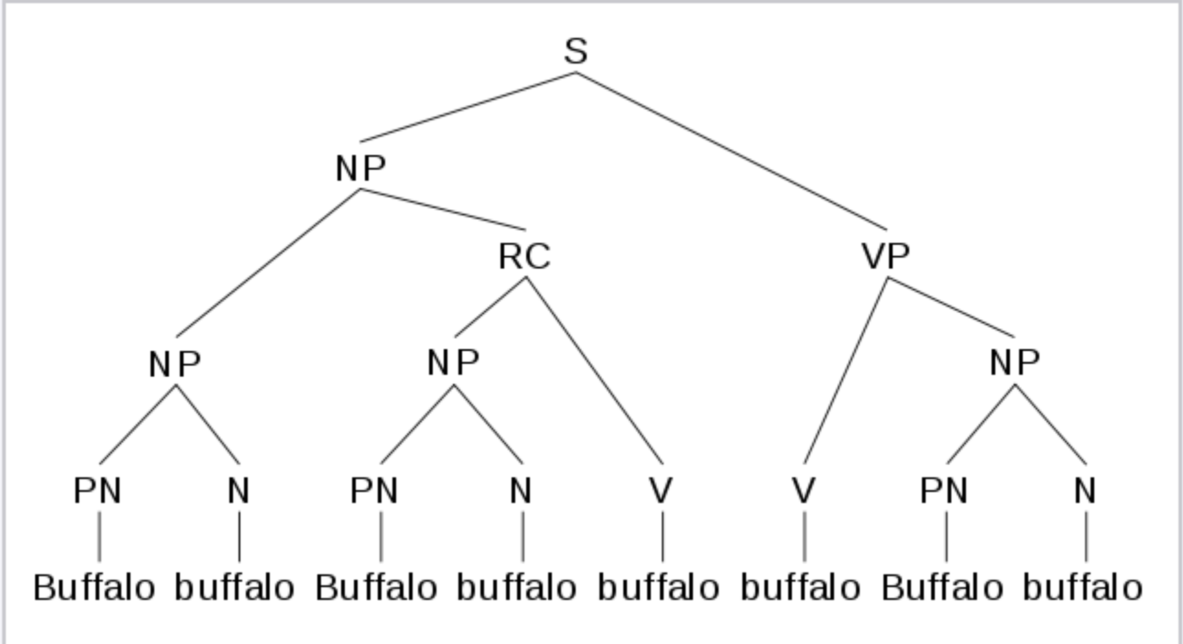
From Wikipedia, the free encyclopedia

"**Buffalo buffalo Buffalo buffalo buffalo buffalo Buffalo buffalo**" is a grammatically correct sentence in English, often presented as an example of how homonyms and homophones can be used to create complicated linguistic constructs through lexical ambiguity. It has been discussed in literature in various forms since 1967, when it appeared in Dmitri Borgmann's *Beyond Language: Adventures in Word and Thought*.

The sentence employs three distinct meanings of the word *buffalo*:

- as an adjectival proper noun to refer to a specific place named Buffalo, the city of Buffalo, New York, being the most notable;
- as a verb *to buffalo*, meaning (in American English[1]) "to bully, harass, or intimidate" or "to baffle"; and
- as a noun to refer to the animal, bison (often called *buffalo* in North America). The plural is also *buffalo*.

A semantically equivalent form preserving the original word order is: "Buffalo bison that other Buffalo bison bully also bully Buffalo bison."



Simplified parse tree

S = sentence
NP = noun phrase
RC = relative clause
VP = verb phrase
PN = proper noun
N = noun
V = verb

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PCFG Induction

Learning Probabilities

- Simplest way:
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$$P(\alpha \rightarrow \beta \,|\, \alpha) = \frac{Count(\alpha \rightarrow \beta)}{\sum_\gamma Count(\alpha \rightarrow \gamma)} = \frac{Count(\alpha \rightarrow \beta)}{Count(\alpha)}$$

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

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

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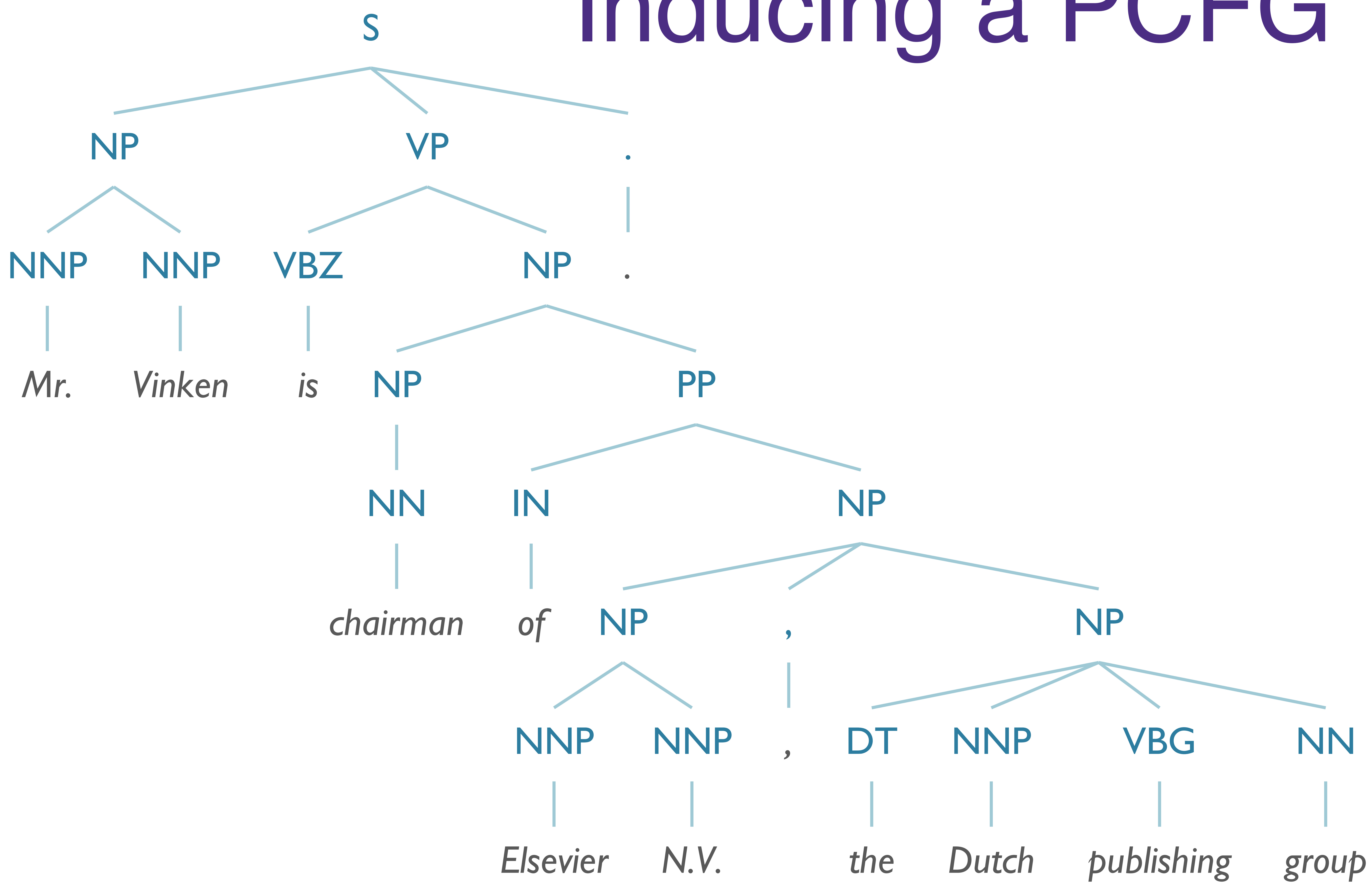

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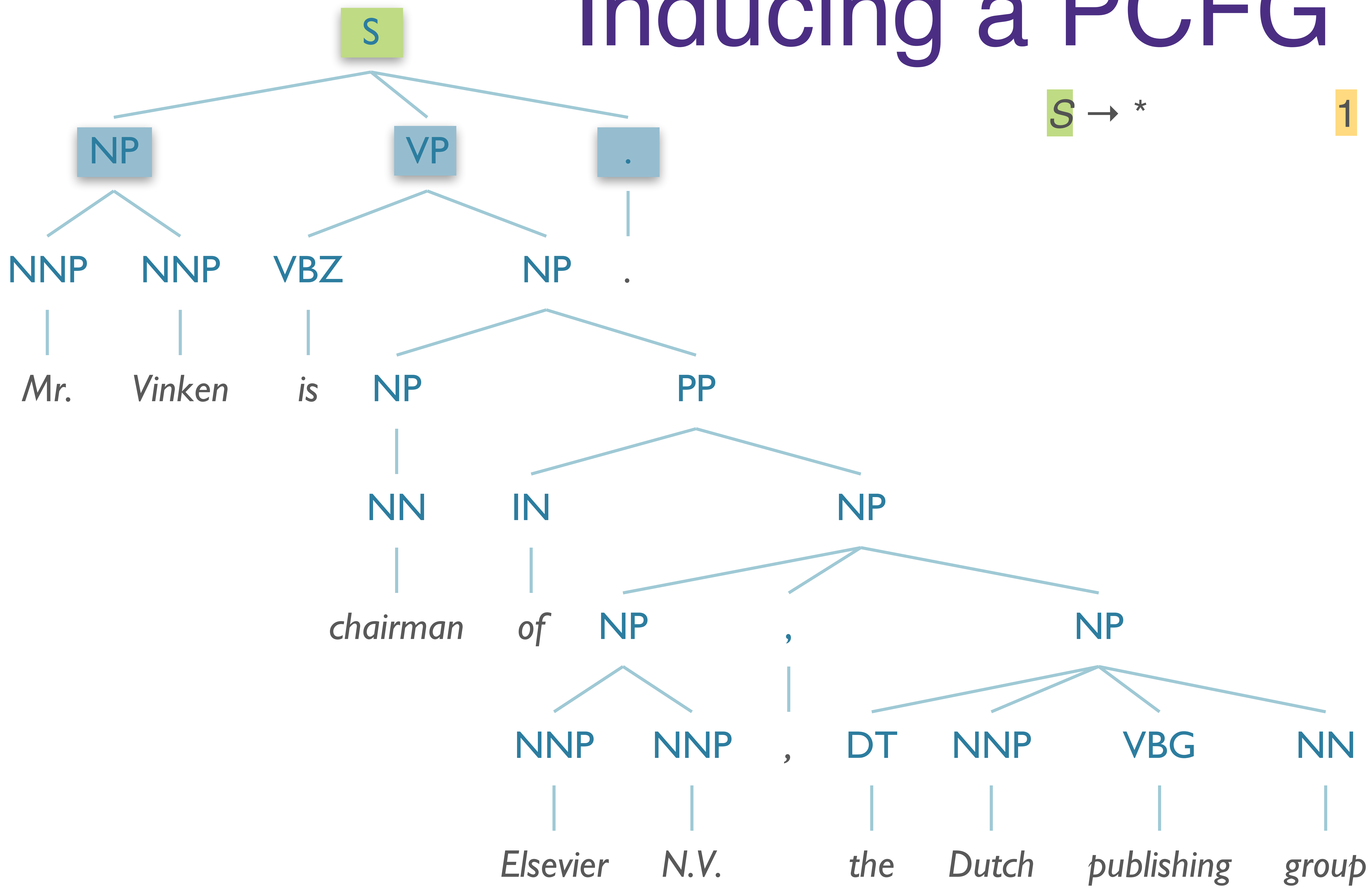
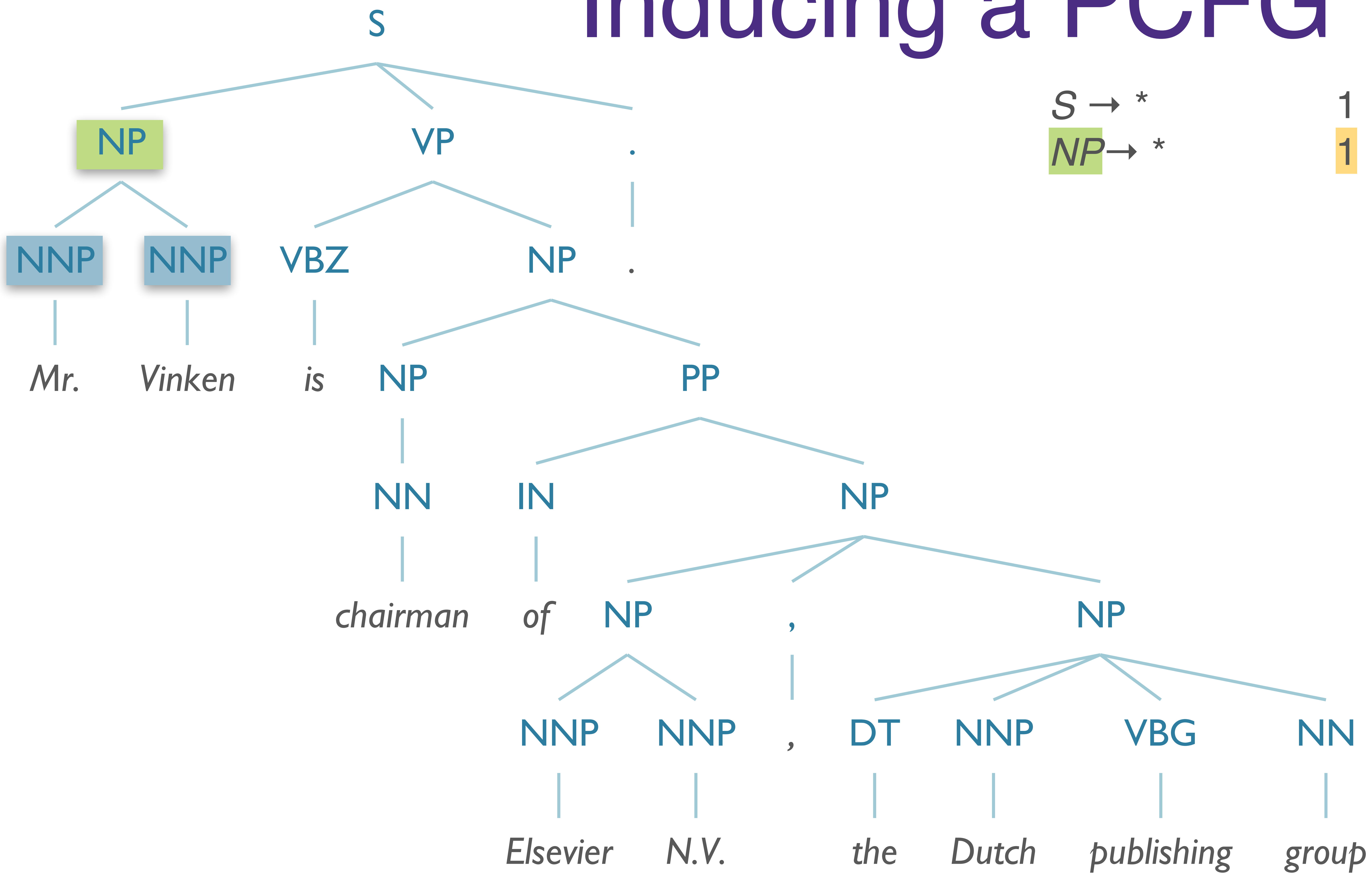


$S \rightarrow *$	1	$S \rightarrow NP\,VP\,.$	1

Inducing a PCFG



*S → **	1	*S → NP VP .*	1
*NP→ **	1	*NP→ NNP NNP*	1

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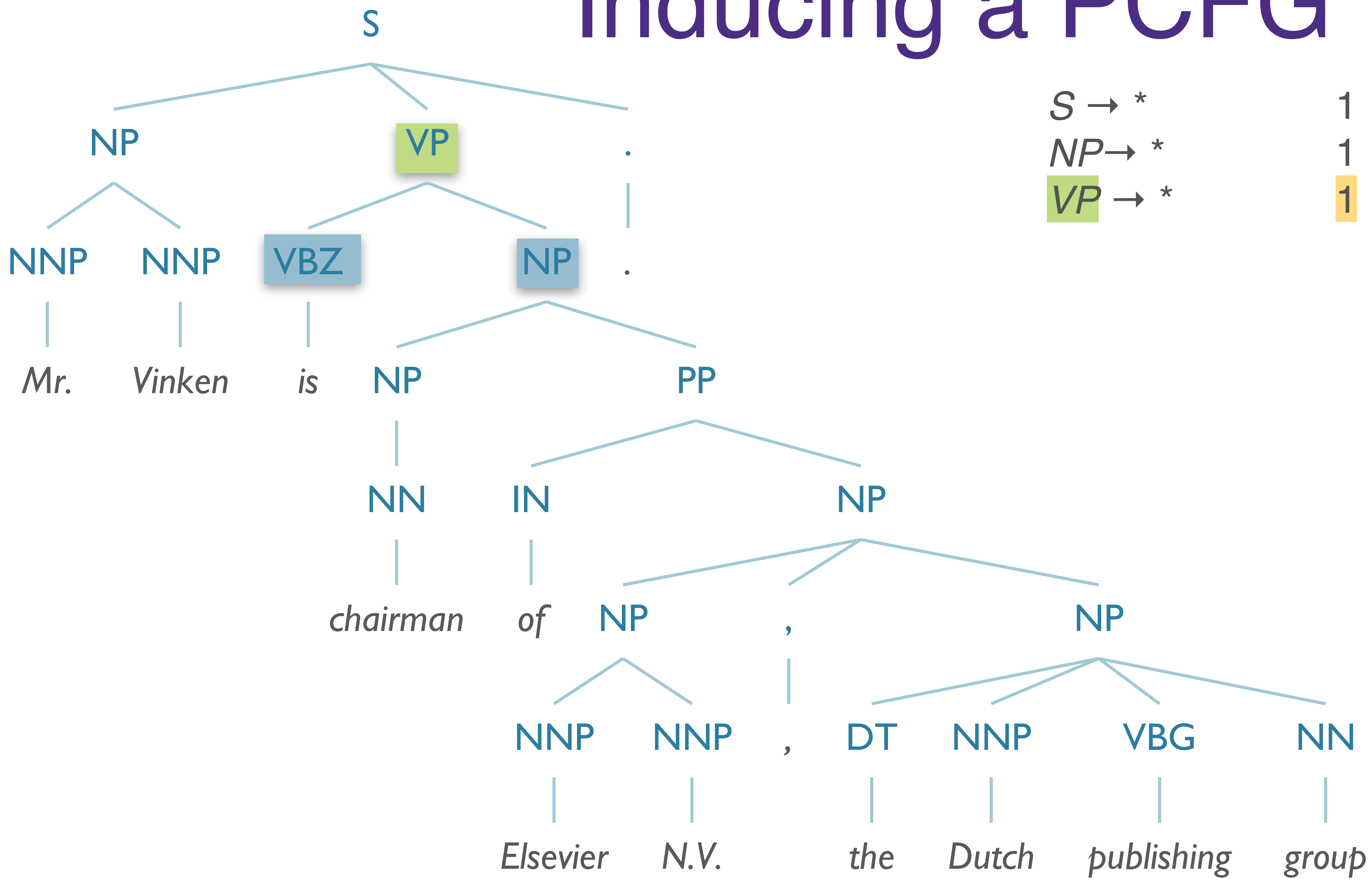

$S \rightarrow *$	1	$S \rightarrow NP\ VP\ .$	1
$NP \rightarrow *$	1	$NP \rightarrow NNP\ NNP$	1
$VP \rightarrow *$	1	$VP \rightarrow VBZ\ NP$	1

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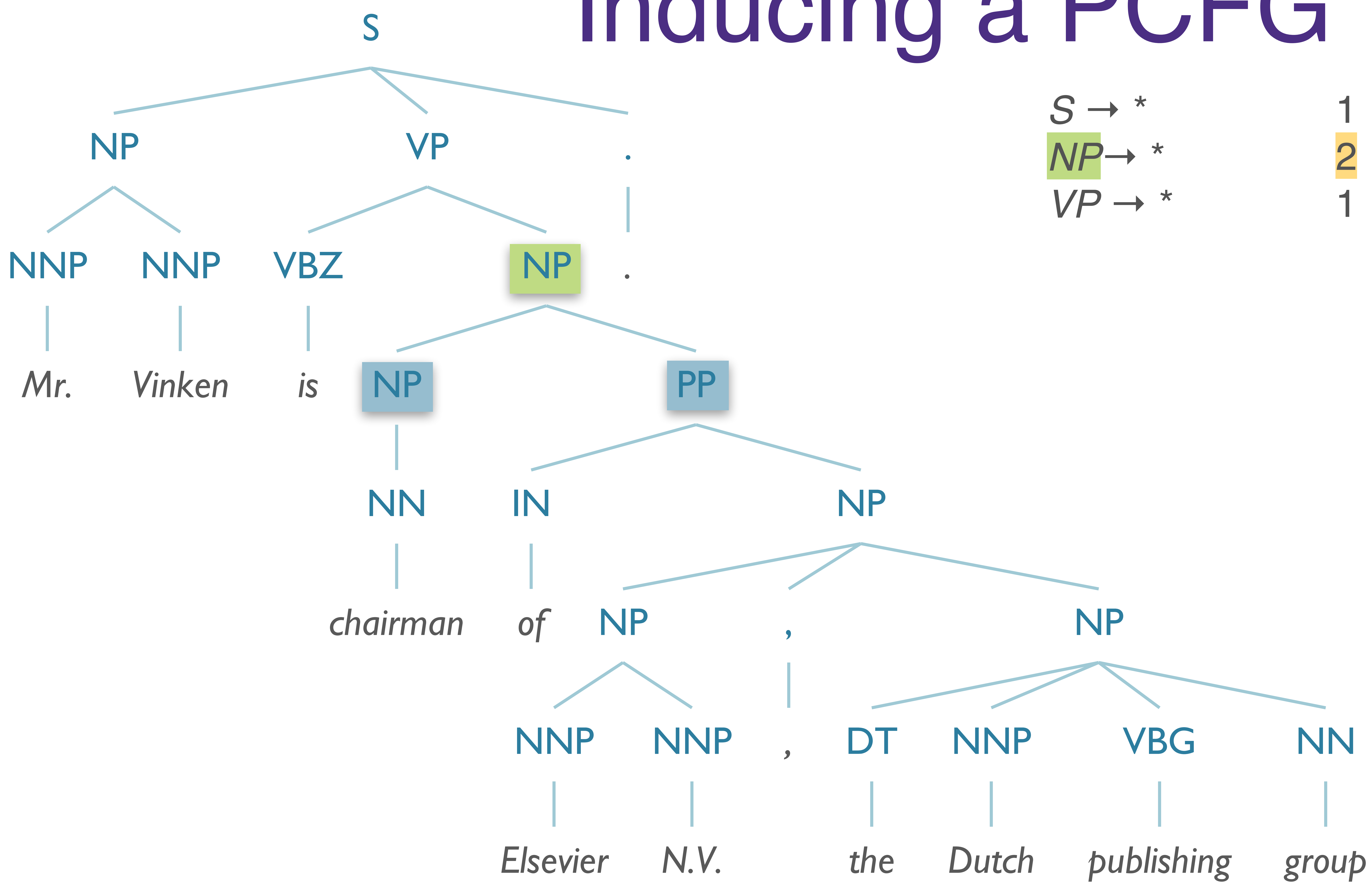

S → *	1	S → NP VP .	1
NP→ *	2	NP → NNP NNP	1
VP → *	1	VP → VBZ NP	1
		NP→ NP PP	1

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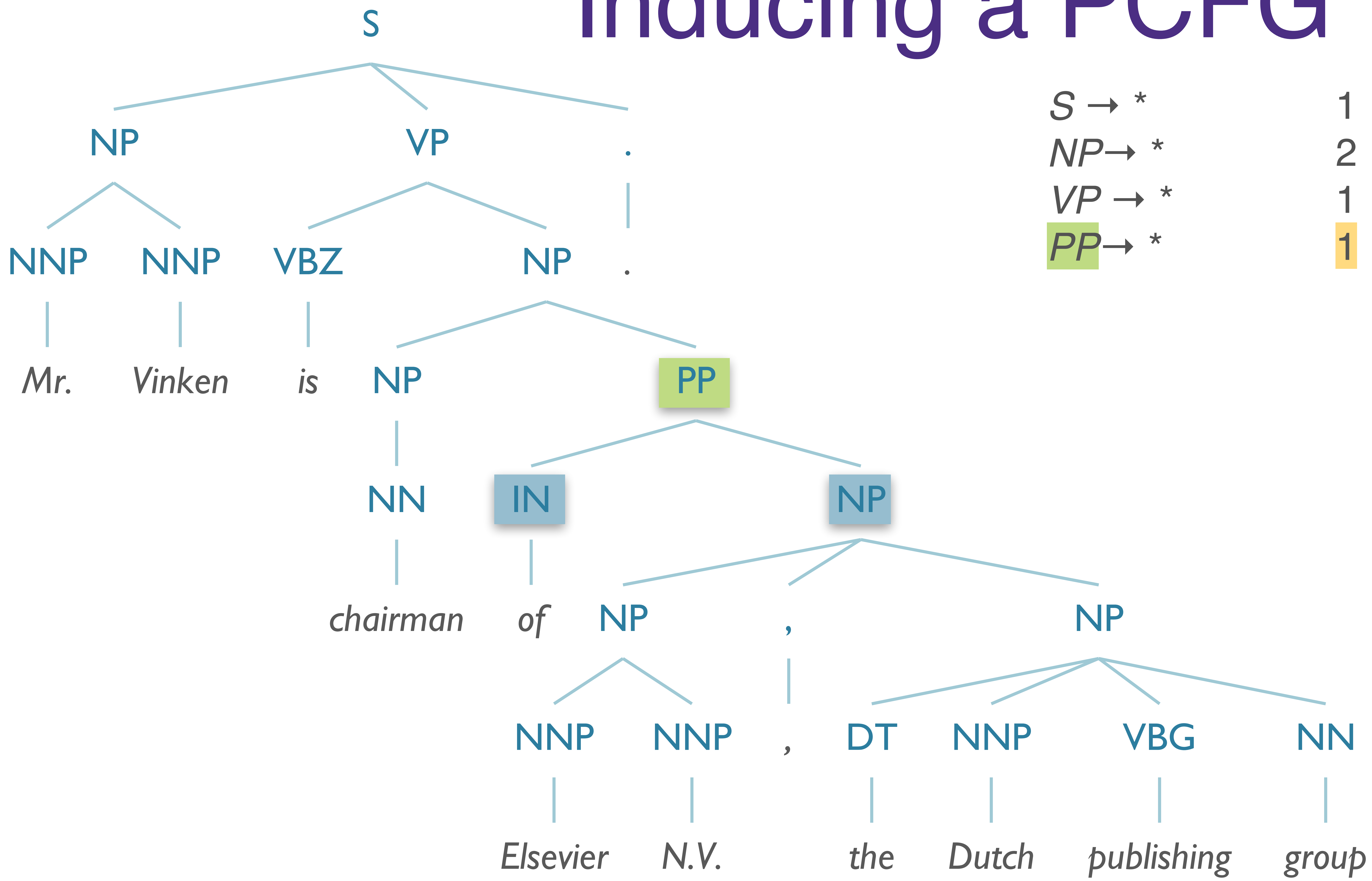

S → *	1	*S → NP VP .*	1
NP→ *	2	*NP → NNP NNP*	1
VP → *	1	*VP → VBZ NP*	1
PP→ *	1	*NP→ NP PP*	1
		PP→ IN NP	1

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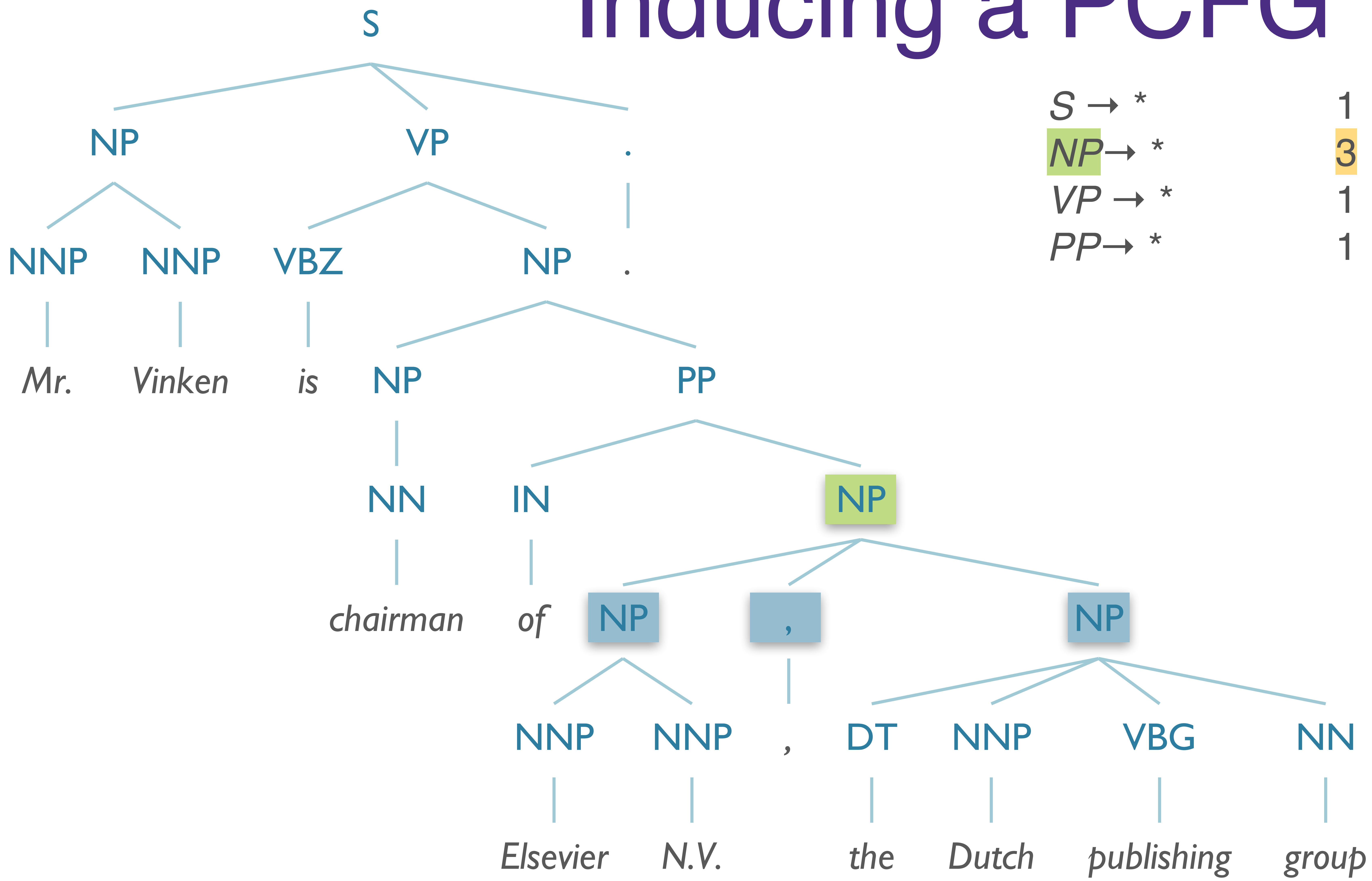

$S \rightarrow *$	1	$S \rightarrow NP\ VP\ .$	1
$NP \rightarrow *$	3	$NP \rightarrow NNP\ NNP$	1
$VP \rightarrow *$	1	$VP \rightarrow VBZ\ NP$	1
$PP \rightarrow *$	1	$NP \rightarrow NP\ PP$	1
		$PP \rightarrow IN\ NP$	1
		$NP \rightarrow NP\ ,\ NP$	1

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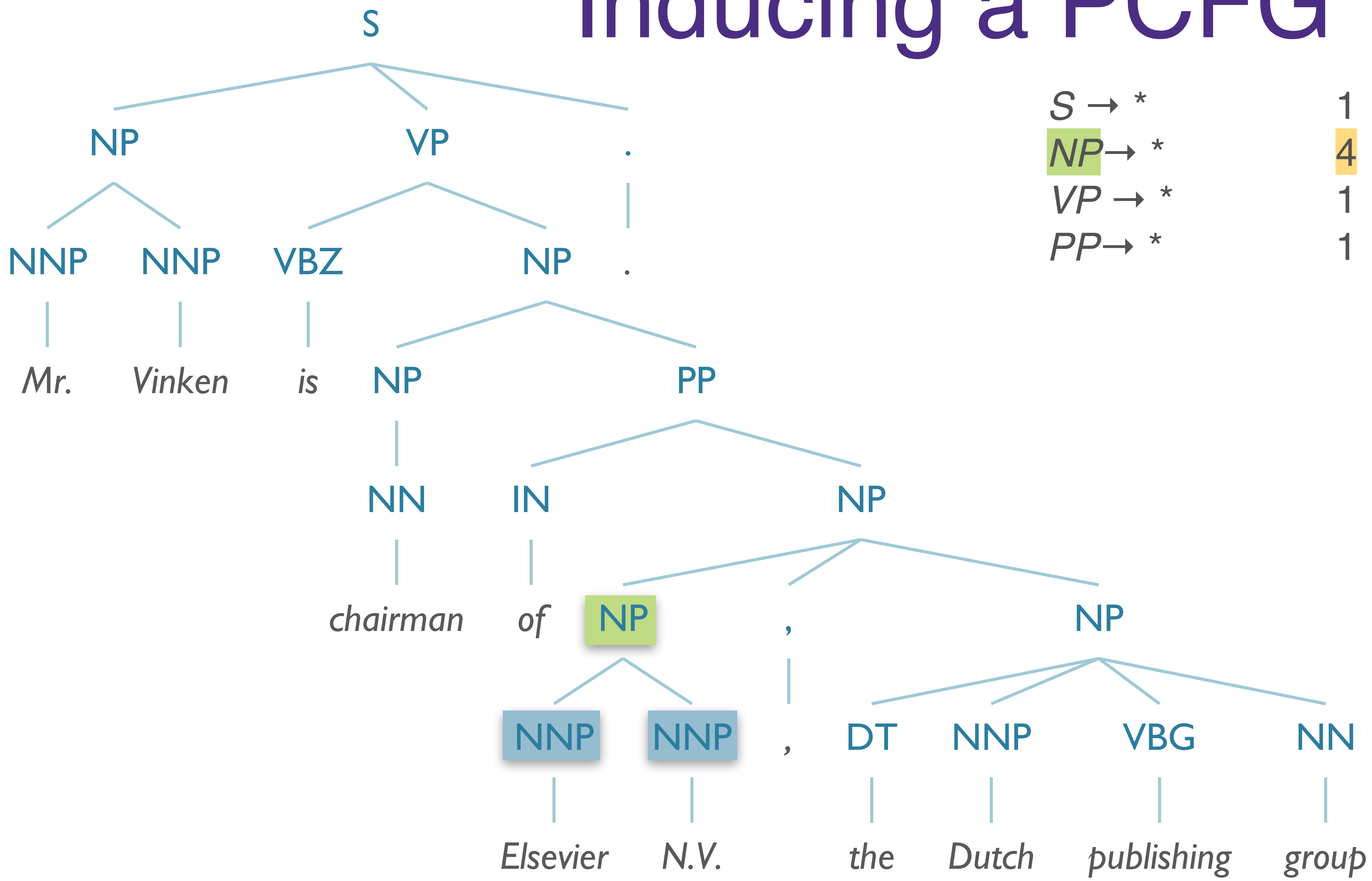

*S → **	1	*S → NP VP .*	1
*NP→ **	4	*NP→ NNP NNP*	2
*VP → **	1	*VP → VBZ NP*	1
*PP→ **	1	*NP→ NP PP*	1
		PP→ IN NP	1
		NP→ NP , NP	1

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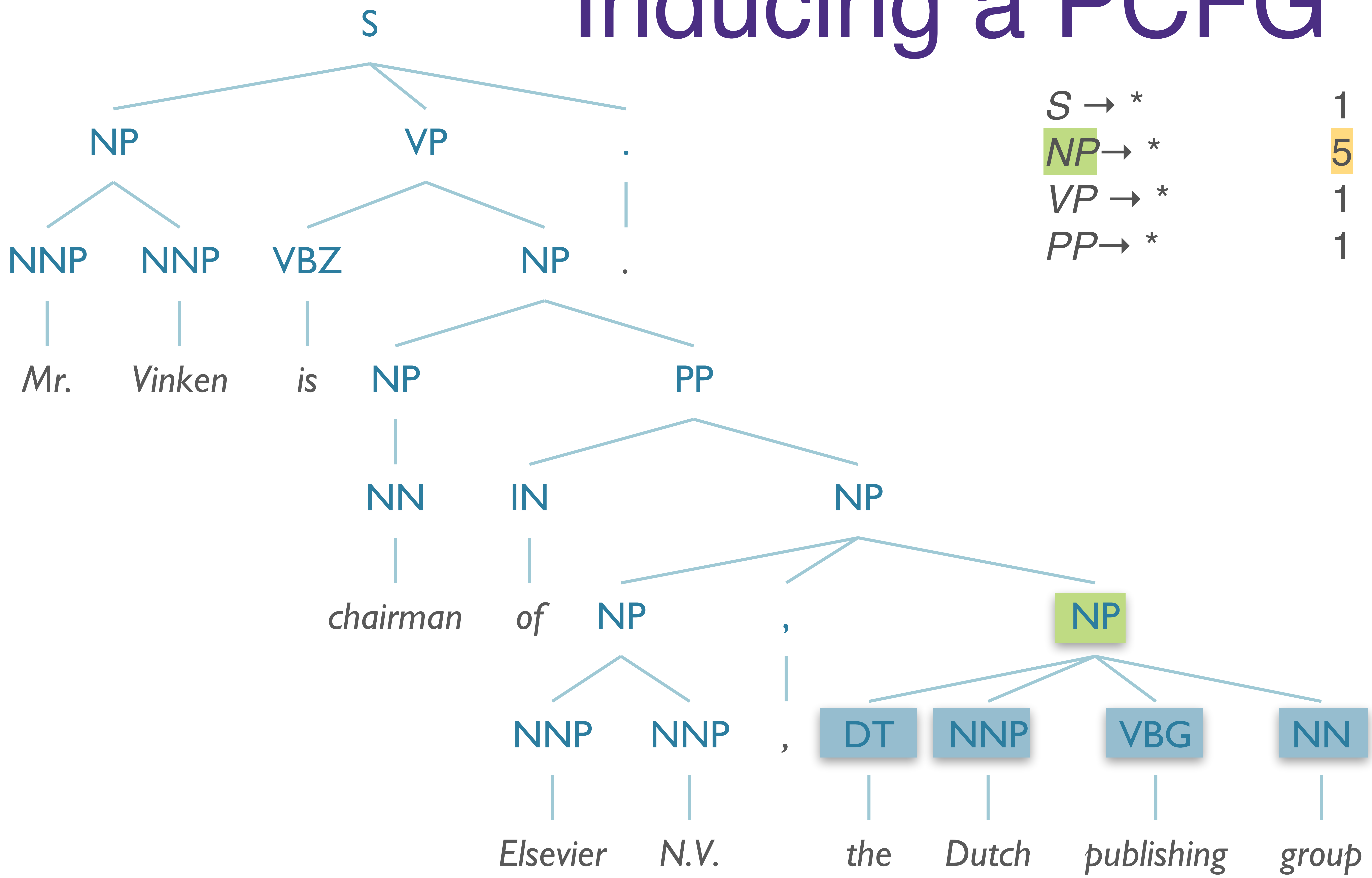

S → *	1	*S → NP VP .*	1
NP→ *	5	*NP→ NNP NNP*	2
VP → *	1	*VP → VBZ NP*	1
PP→ *	1	*NP→ NP PP*	1
		PP→ IN NP	1
		NP→ NP , NP	1
		NP→ DT NNP VBG NN	1

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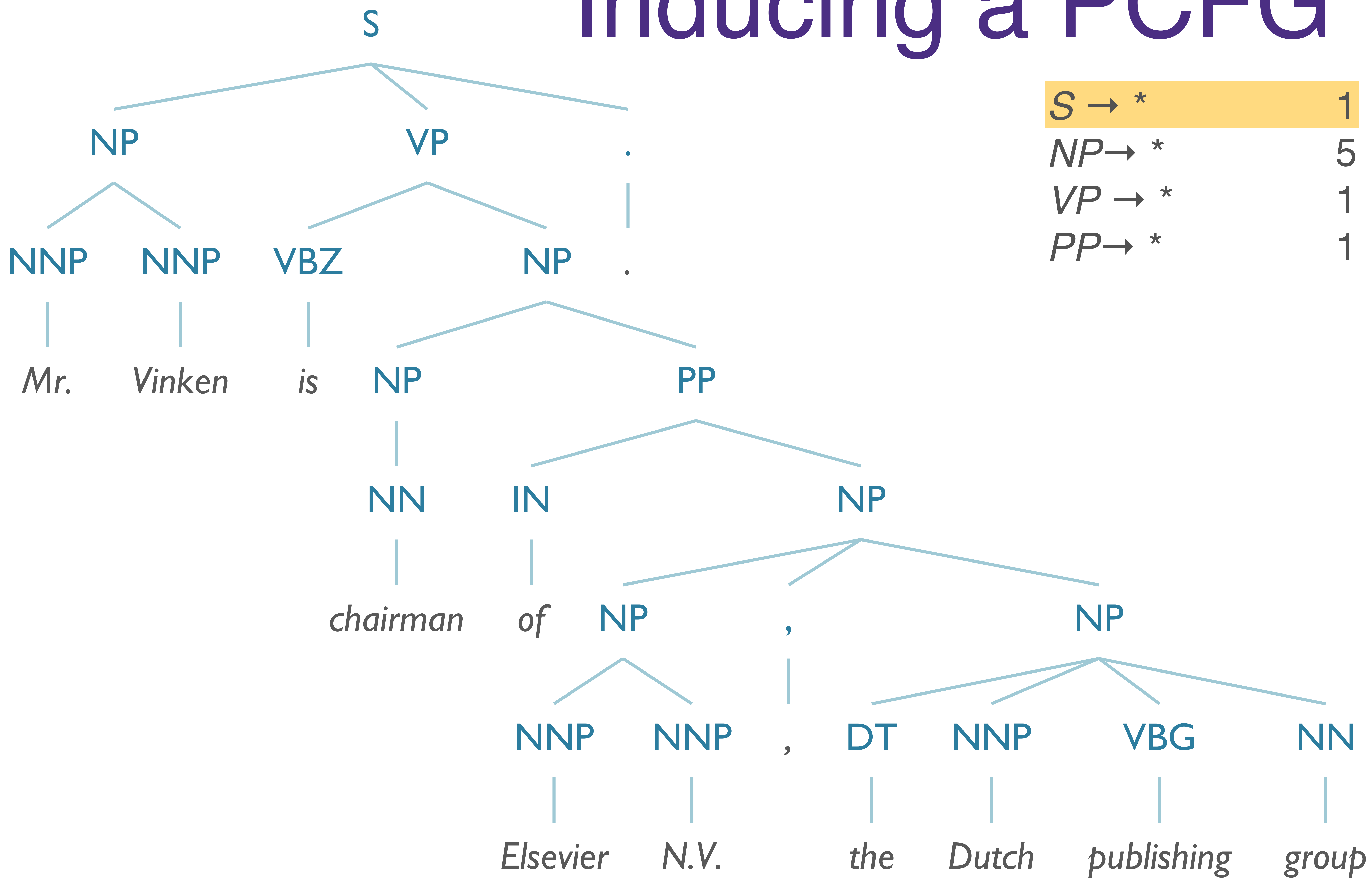

*S → **	1
*NP→ **	5
*VP → **	1
*PP→ **	1

S → NP VP .	1
NP→ NNP NNP	2
VP → VBZ NP	1
NP→ NP PP	1
PP→ IN NP	1
NP→ NP , NP	1
NP→ DT NNP VBG NN	1

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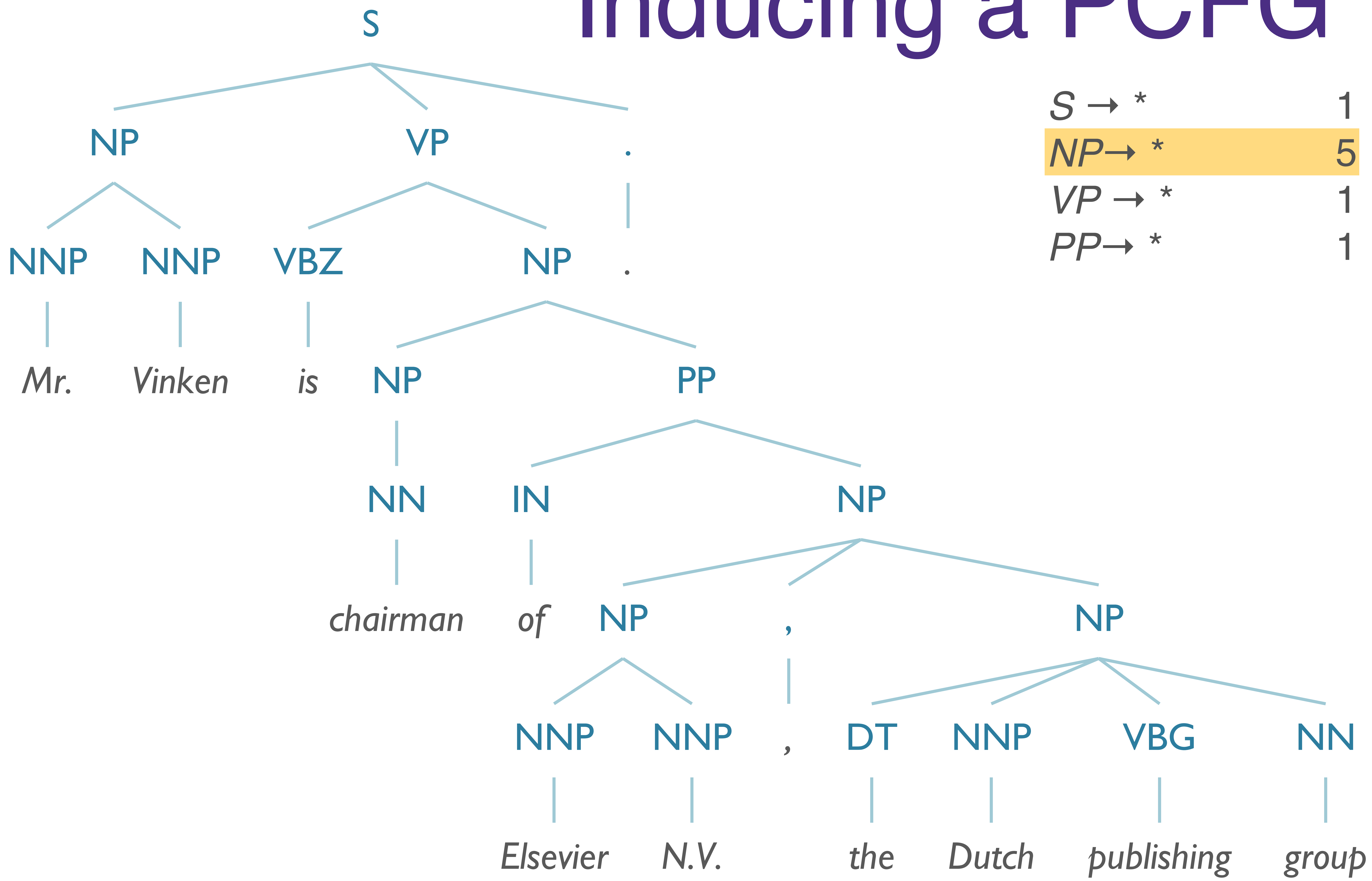

S → *	1	*S → NP VP .*	1
NP→ *	5	*NP→ NNP NNP*	2/5
VP → *	1	*VP → VBZ NP*	1
PP→ *	1	*NP→ NP PP*	1/5
		PP→ IN NP	1
		NP→ NP , NP	1/5
		NP→ DT NNP VBG NN	1/5

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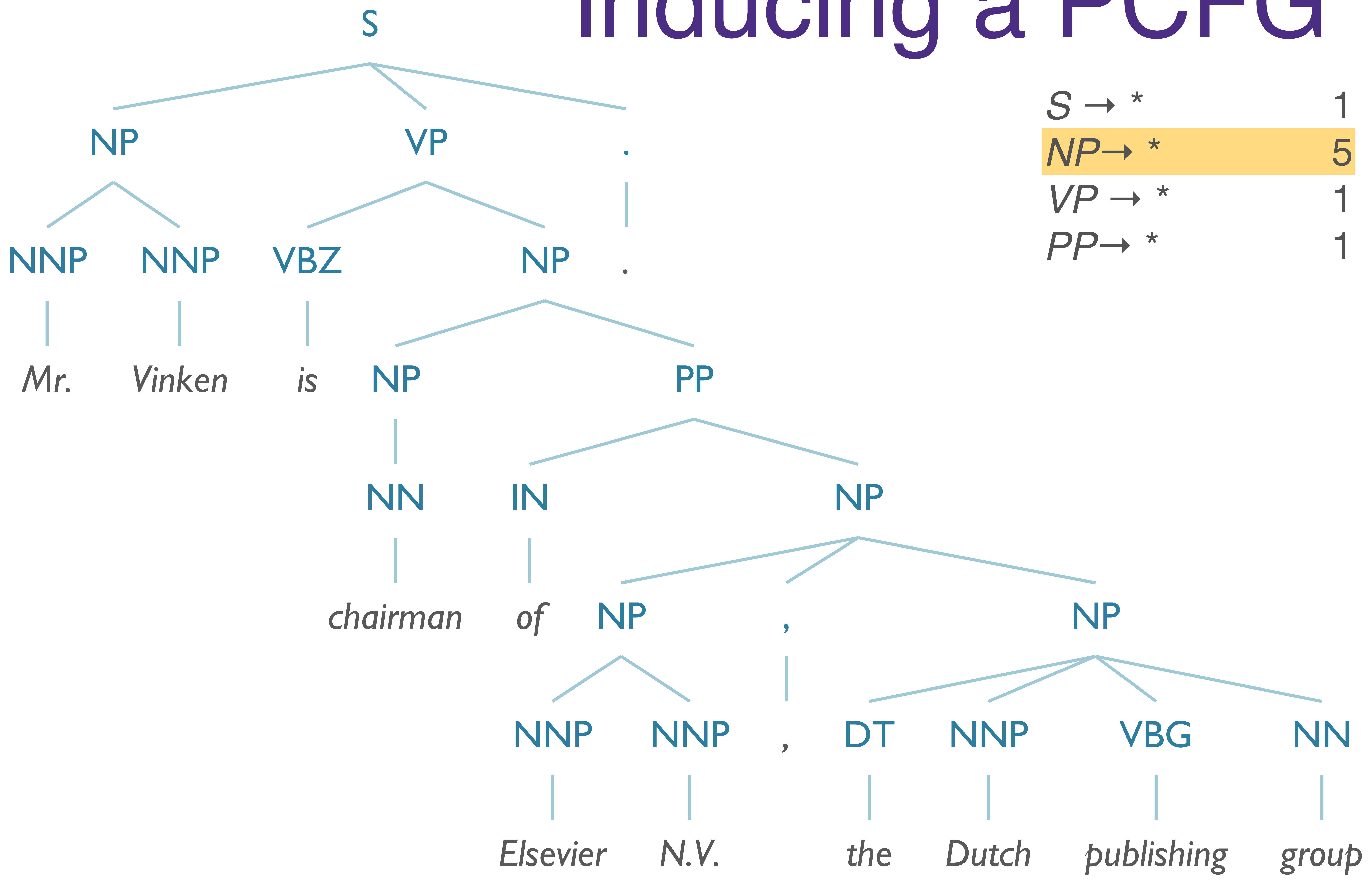

S → *	1
NP→ *	5
VP → *	1
PP→ *	1

S → NP VP .	1
NP→ NNP NNP	0.4
VP → VBZ NP	1
NP→ NP PP	0.2
PP→ IN NP	1
NP→ NP , NP	0.2
NP→ DT NNP VBG NN	0.2

Problems with PCFGs

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- Independence Assumption
  - Assume that rule probabilities are independent

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- Lack of Lexical Conditioning
  - Lexical items should influence the choice of analysis

Issues with PCFGs: Independence Assumption

- *Context Free ⇒ Independence Assumption*
  - Rule expansion is context-independent
  - Allows us to multiply probabilities

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Semantic Role of **NPs** in Switchboard Corpus

	Pronomial	**Non-Pronomial**
Subject	91%	9%
Object	34%	66%

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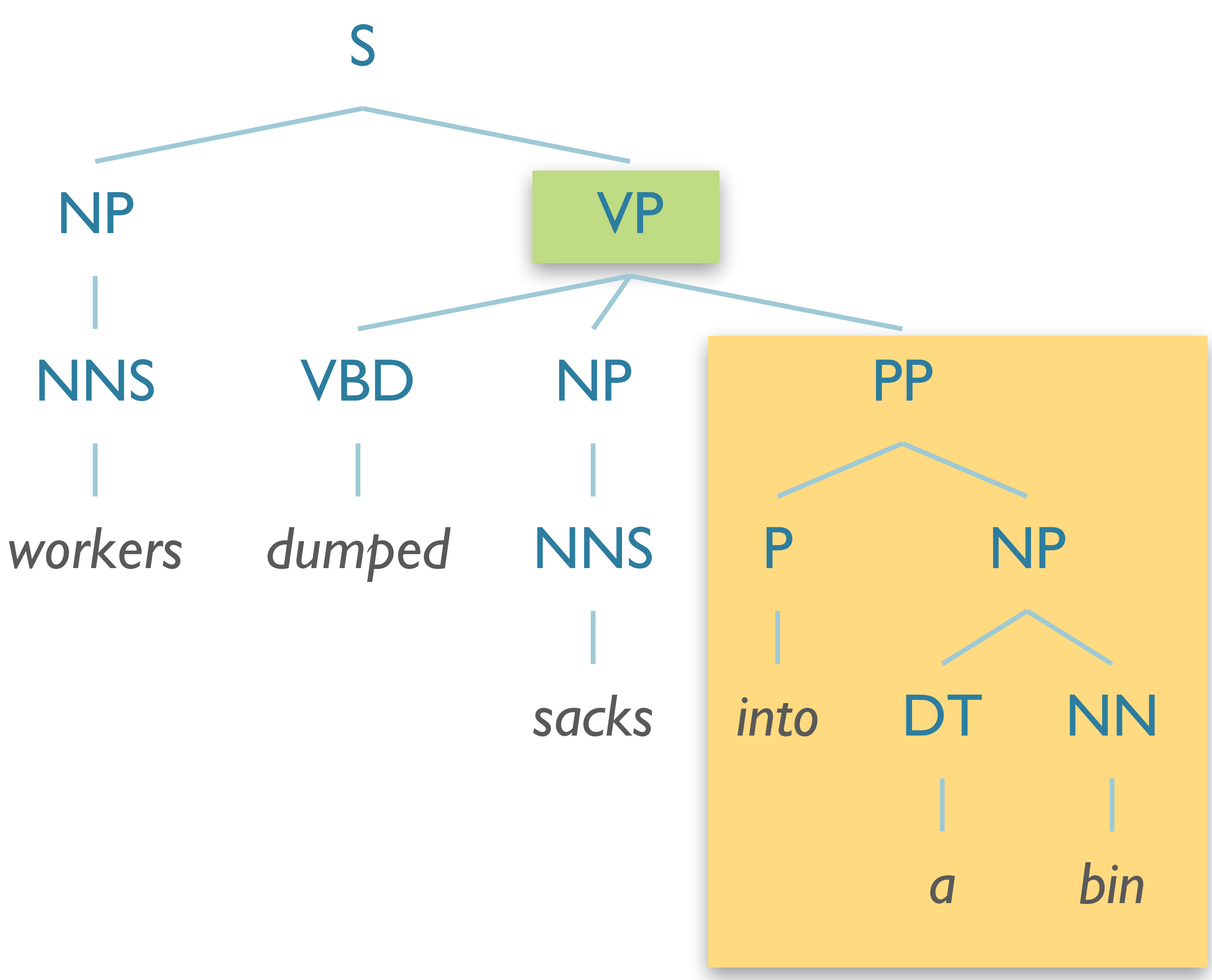
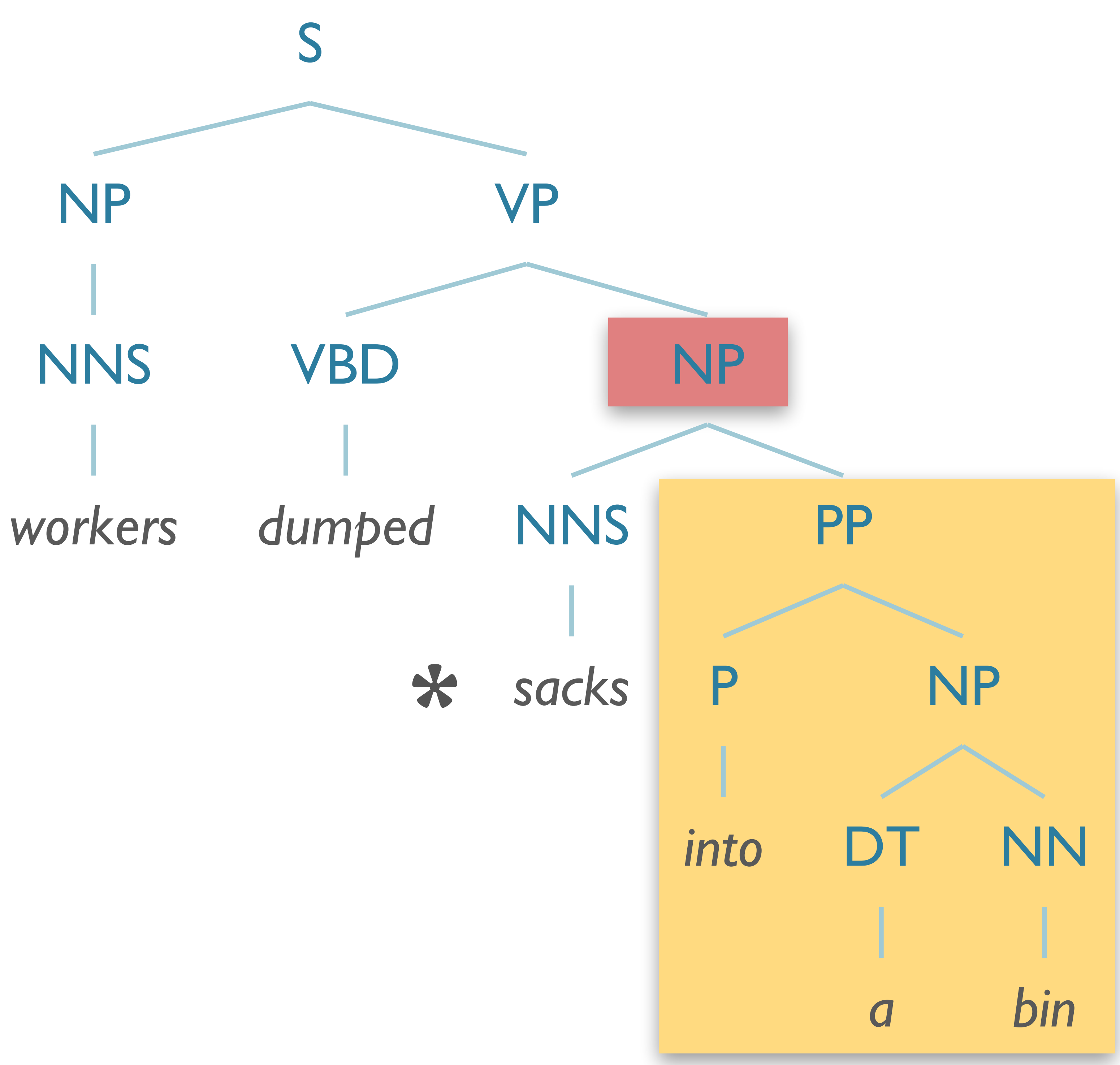
…Can try **parent annotation**

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

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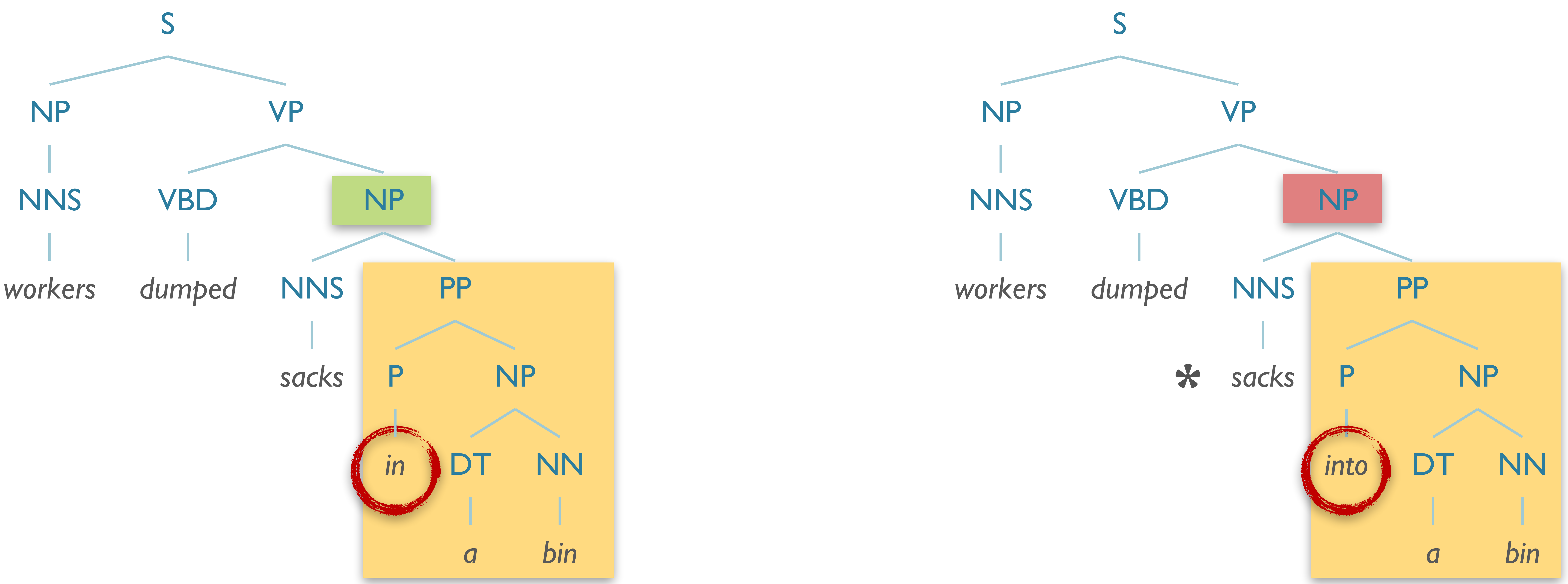

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OK!

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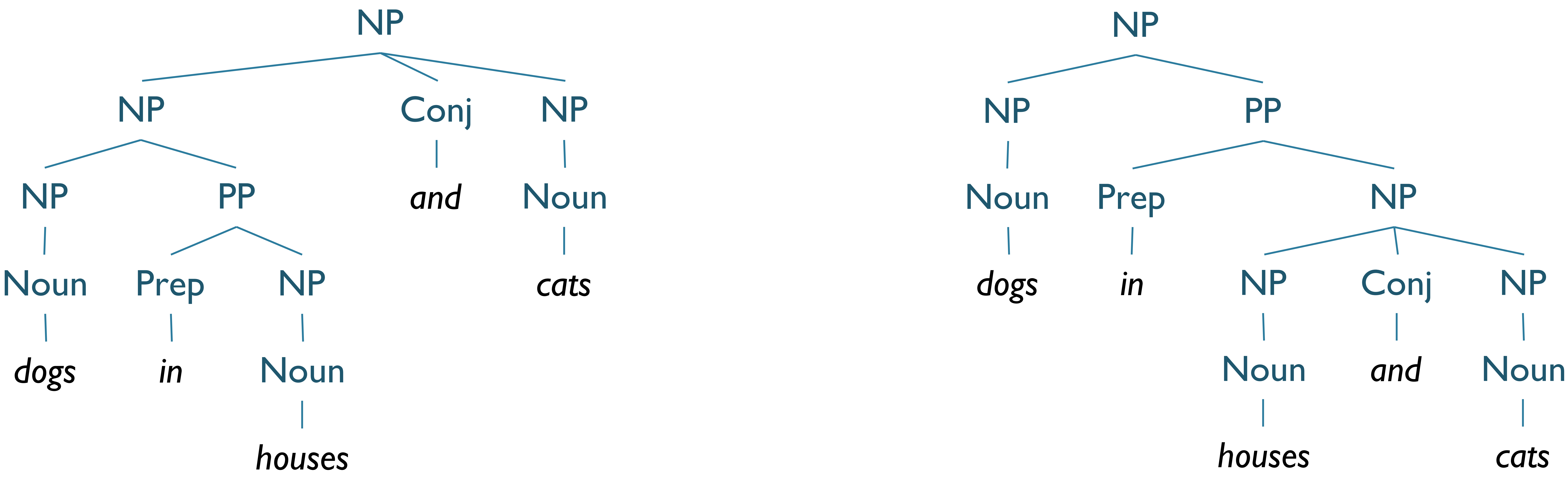
not OK

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



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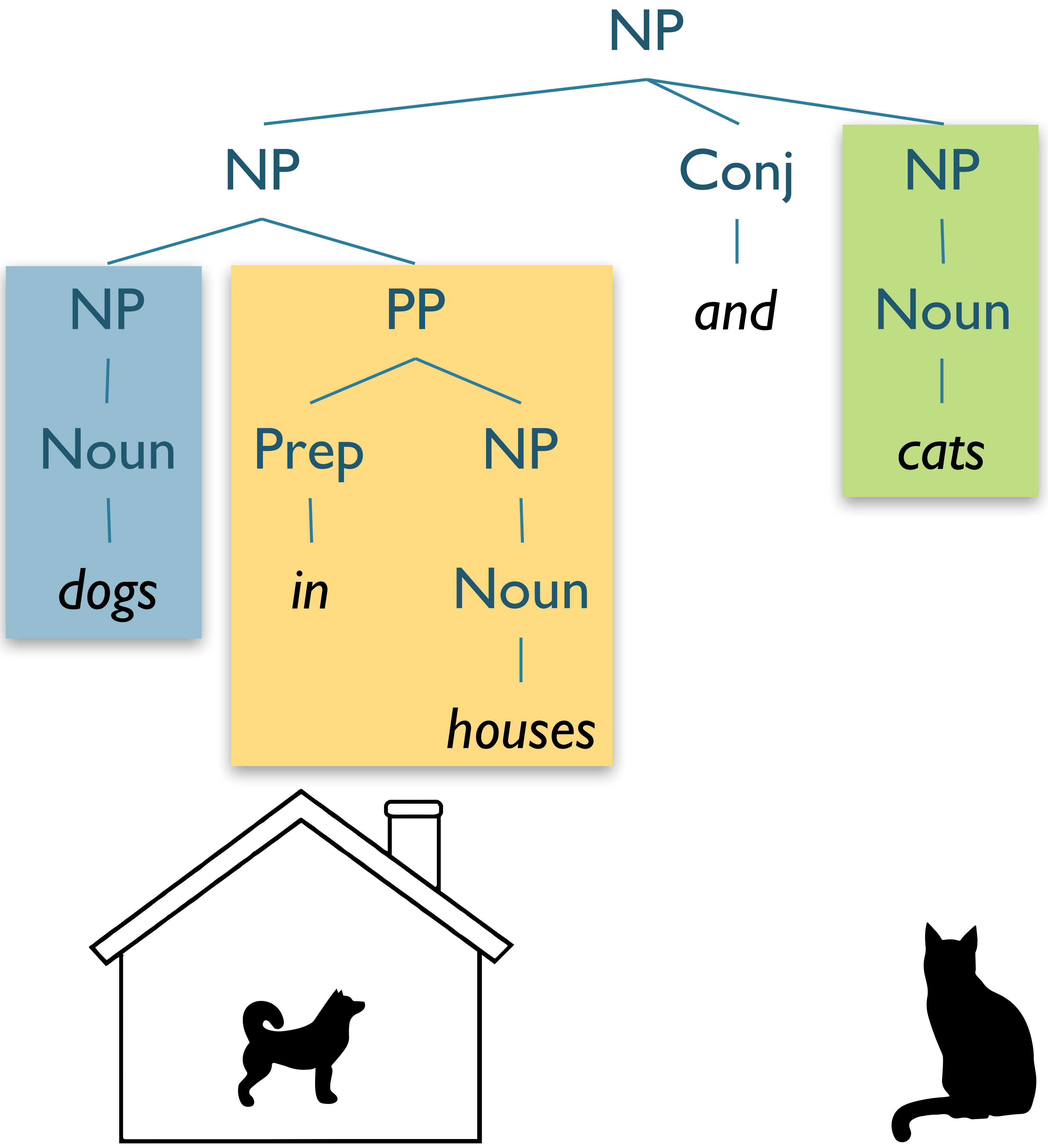

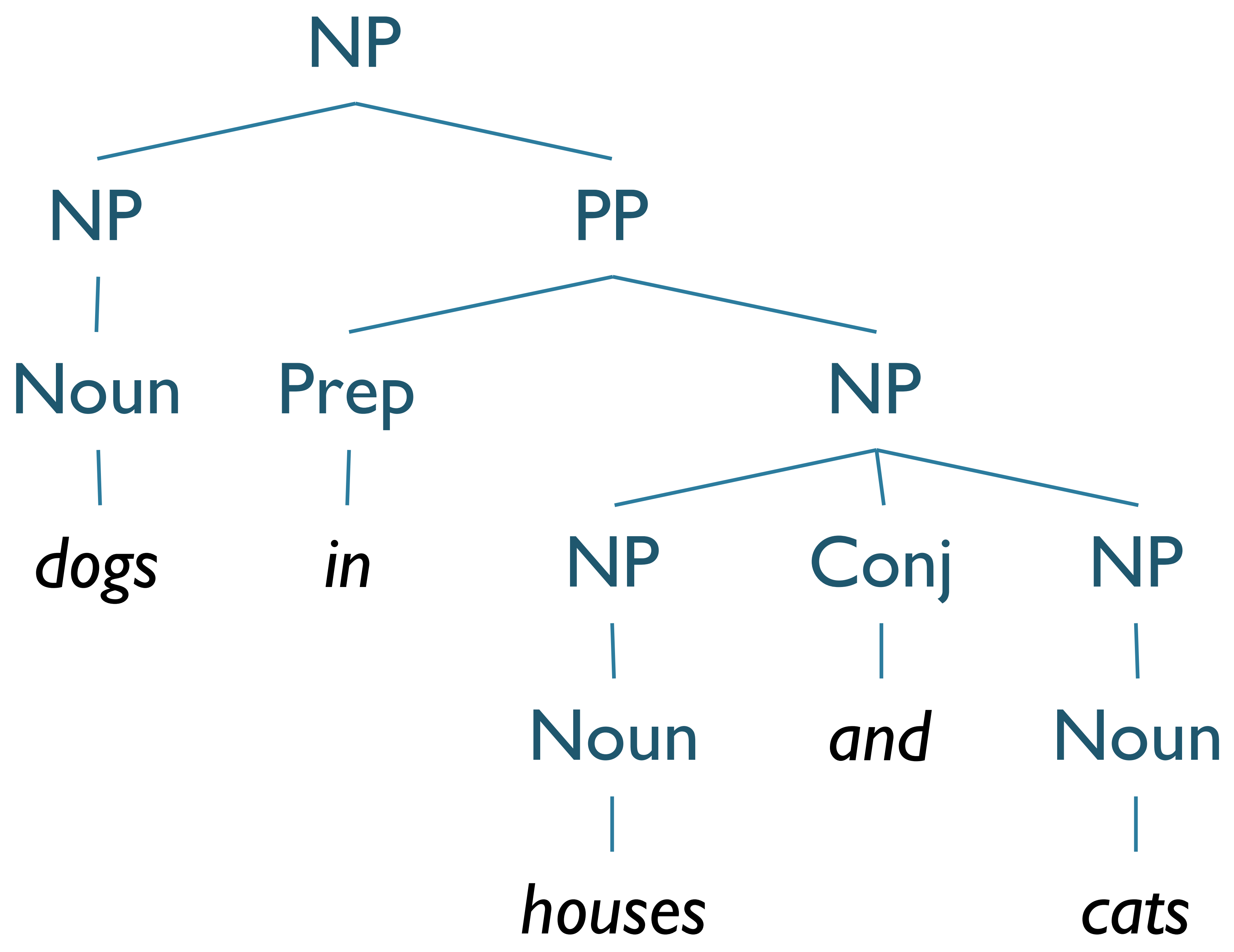

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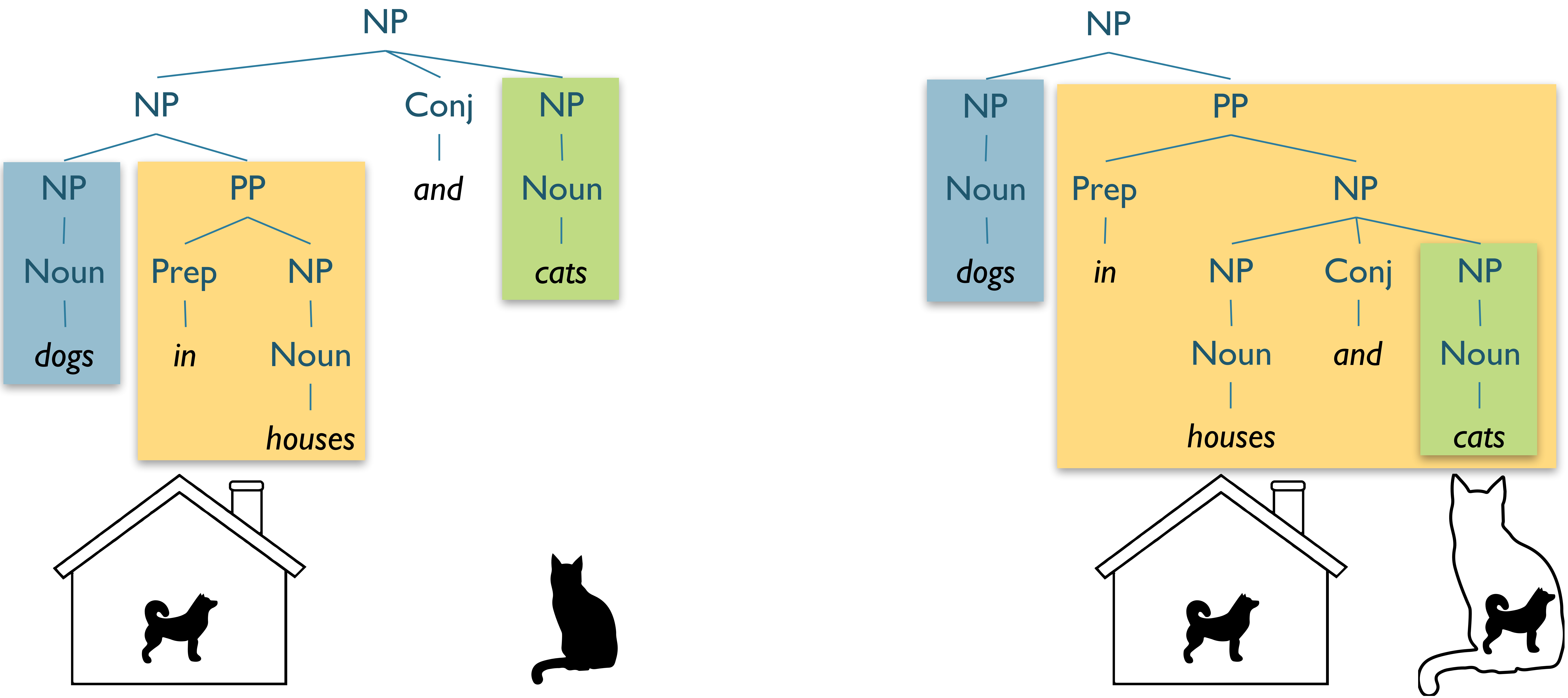

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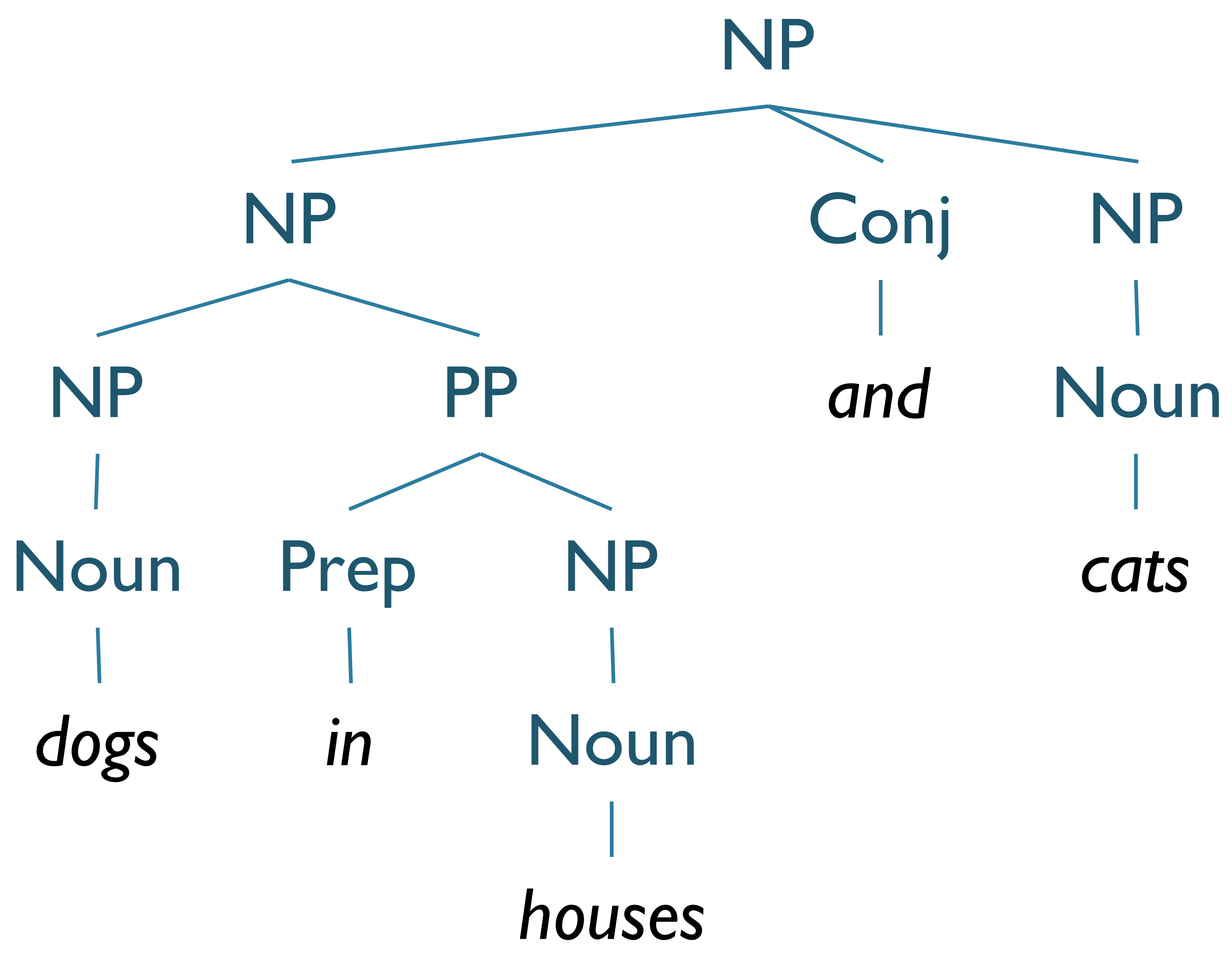

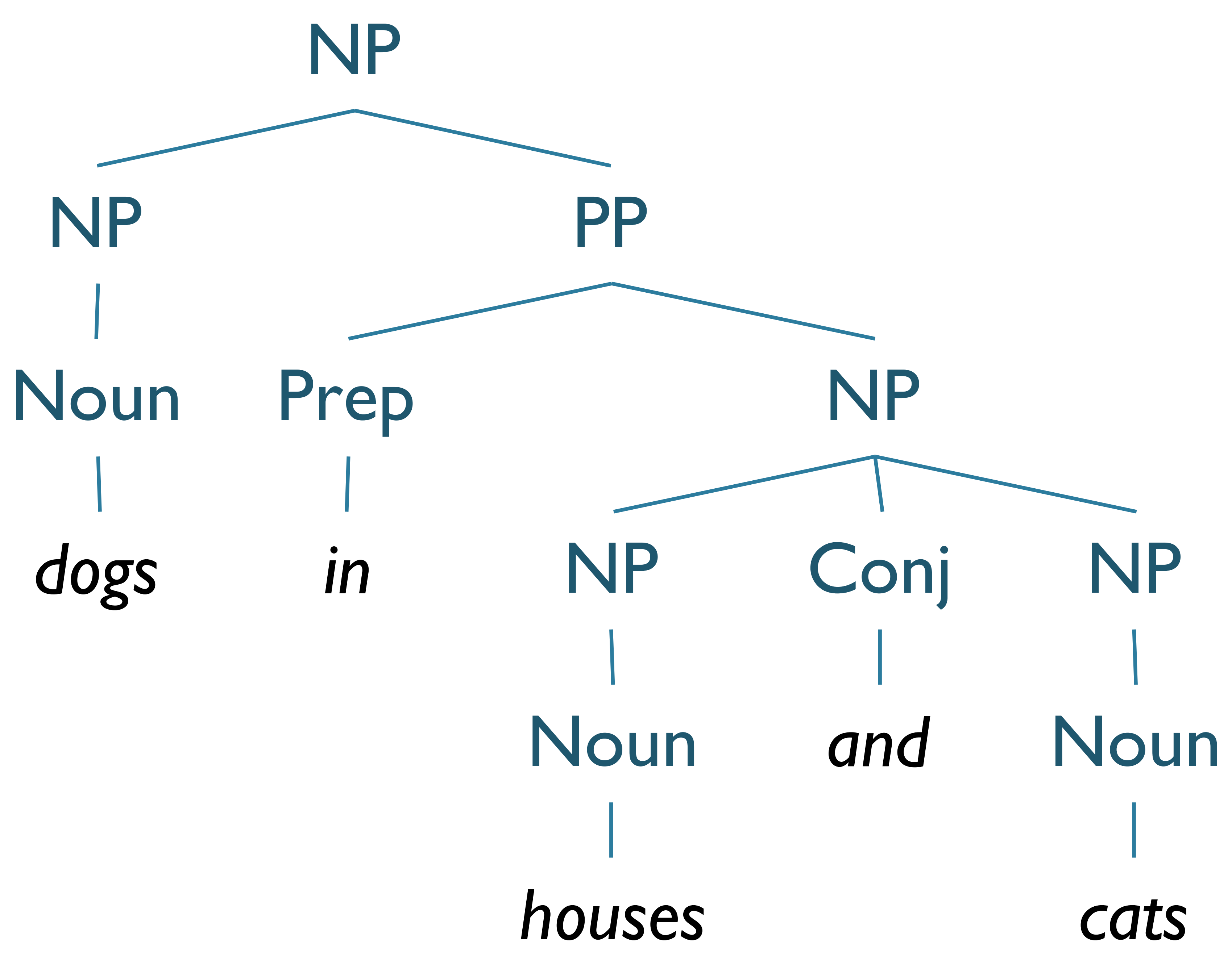

NP → NP Conj NP
NP → NP PP
Noun → "dogs"
PP → Prep NP
Prep → "in"
NP → Noun
Noun → "houses"
Conj → "and"
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Same Rules!

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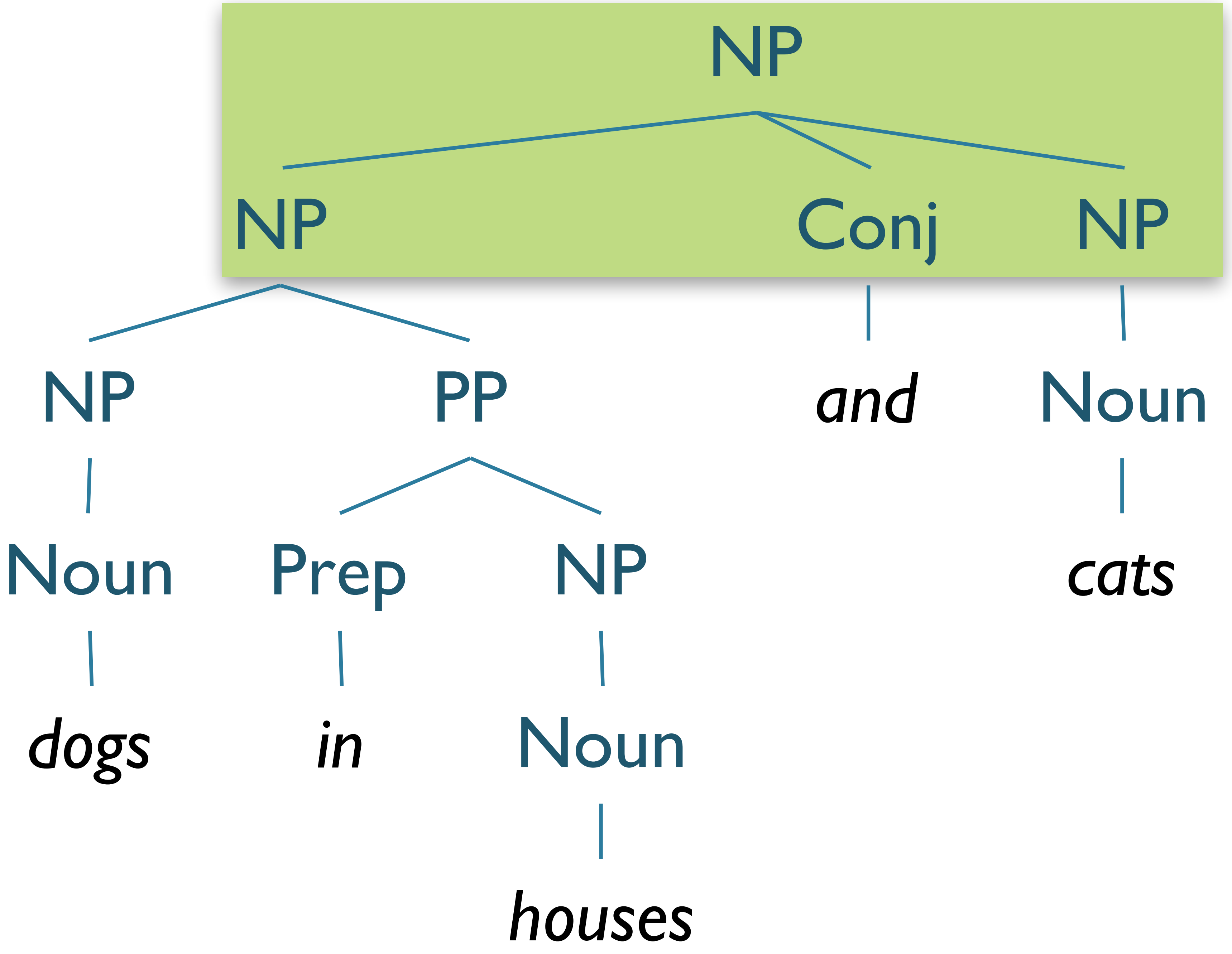

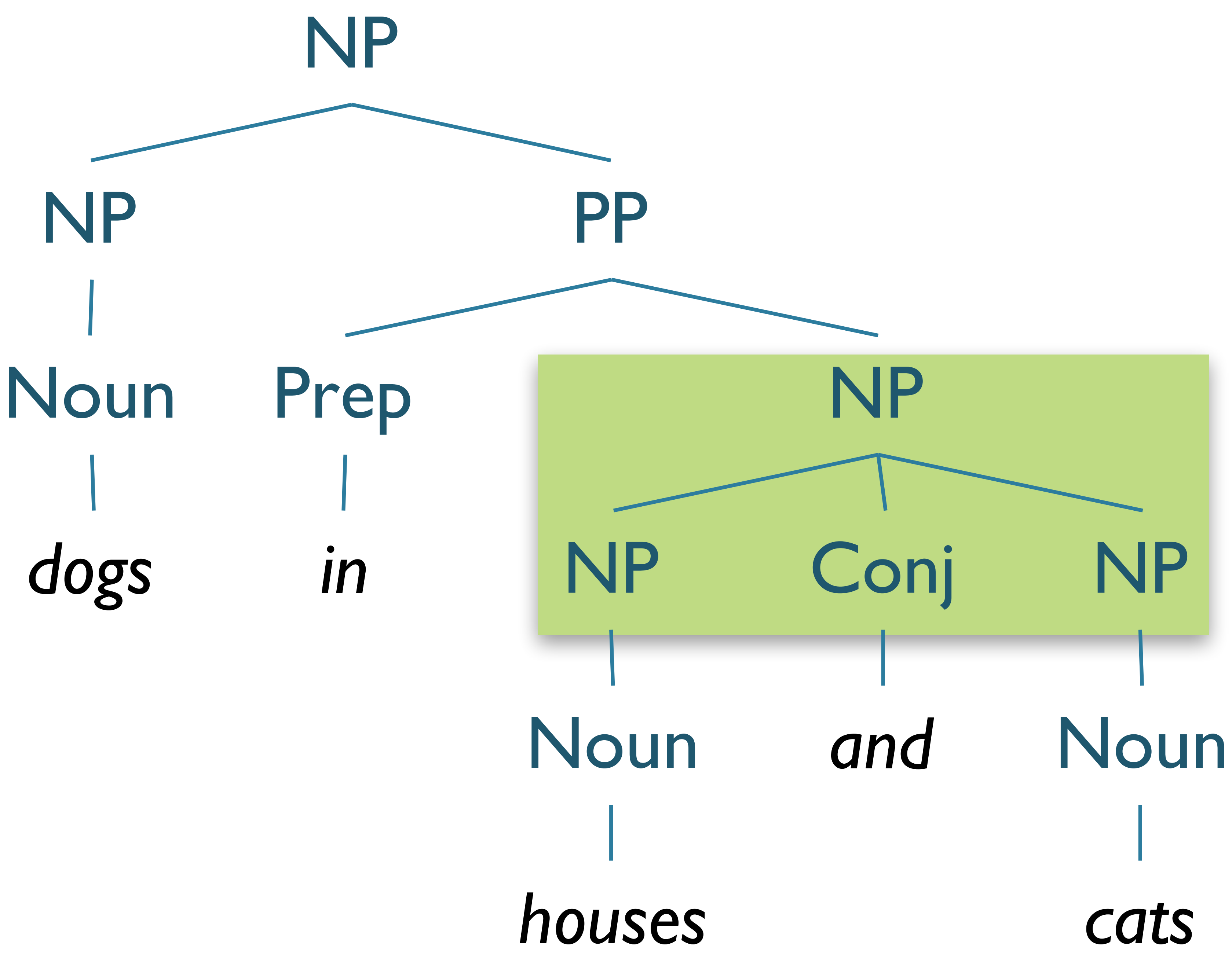

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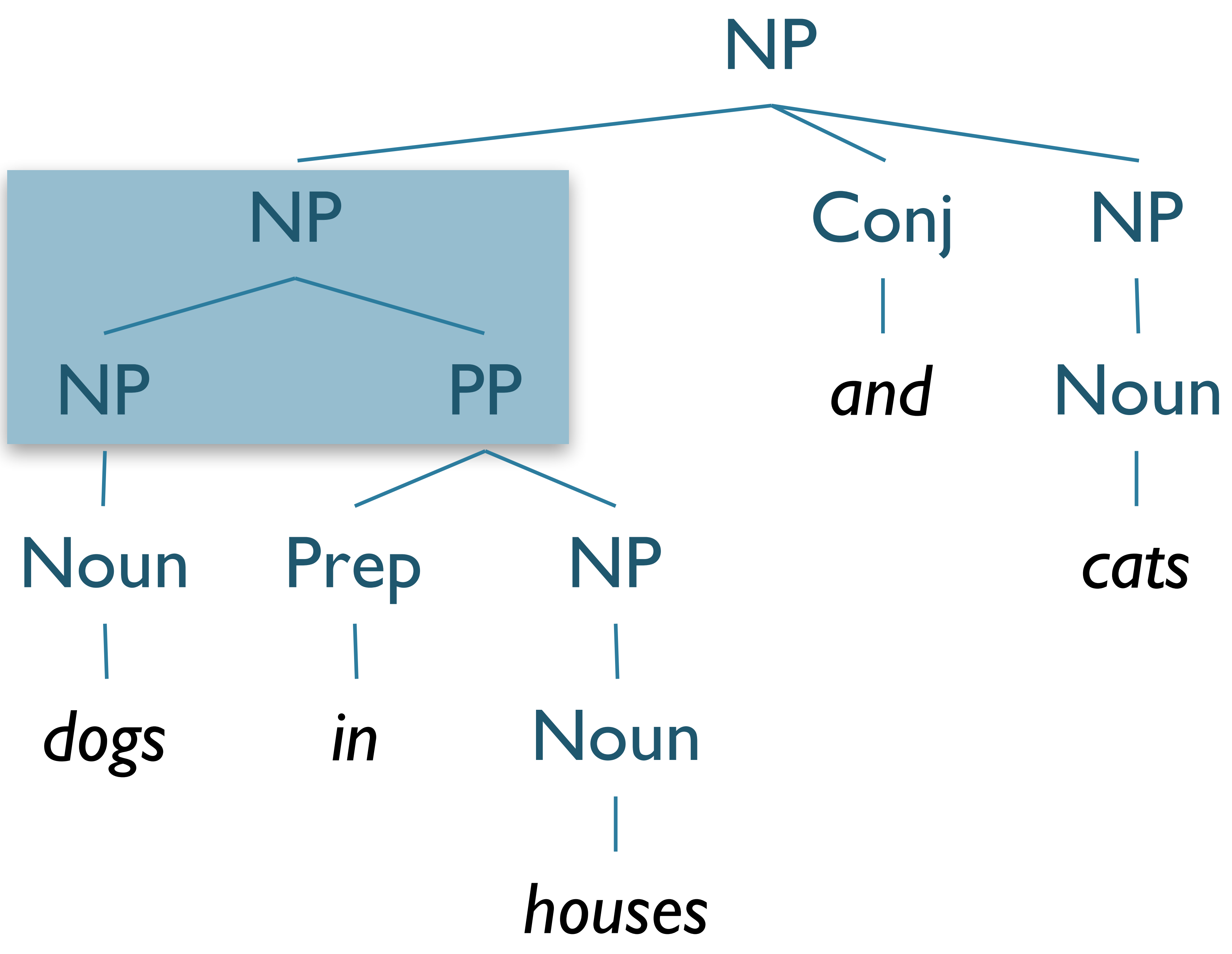

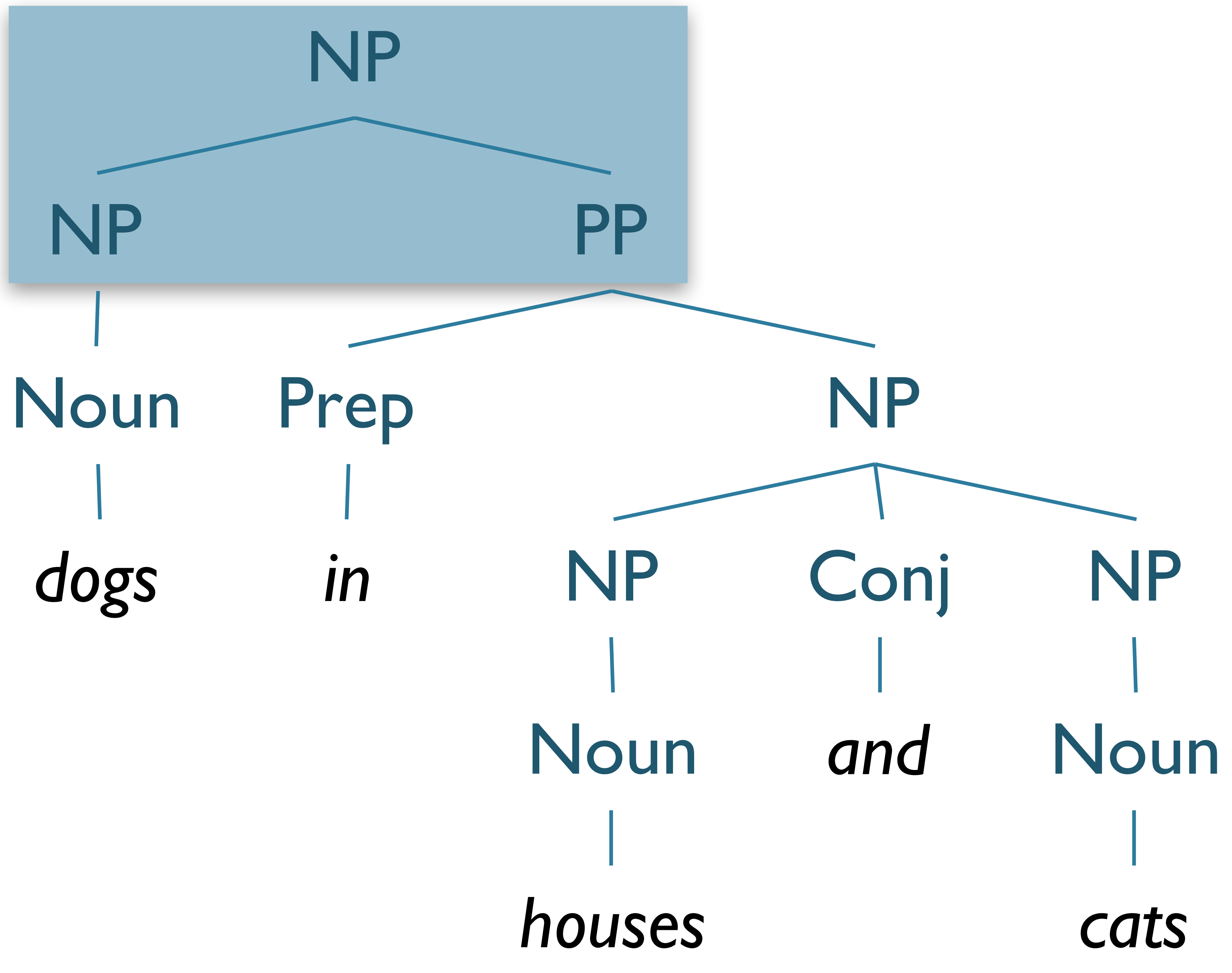

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Improving PCFGs

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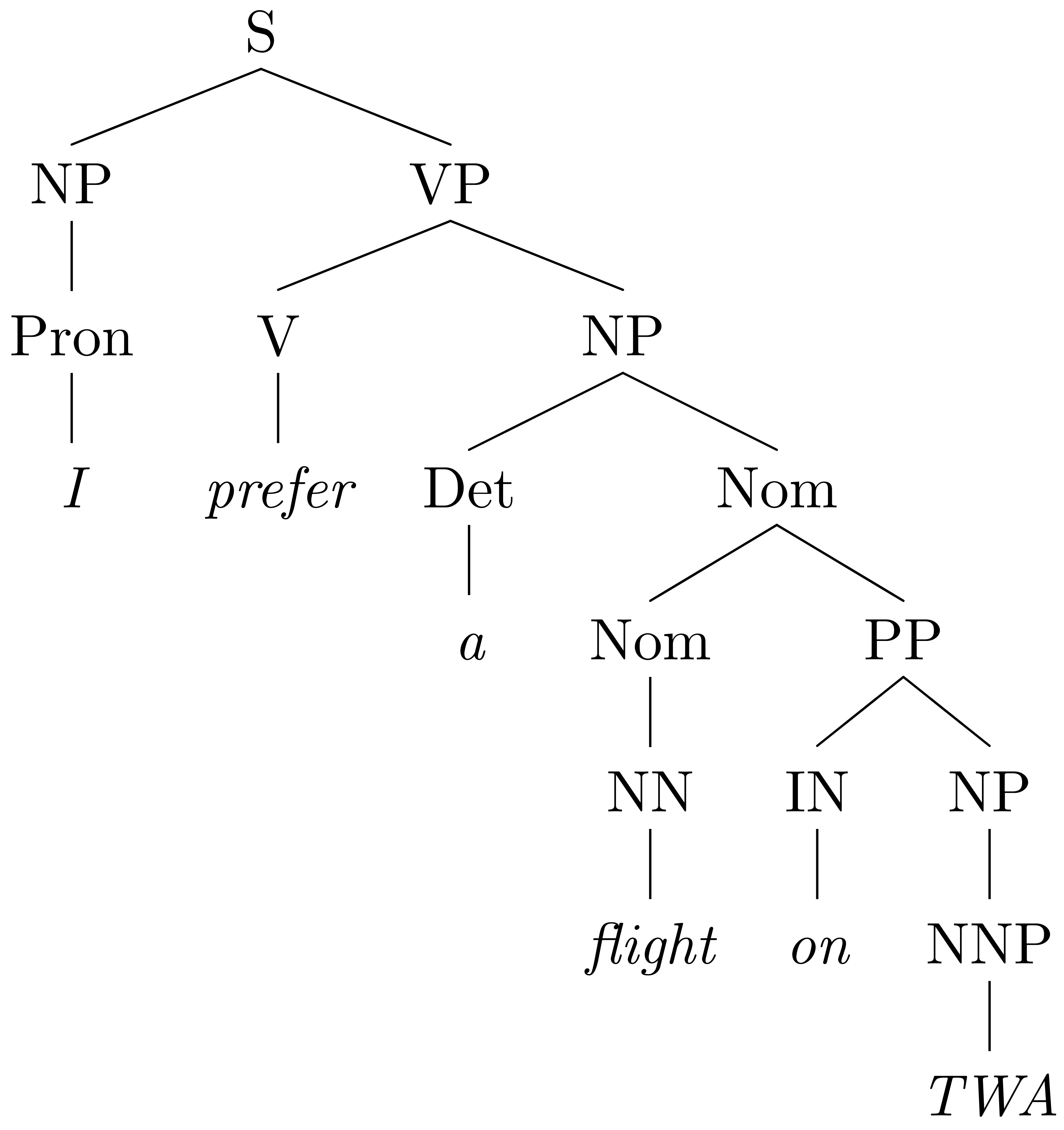
- **Parent Annotation**
- Lexicalization
- Markovization
- Reranking

Improving PCFGs: Parent Annotation

- To handle the $NP \rightarrow PRP$ $[0.91$ **if** $NP_{\Theta=subject}$ **else** $0.34]$



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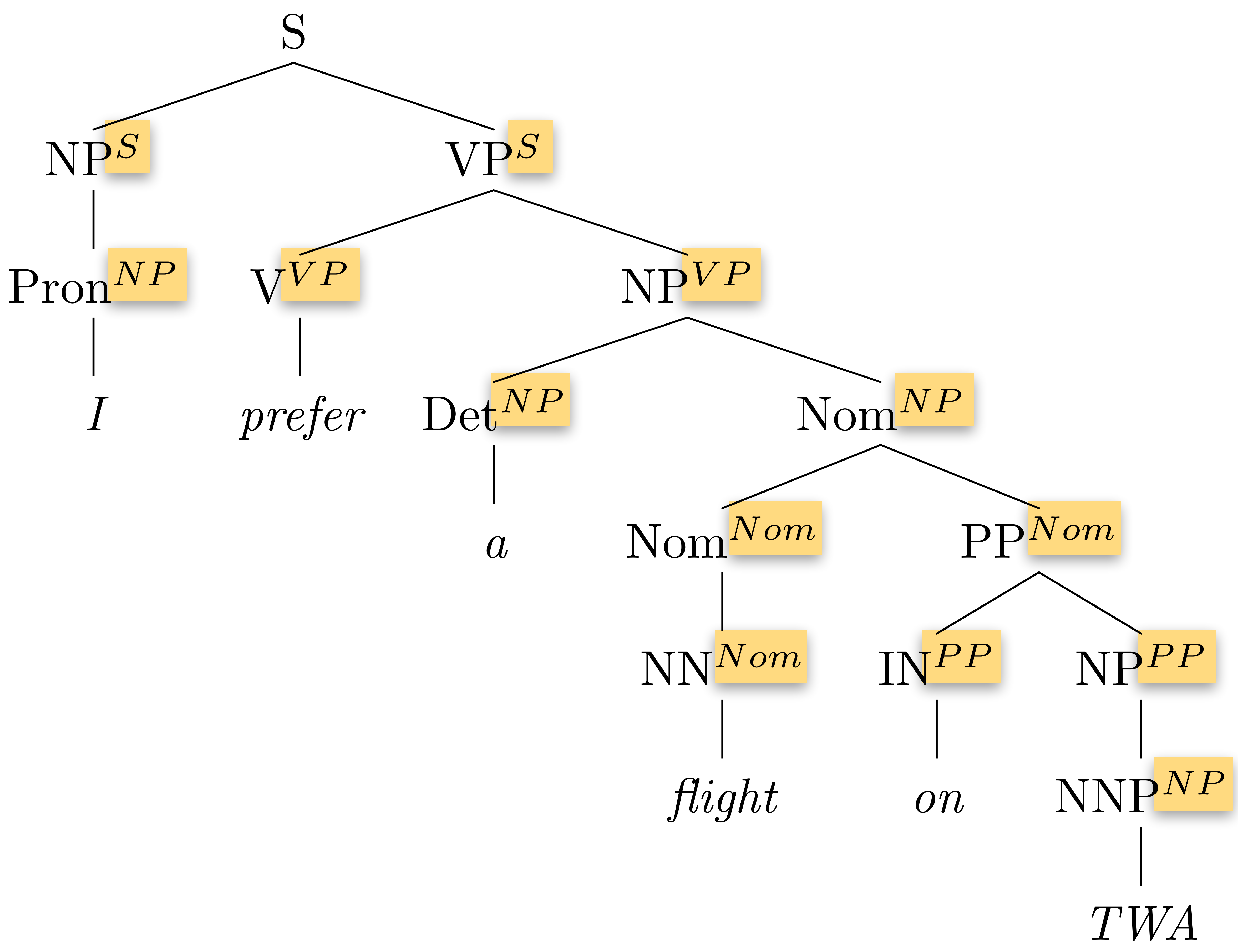

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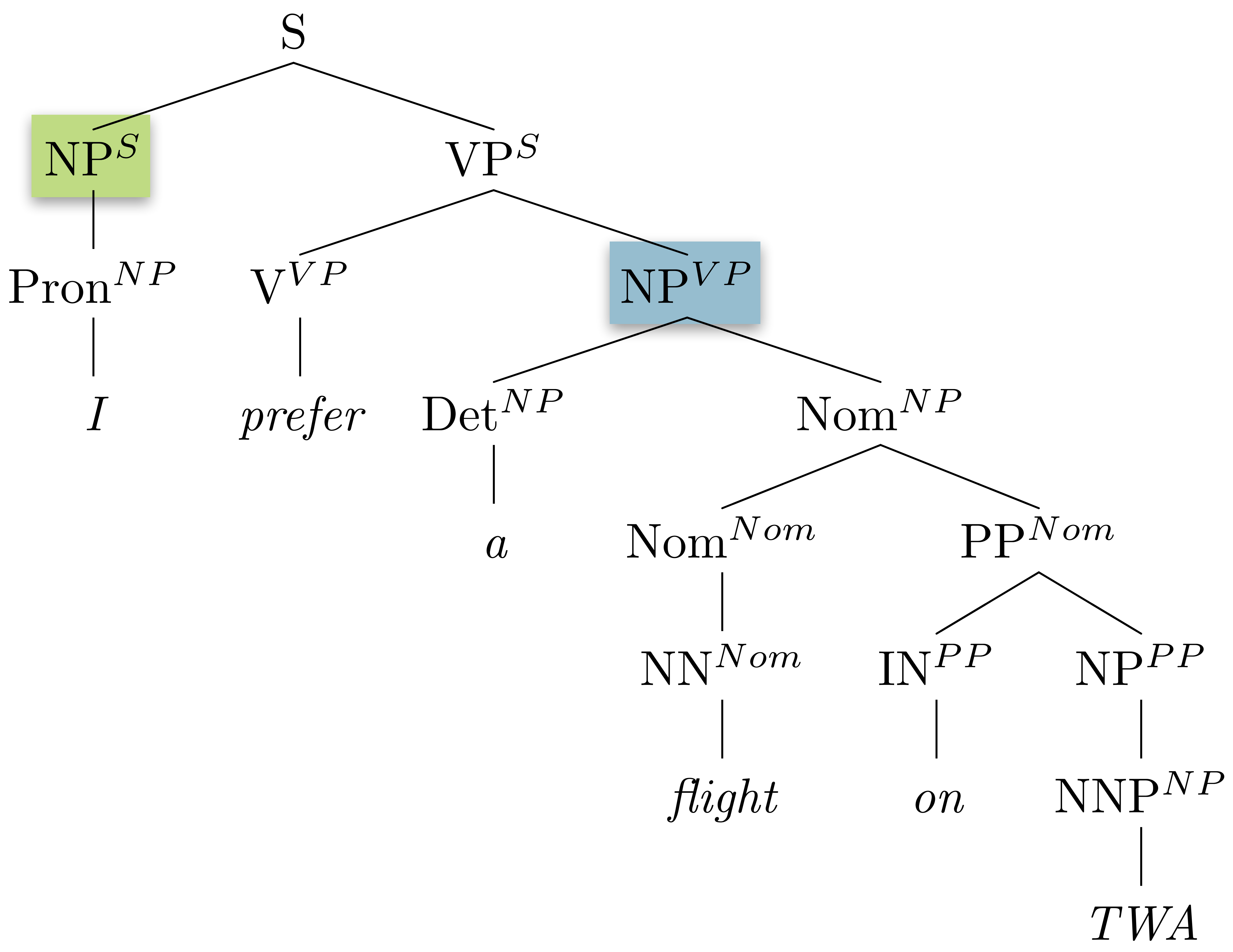

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- Advantages:
  - Captures structural dependencies in grammar
- Disadvantages:
  - Explodes number of rules in grammar
    - Same problem with subcategorization
  - Results in sparsity problems
- Strategies to find an optimal number of splits
  - Petrov 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

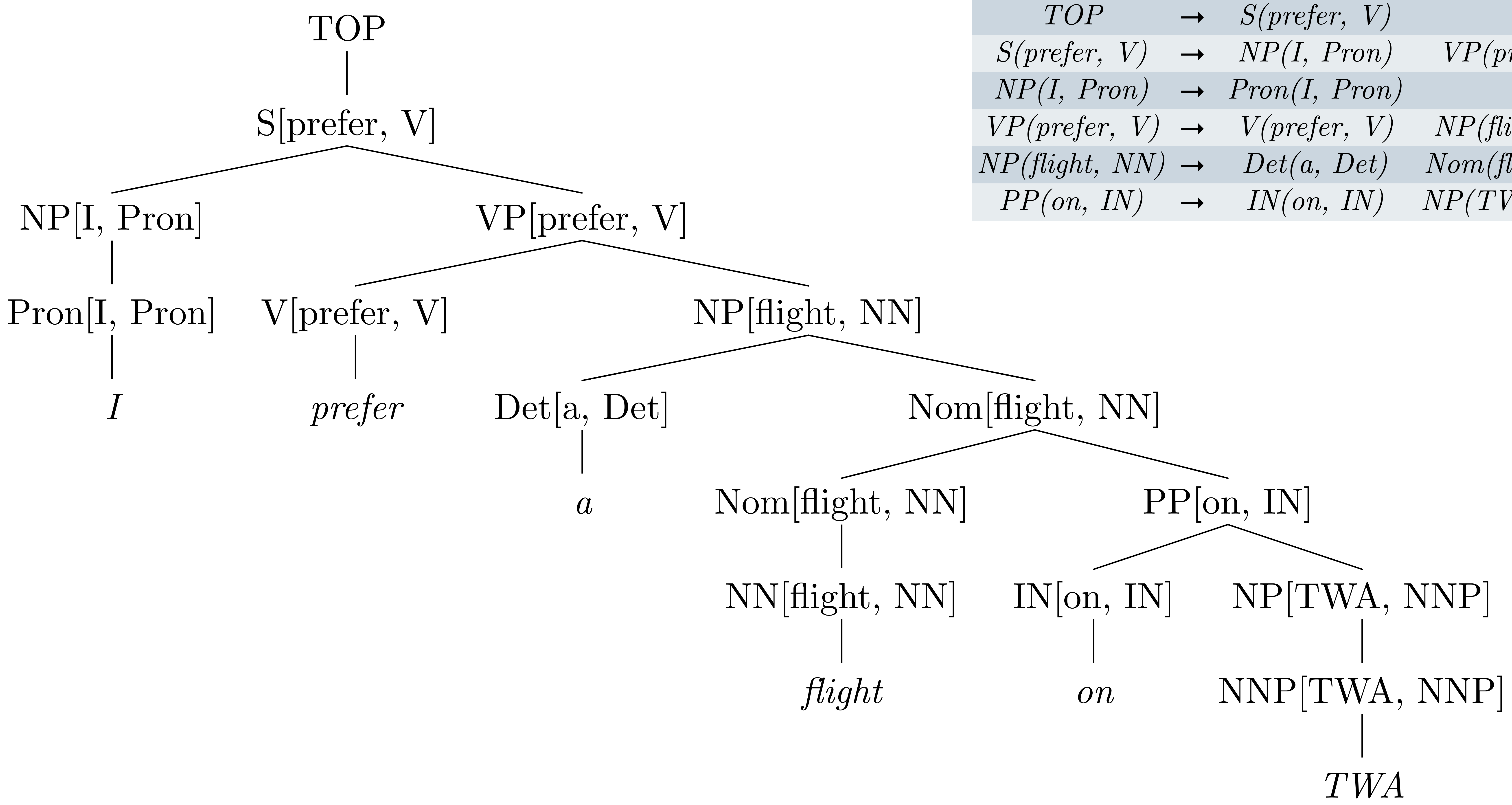
$$VP \rightarrow VBD\ NP\ PP$$

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

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

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

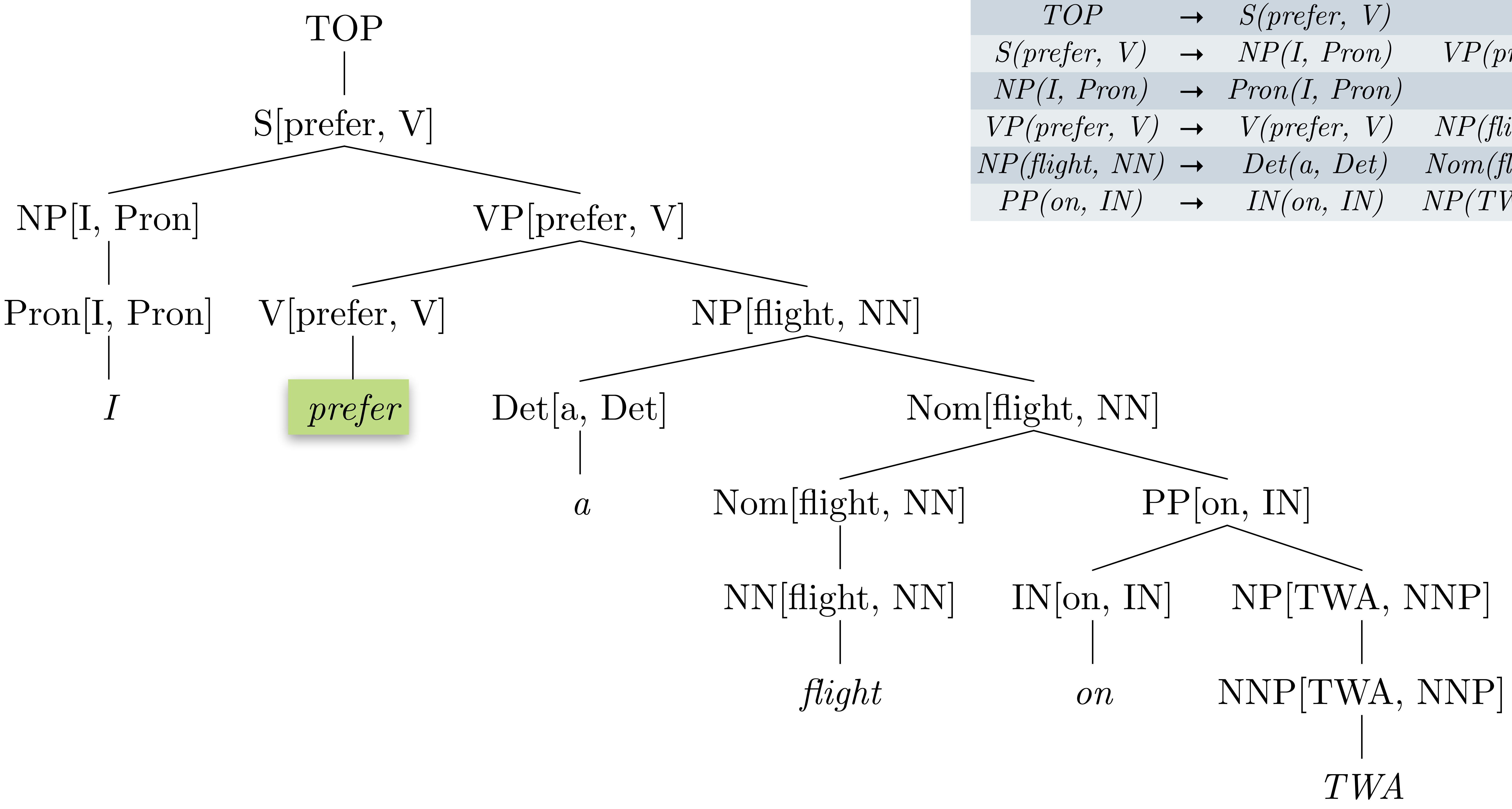
Lexicalized Parse Tree



Internal Rules			
TOP	→	*S(prefer, V)*	
S(prefer, V)	→	*NP(I, Pron)*	*VP(prefer, V)*
NP(I, Pron)	→	*Pron(I, Pron)*	
VP(prefer, V)	→	*V(prefer, V)*	*NP(flight, NN)*
NP(flight, NN)	→	*Det(a, Det)*	*Nom(flight, NN)*
PP(on, IN)	→	*IN(on, IN)*	*NP(TWA, NNP)*

Lexical Rules		
Pron(I, Pron)	→	I
V(prefer, V)	→	prefer
Det(a, Det)	→	a
NN(flight, NN)	→	flight
IN(on, IN)	→	on
NNP(NWA, NNP)	→	TWA

Lexicalized Parse Tree



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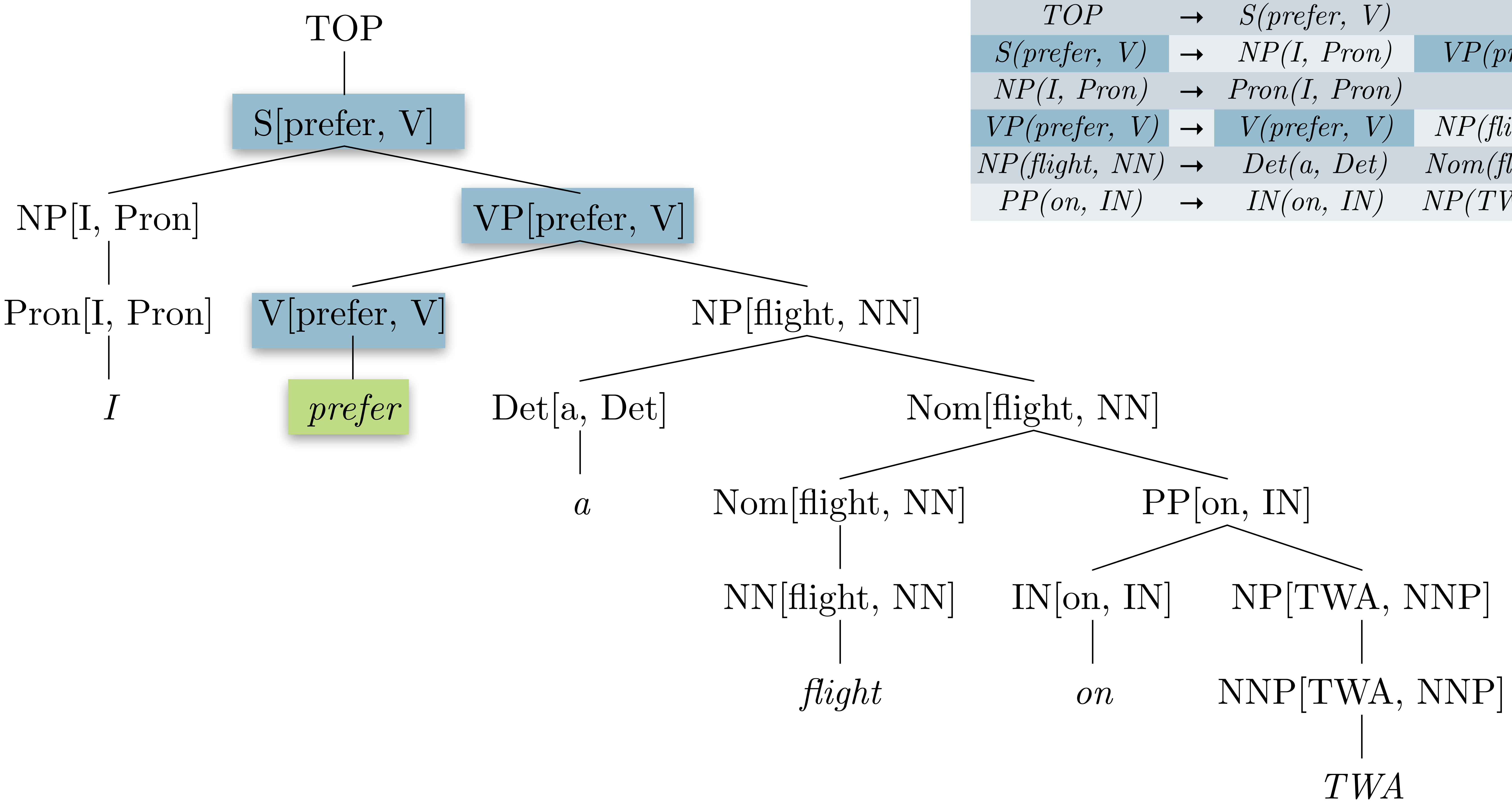
NP(I, Pron)	→	*Pron(I, Pron)*	
VP(prefer, V)	→	*V(prefer, V)*	*NP(flight, NN)*
NP(flight, NN)	→	*Det(a, Det)*	*Nom(flight, NN)*
PP(on, IN)	→	*IN(on, IN)*	*NP(TWA, NNP)*

Lexical Rules		
Pron(I, Pron)	→	I
V(prefer, V)	→	prefer
Det(a, Det)	→	a
NN(flight, NN)	→	flight
IN(on, IN)	→	on
NNP(NWA, NNP)	→	TWA

Lexicalized Parse Tree



Internal Rules			
TOP	→	*S(prefer, V)*	
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NP(I, Pron)	→	*Pron(I, Pron)*	
VP(prefer, V)	→	*V(prefer, V)*	*NP(flight, NN)*
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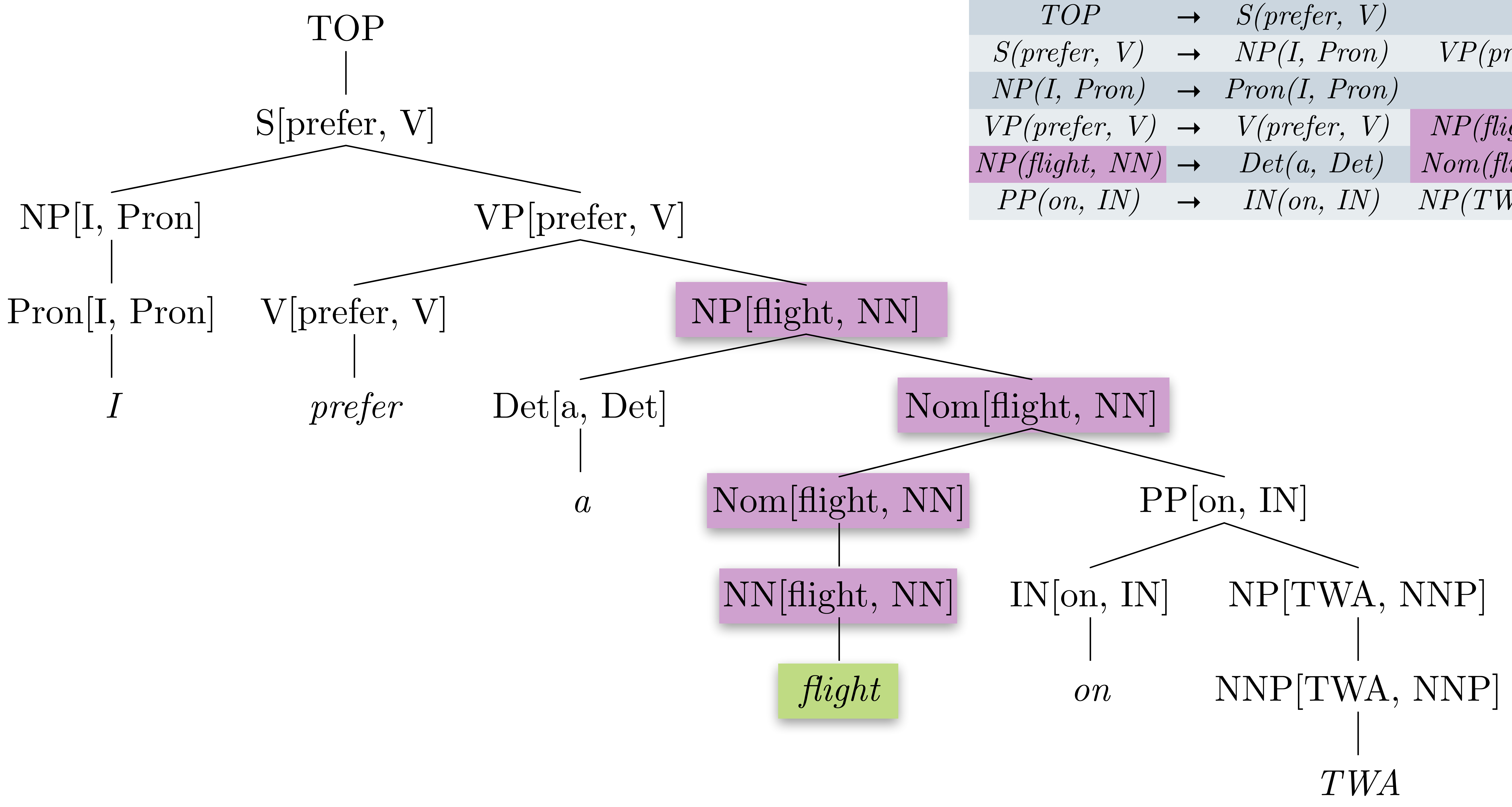

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Improving PCFGs: Lexical Dependencies

- Upshot: heads propagate up tree:

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Improving PCFGs: Lexical Dependencies

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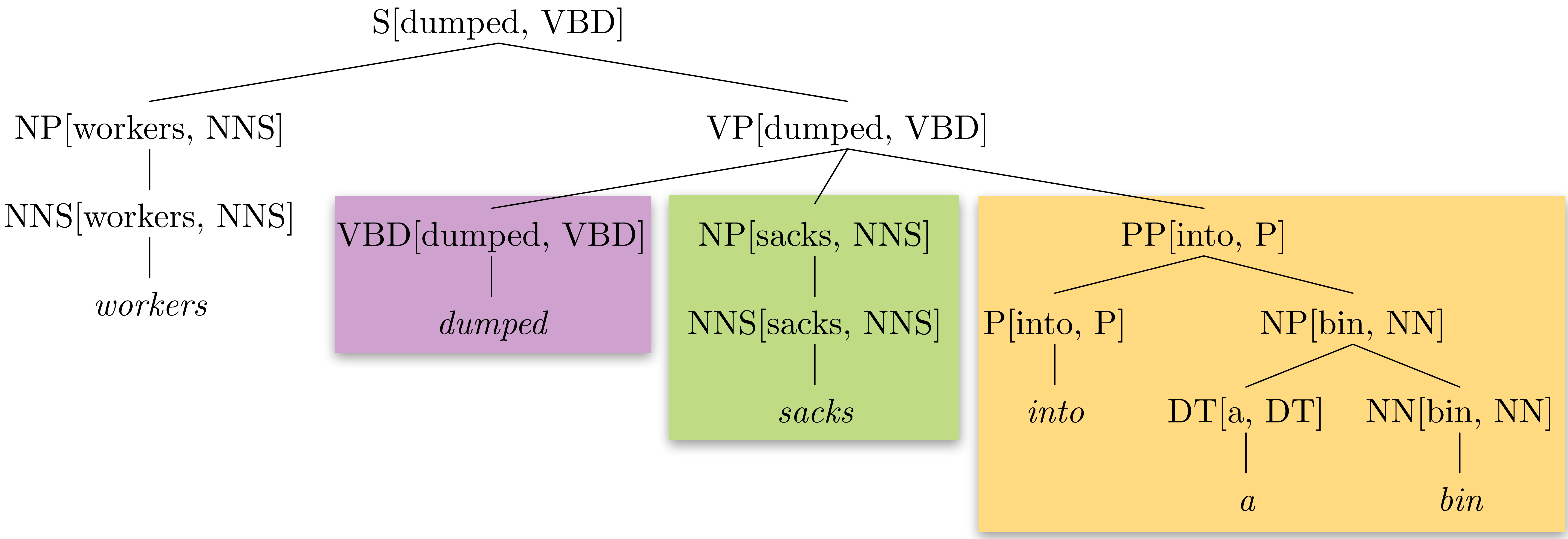


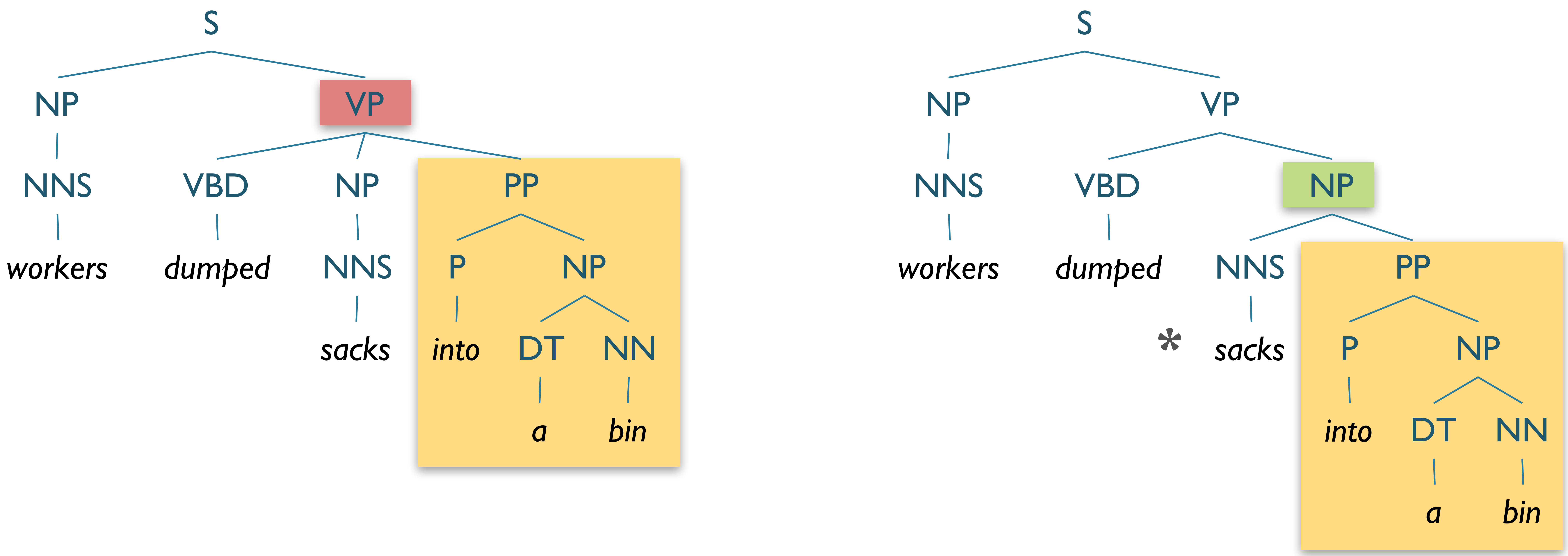
Improving PCFGs: Lexical Dependencies

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

Improving PCFGs: Collins Parser

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

Collins Parser Example



Collins Parser Example

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

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

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$$P_R(into \mid PP, sacks)$$

$$= \frac{Count\left(X\left(sacks\right) \rightarrow \ldots\ PP\left(into\right)\ \ldots\right)}{\sum_{\beta} Count\left(X\left(sacks\right) \rightarrow \ldots\ PP\ \ldots\right)}$$

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

Improving PCFGs

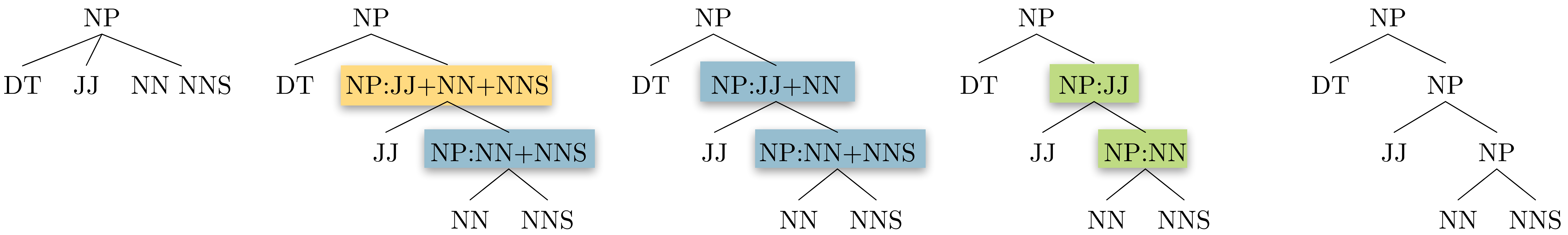
- Parent Annotation
- Lexicalization
- **Markovization**
- Reranking

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

Original | Order 3 | Order 2 | Order 1 | Order 0



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?
- Results from Collins and Koo (2005), 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: e.g. singletons
  - Low probability: constituents $\boldsymbol{X}$ s.t. $P(\boldsymbol{X}) < 10^{-200}$
  - Low relative probability:
    - Exclude $\boldsymbol{X}$ if there exists $\boldsymbol{Y}$ s.t. $P(\boldsymbol{Y}) > 100 \times P(\boldsymbol{X})$