Probabilistic Parsing: Issues & Improvement

LING 571 — Deep Processing Techniques for NLP

October 14, 2019

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Announcements

- HW2 grades posted
- Reference code soon available in
  - `/dropbox/20-21/571/hw2/reference_code`
- NB: not needed for HW3; you can assume that all grammars are already in CNF

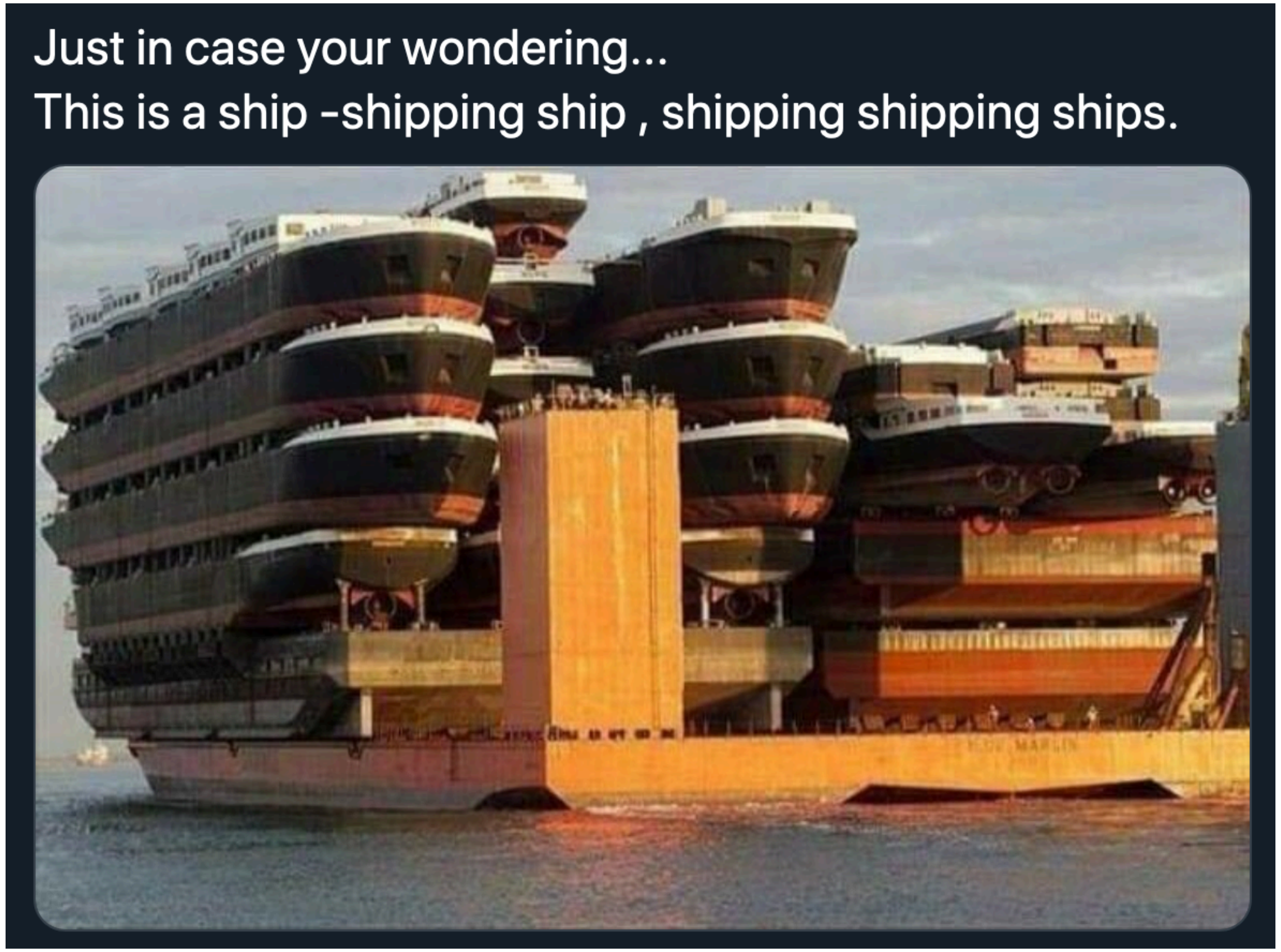
Homework Tips

- Use `nltk.load` for reading grammars; will save you and TA time and headaches
- Run your code on patas to produce the output you submit in TAR file
  - Some discrepancies found that seem due to different environment
  - When in doubt, use full paths to python binaries, etc
- `readme.{txt|pdf}`: this should NOT be inside your TAR file, but a separate upload on Canvas

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

Language Does the Darnedest Things



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

PCFG Induction

Learning Probabilities

- Simplest way:
  - Use treebank of parsed sentences

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

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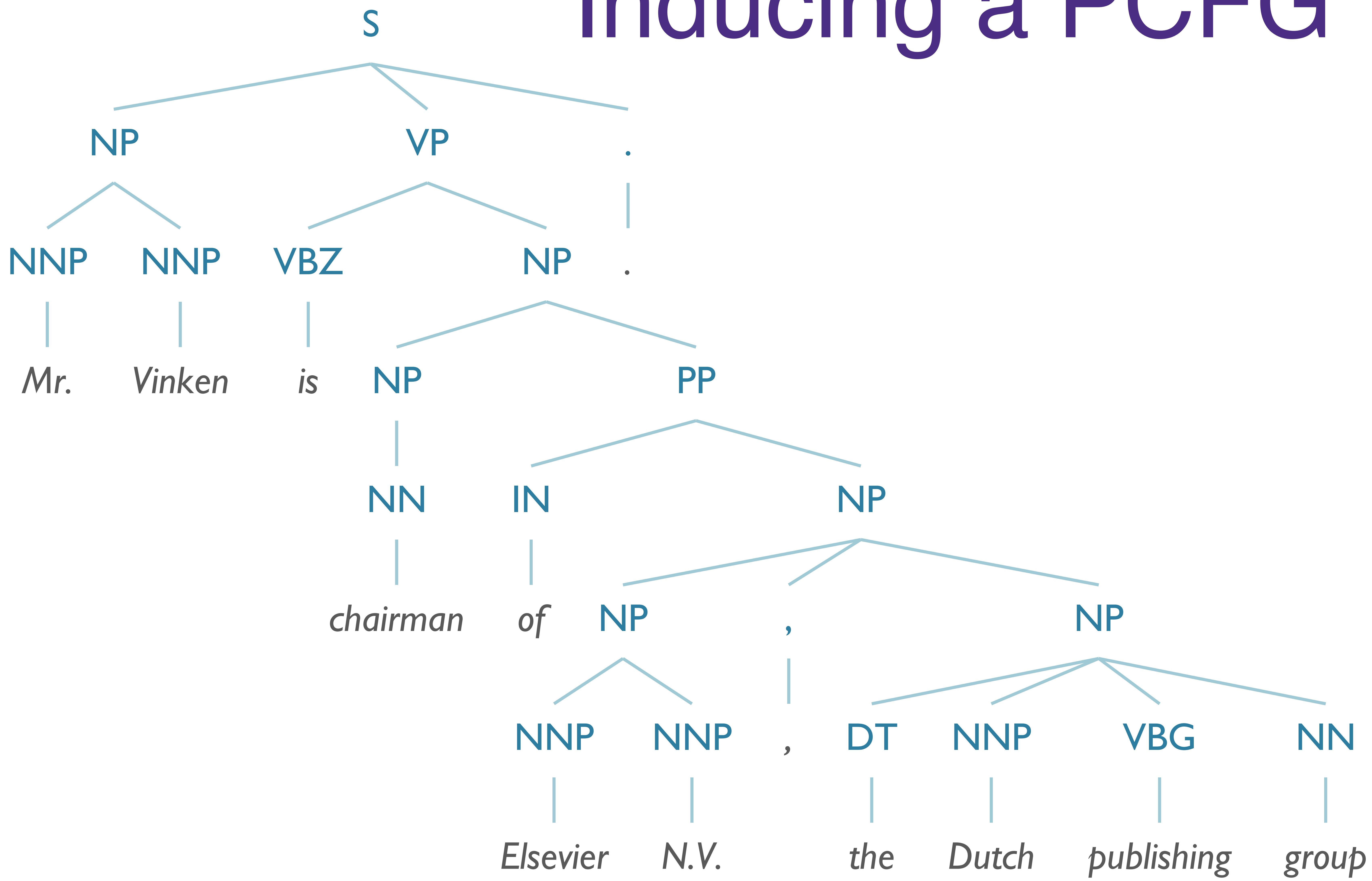

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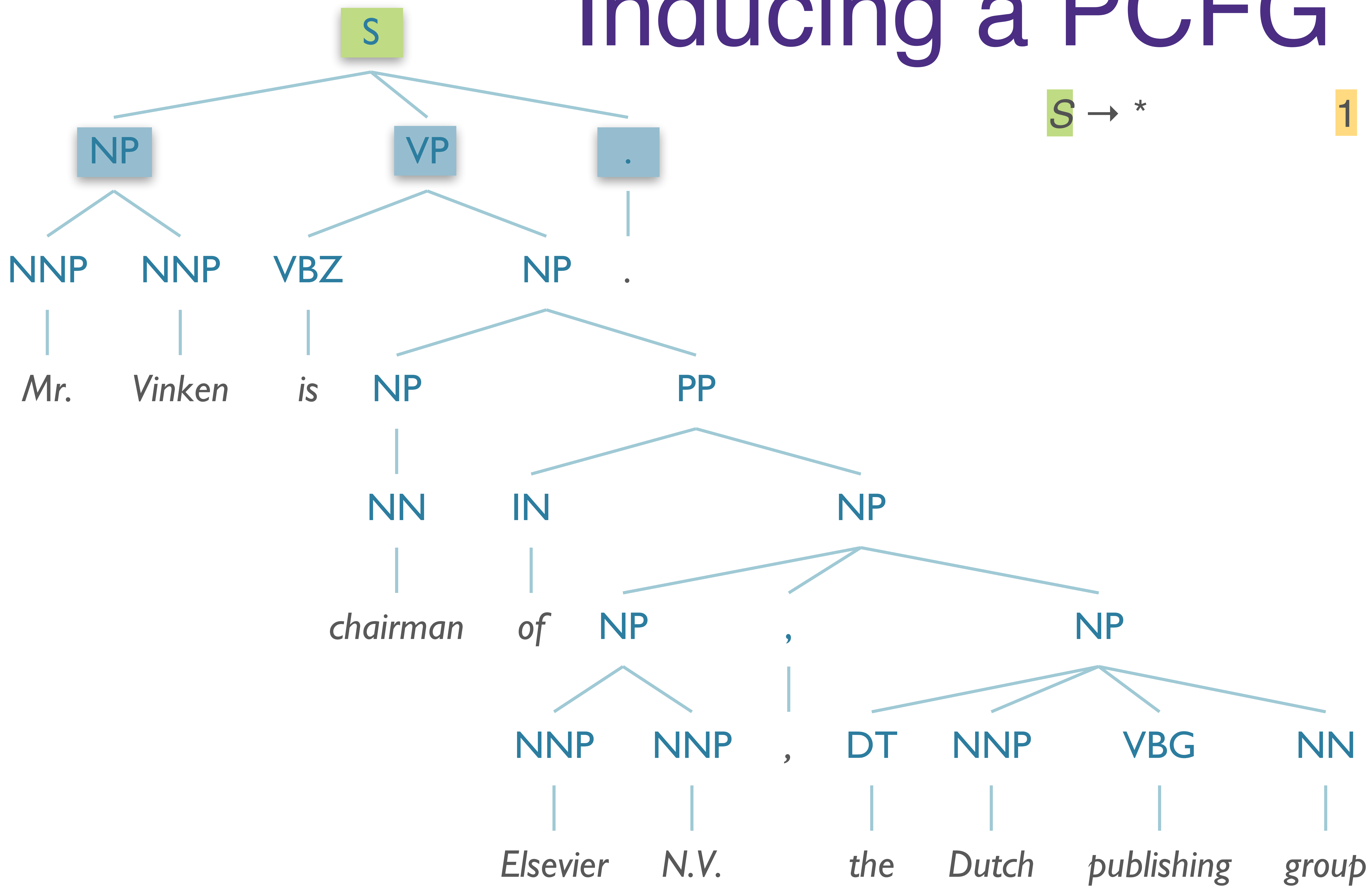

$S \rightarrow *$	1	$S \rightarrow NP\,VP\,.$	1

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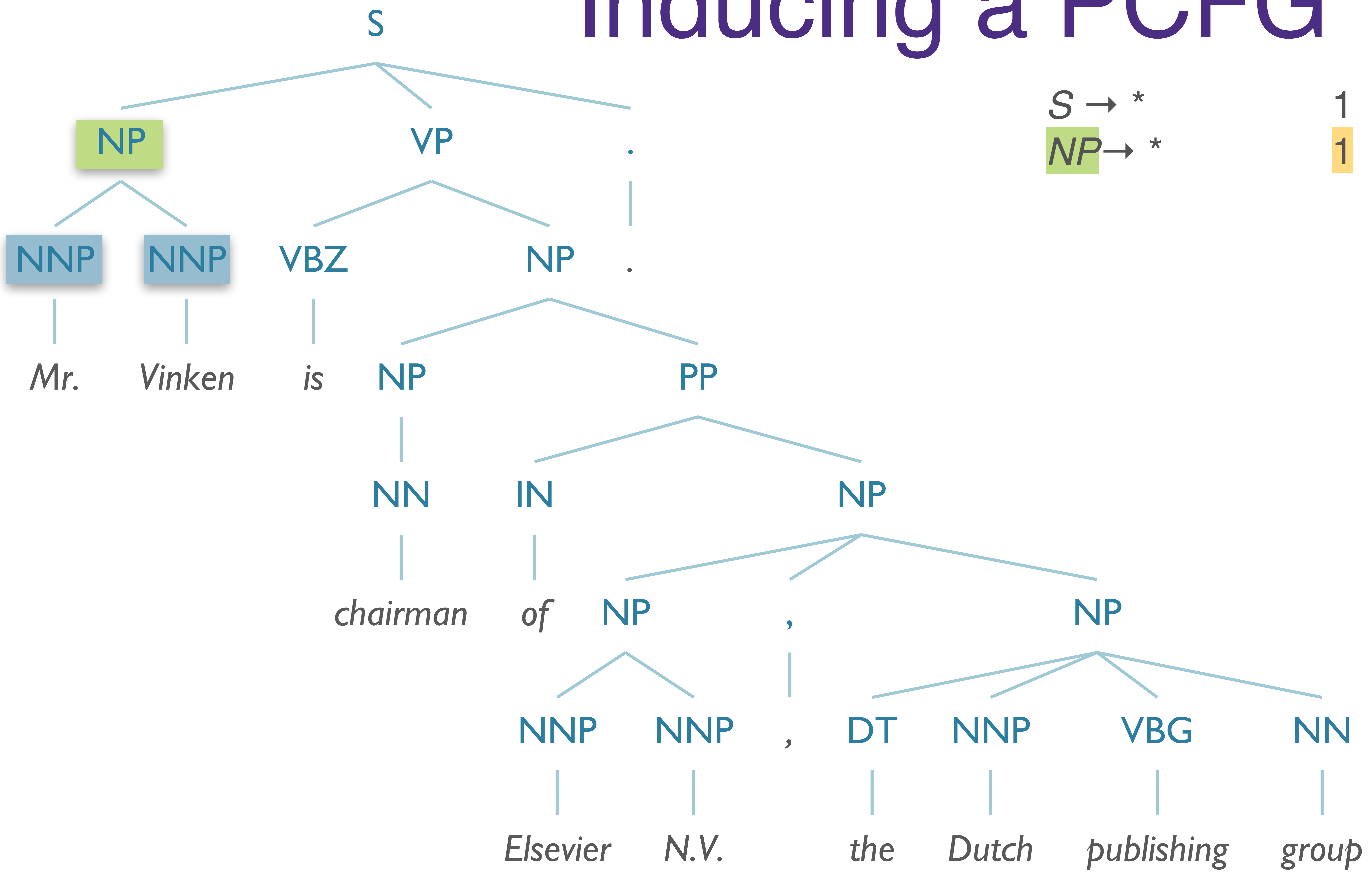

$S \rightarrow *$	1	$S \rightarrow NP\ VP\ .$	1
$NP \rightarrow *$	1	$NP \rightarrow NNP\ NNP$	1

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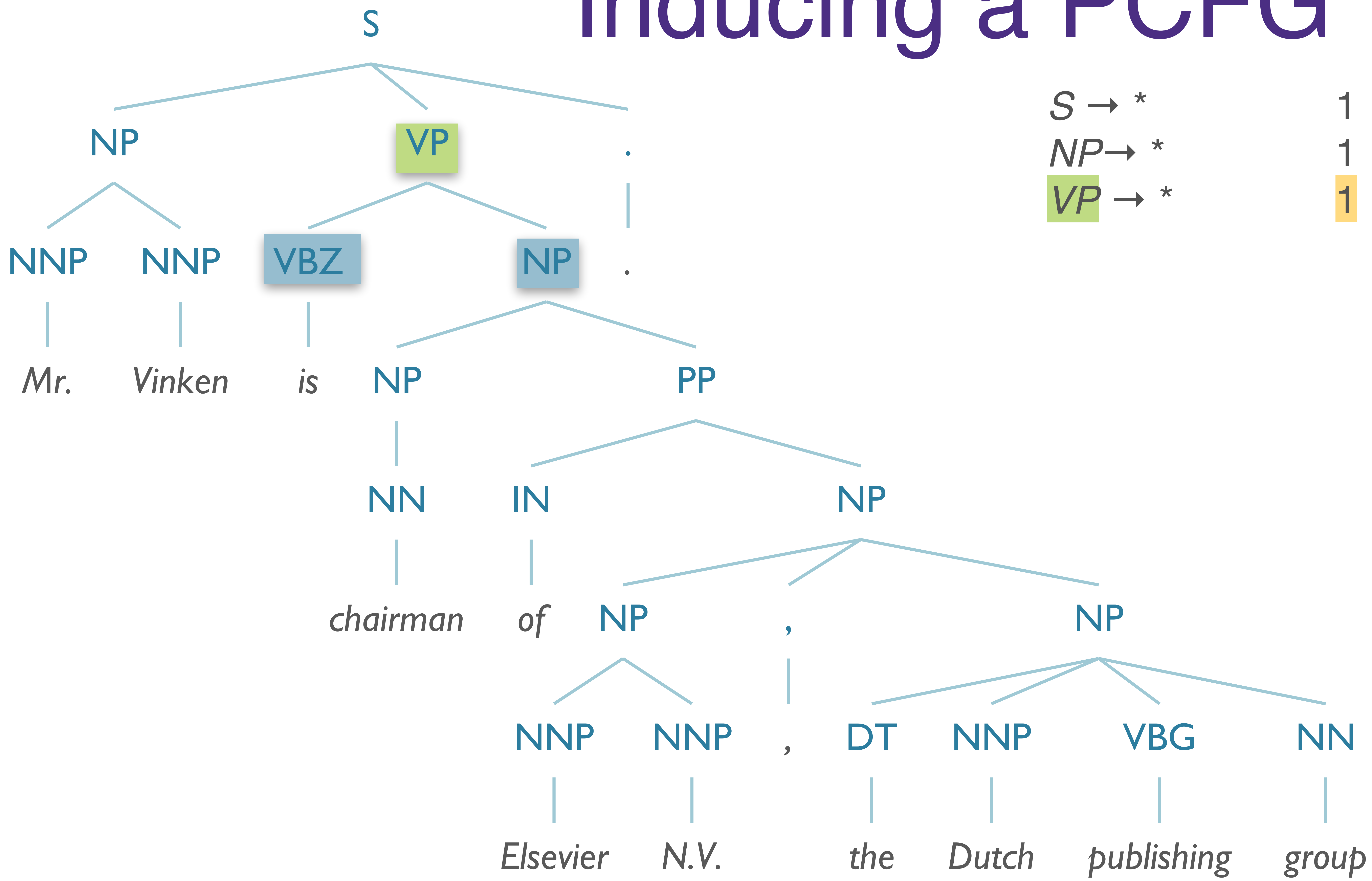

S → *	1	*S* → *NP VP .*	1
NP→ *	1	*NP* → *NNP NNP*	1
VP → *	1	*VP* → *VBZ NP*	1

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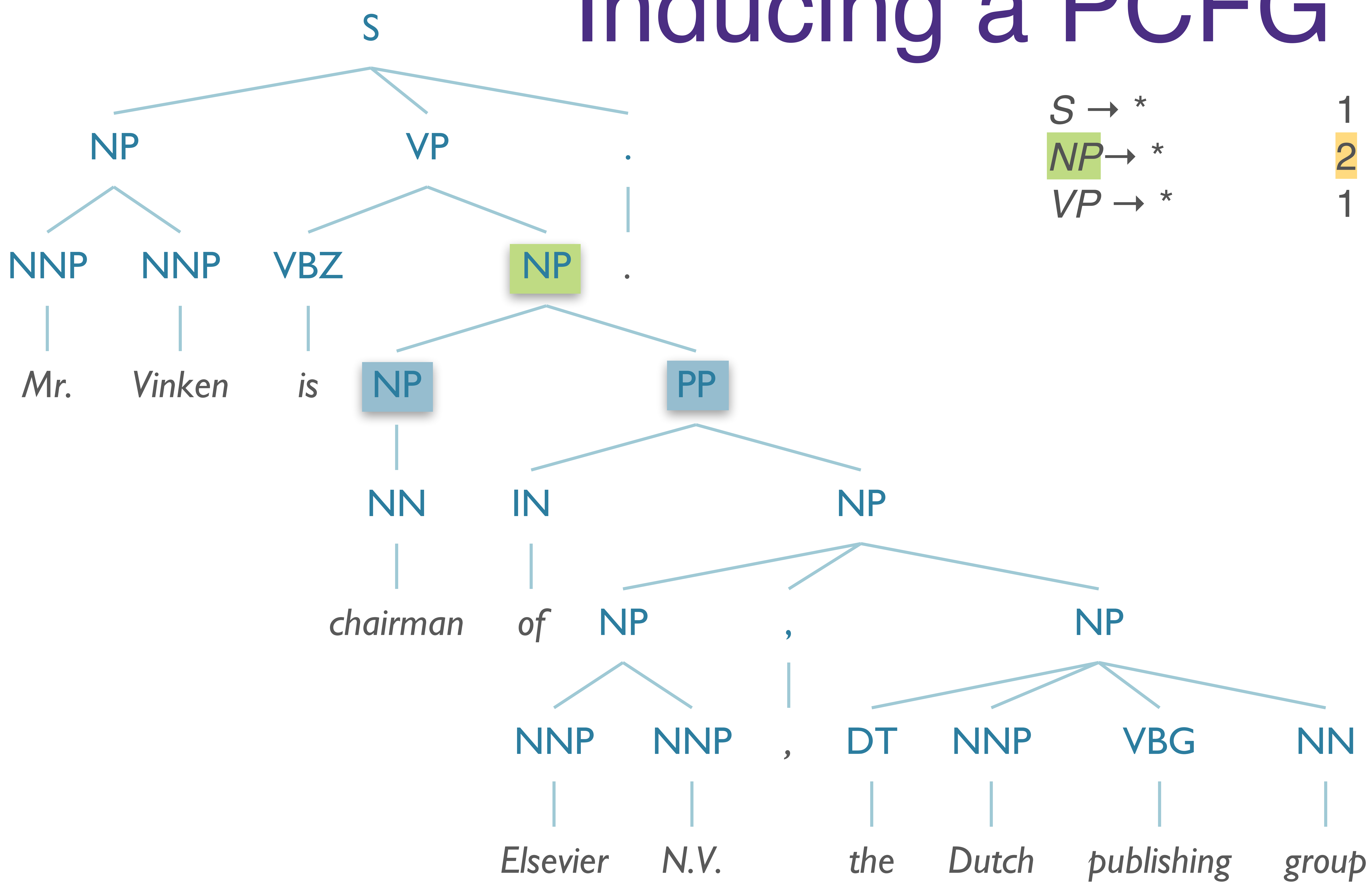

S → *	1	*S* → *NP VP .*	1
NP → *	2	*NP* → *NNP NNP*	1
VP → *	1	*VP* → *VBZ NP*	1
		NP → *NP PP*	1

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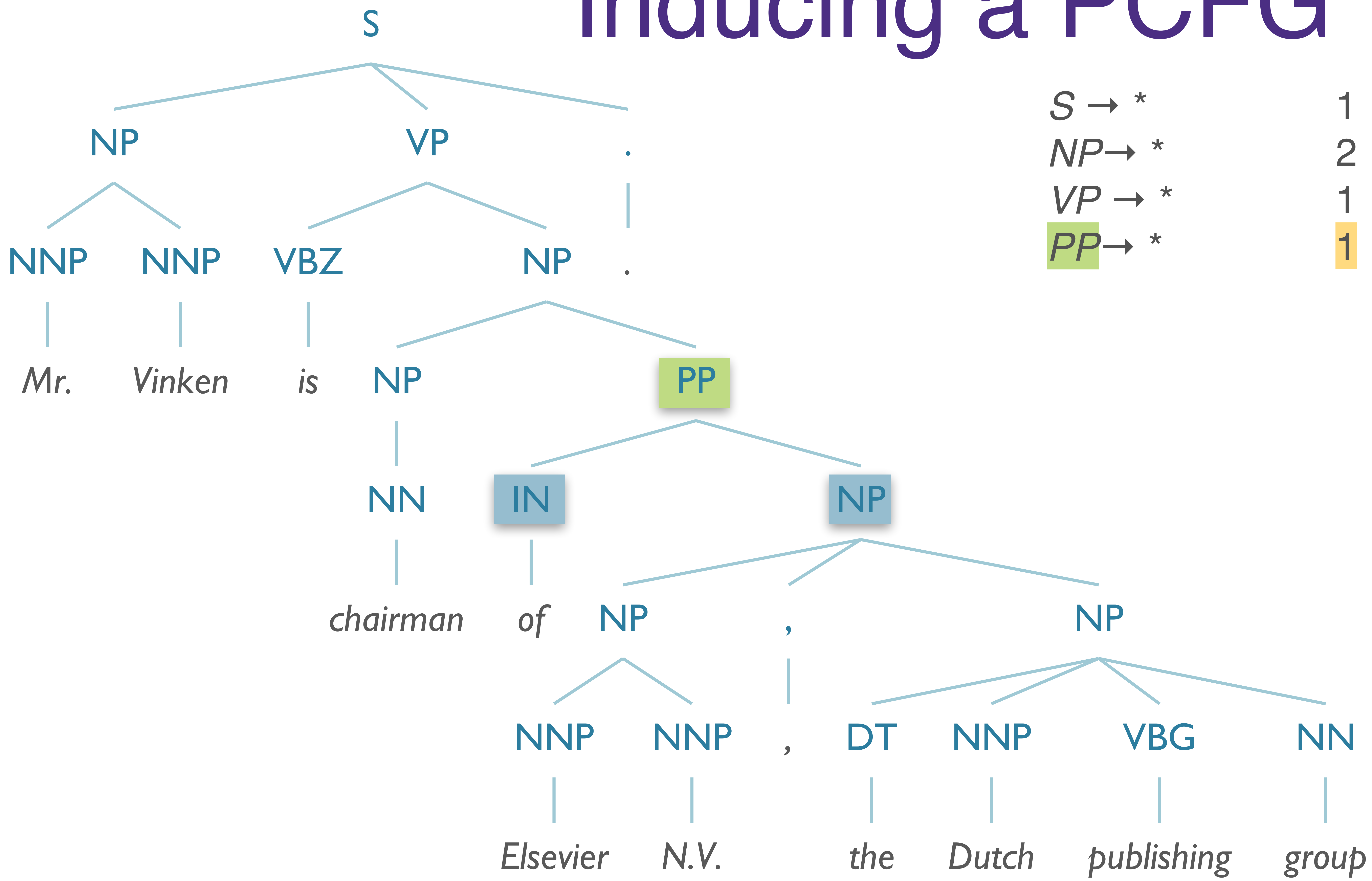

*S → **	1	*S → NP VP .*	1
*NP→ **	2	*NP → NNP NNP*	1
*VP → **	1	*VP → VBZ NP*	1
*PP→ **	1	*NP→ NP PP*	1
		PP→ IN NP	1

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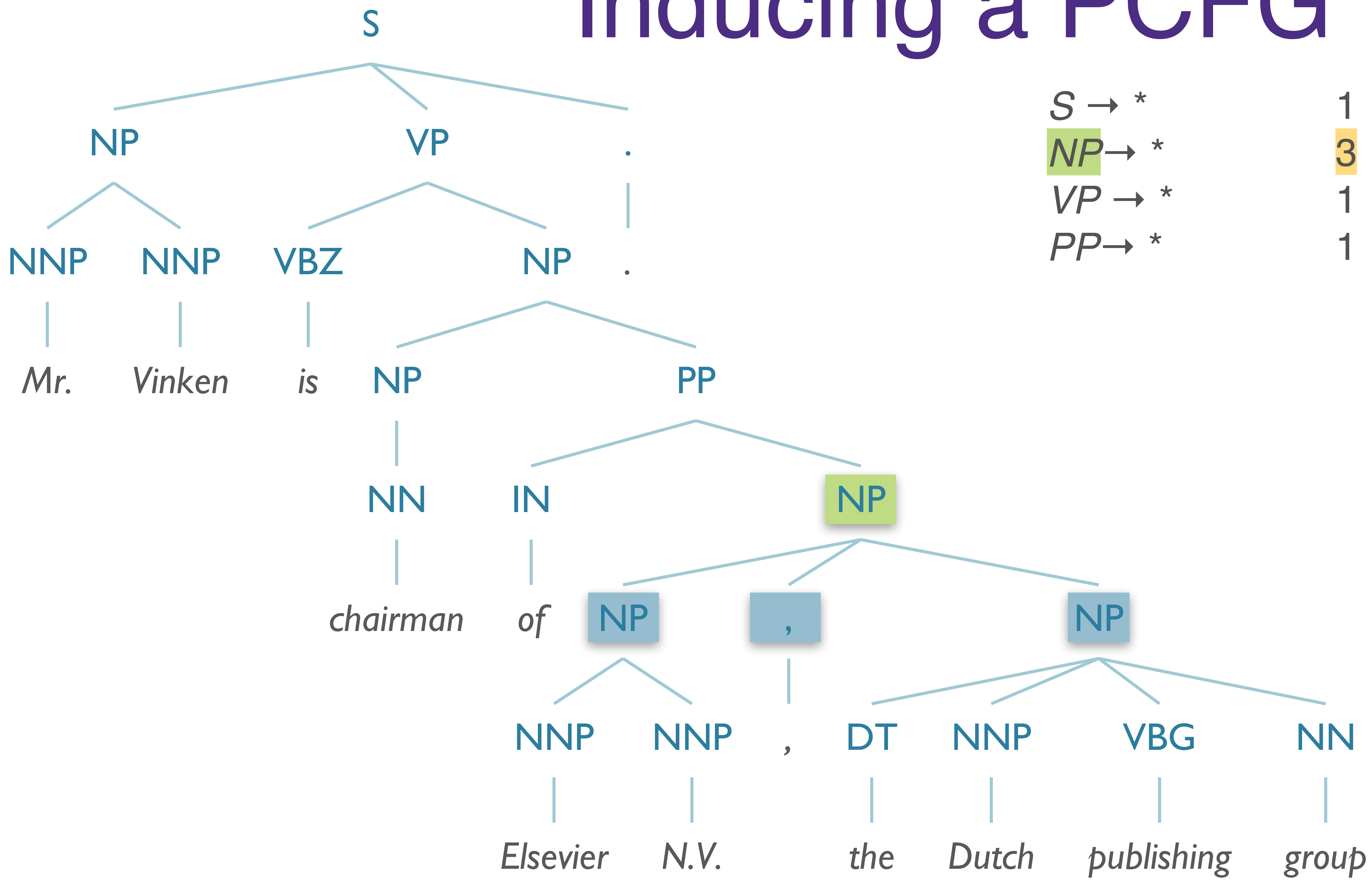

*S → **	1	*S → NP VP .*	1
*NP → **	3	*NP → NNP NNP*	1
*VP → **	1	*VP → VBZ NP*	1
*PP → **	1	*NP → NP PP*	1
		PP → IN NP	1
		NP → NP , NP	1

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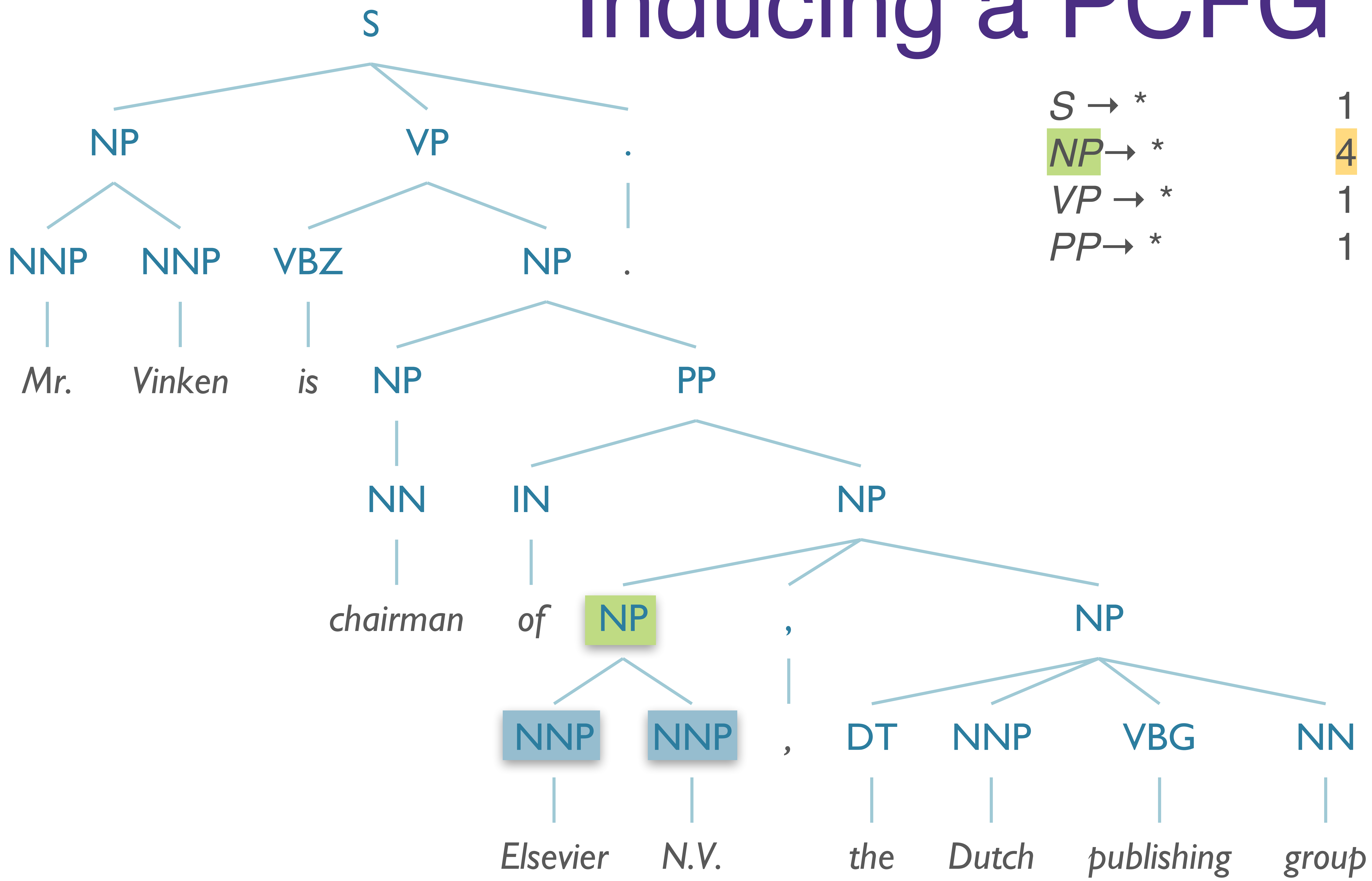

*S → **	1	*S → NP VP .*	1
*NP → **	4	*NP → NNP NNP*	2
*VP → **	1	*VP → VBZ NP*	1
*PP → **	1	*NP → NP PP*	1
		PP → IN NP	1
		NP → NP , NP	1

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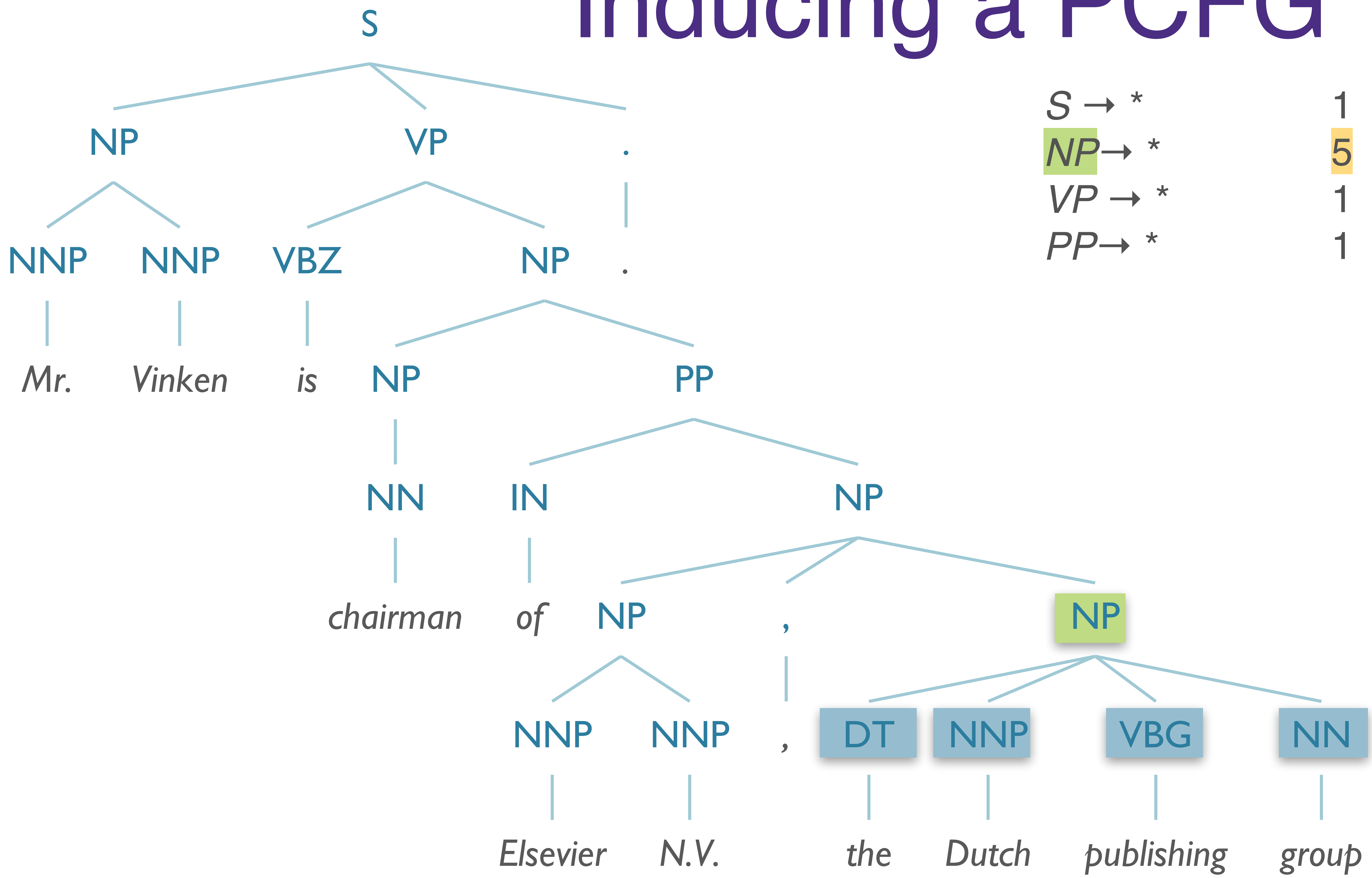

S → *	1	*S → NP VP .*	1
NP→ *	5	*NP→ NNP NNP*	2
VP → *	1	*VP → VBZ NP*	1
PP→ *	1	*NP→ NP PP*	1
		PP→ IN NP	1
		NP→ NP , NP	1
		NP→ DT NNP VBG NN	1

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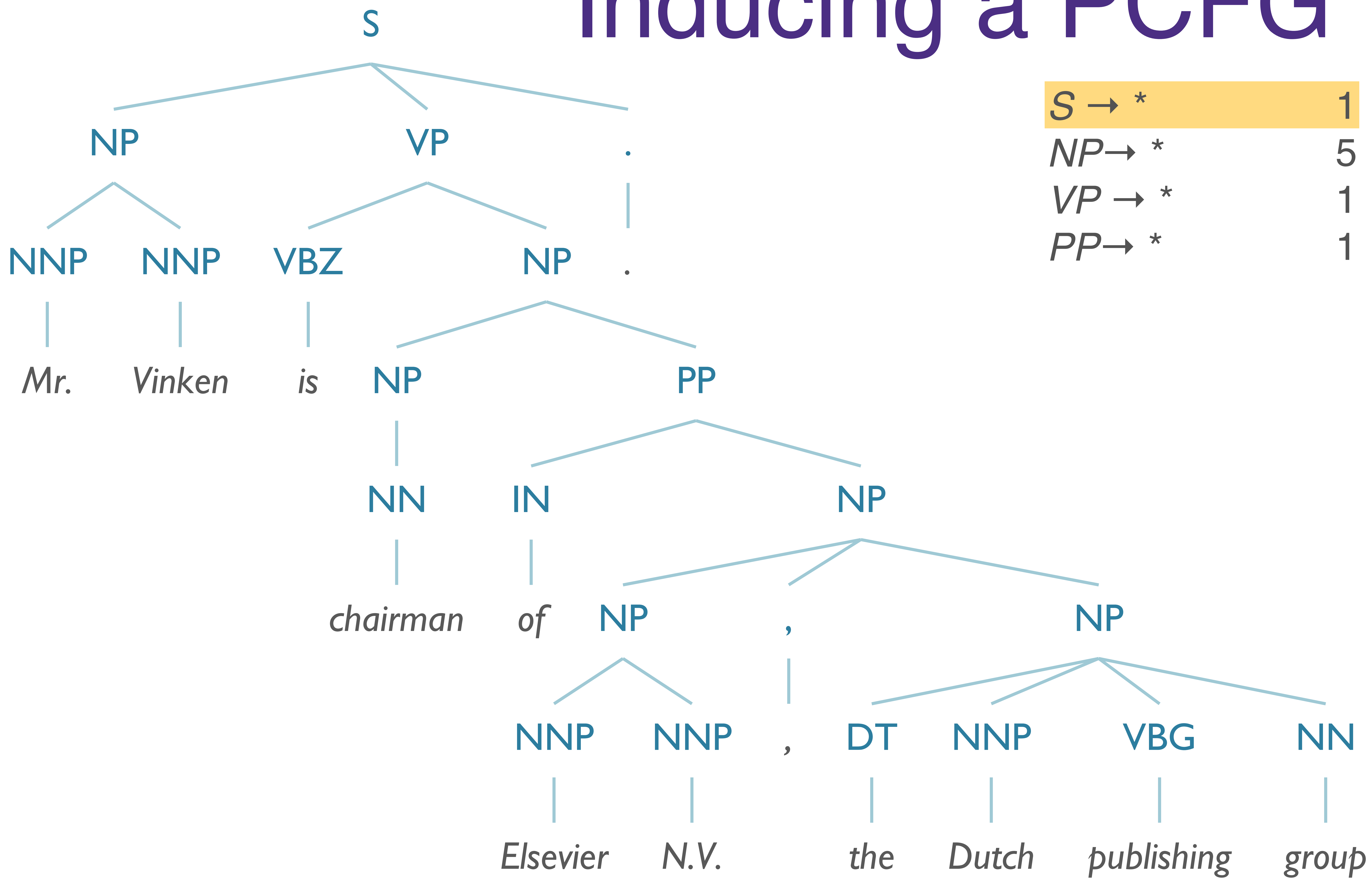

*S → **	1
*NP→ **	5
*VP → **	1
*PP→ **	1

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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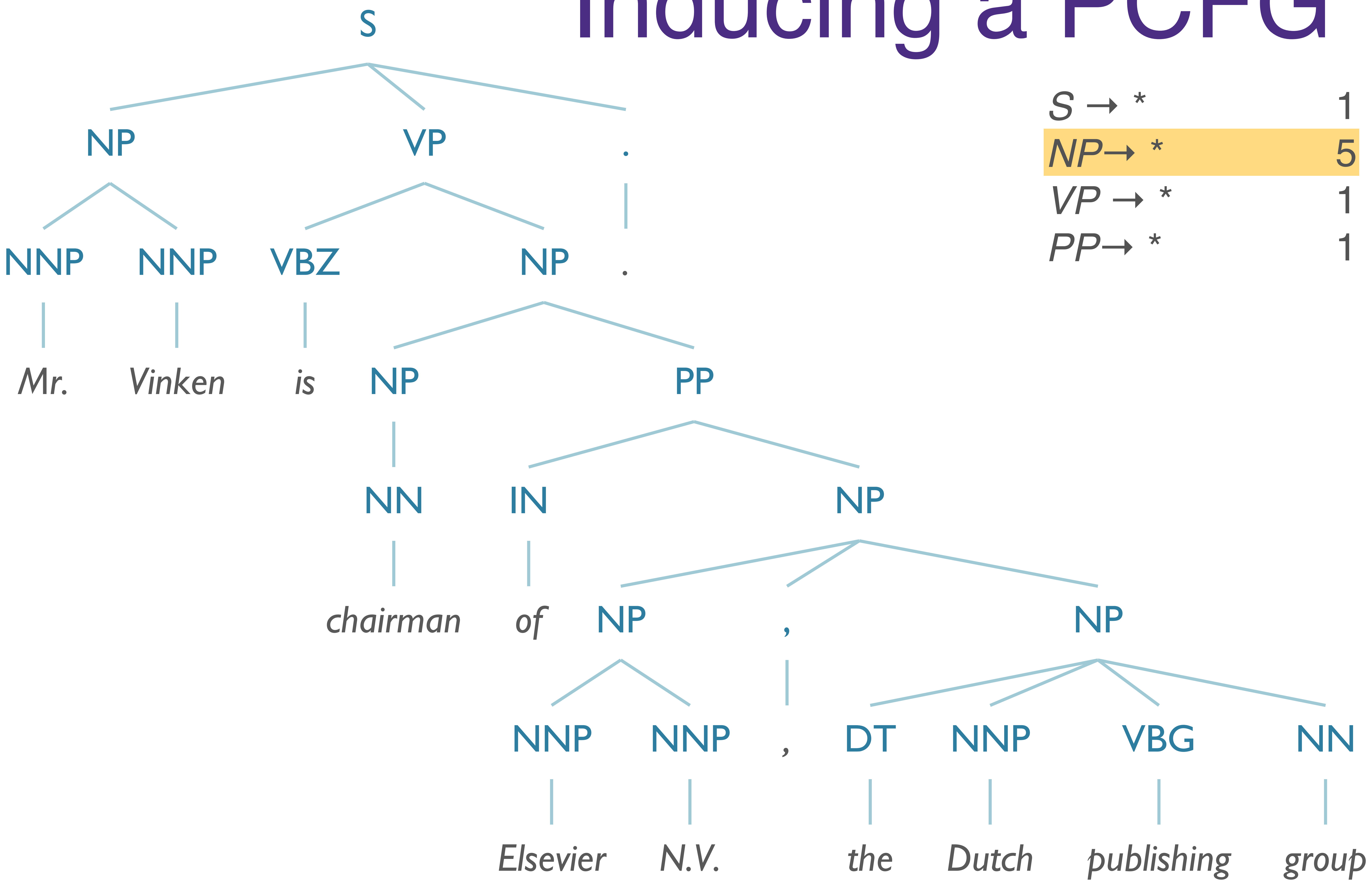

S → *	1
NP→ *	5
VP → *	1
PP→ *	1

S → NP VP .	1
NP→ NNP NNP	2/5
VP → VBZ NP	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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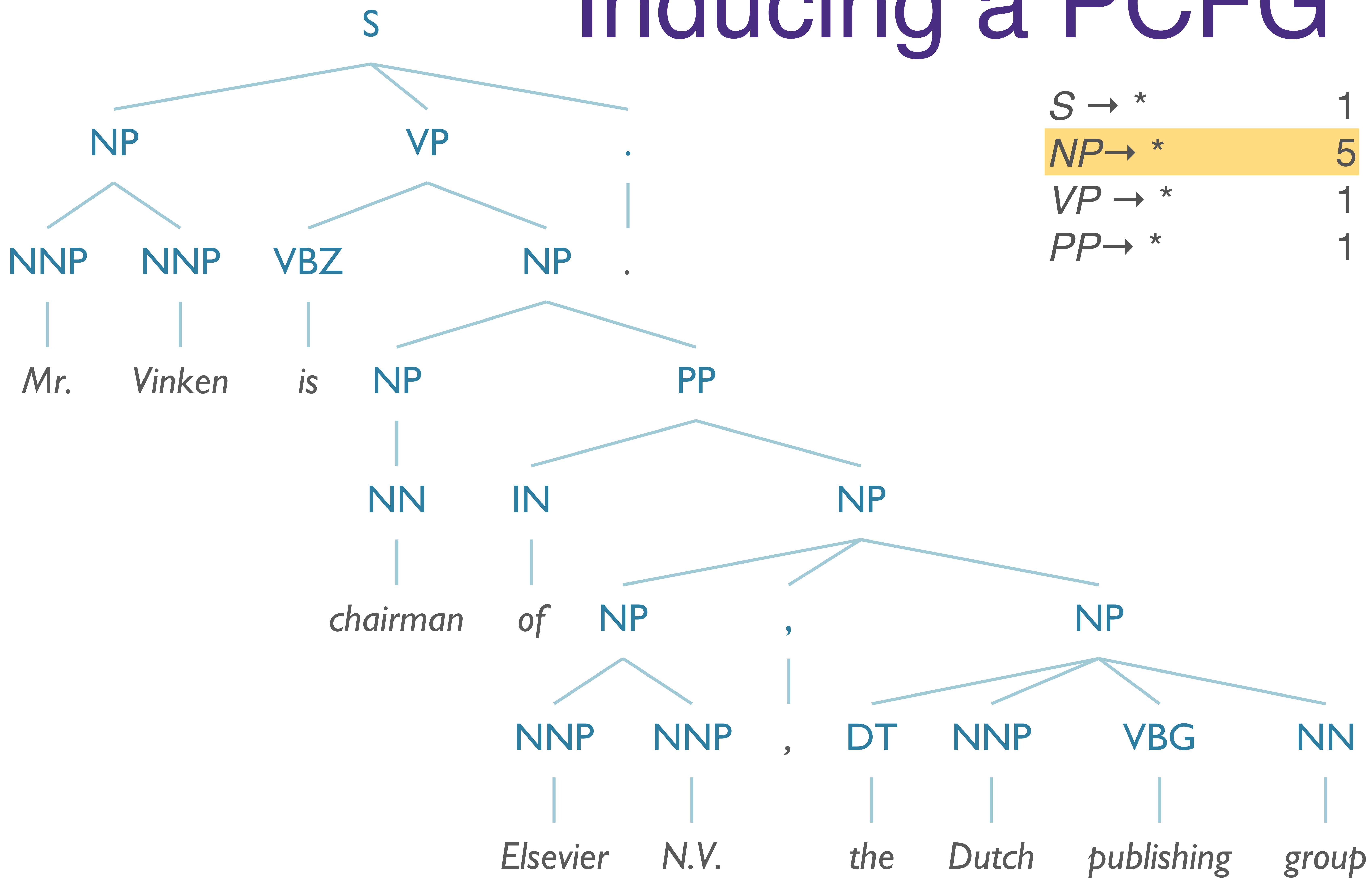

S → *	1
NP→ *	5
VP → *	1
PP→ *	1

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

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- *Context Free ⇒ Independence Assumption*
  - Rule expansion is context-independent
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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**

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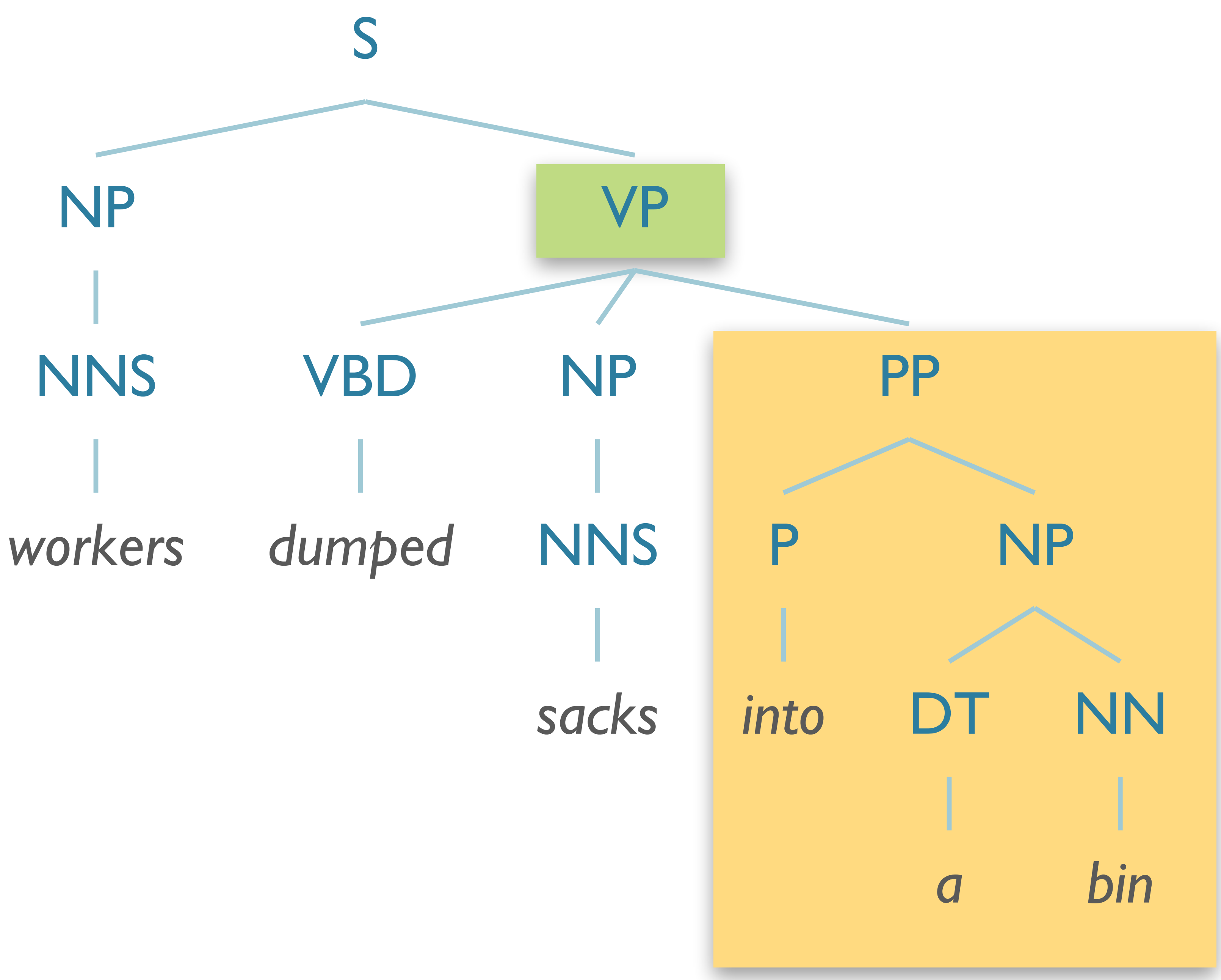

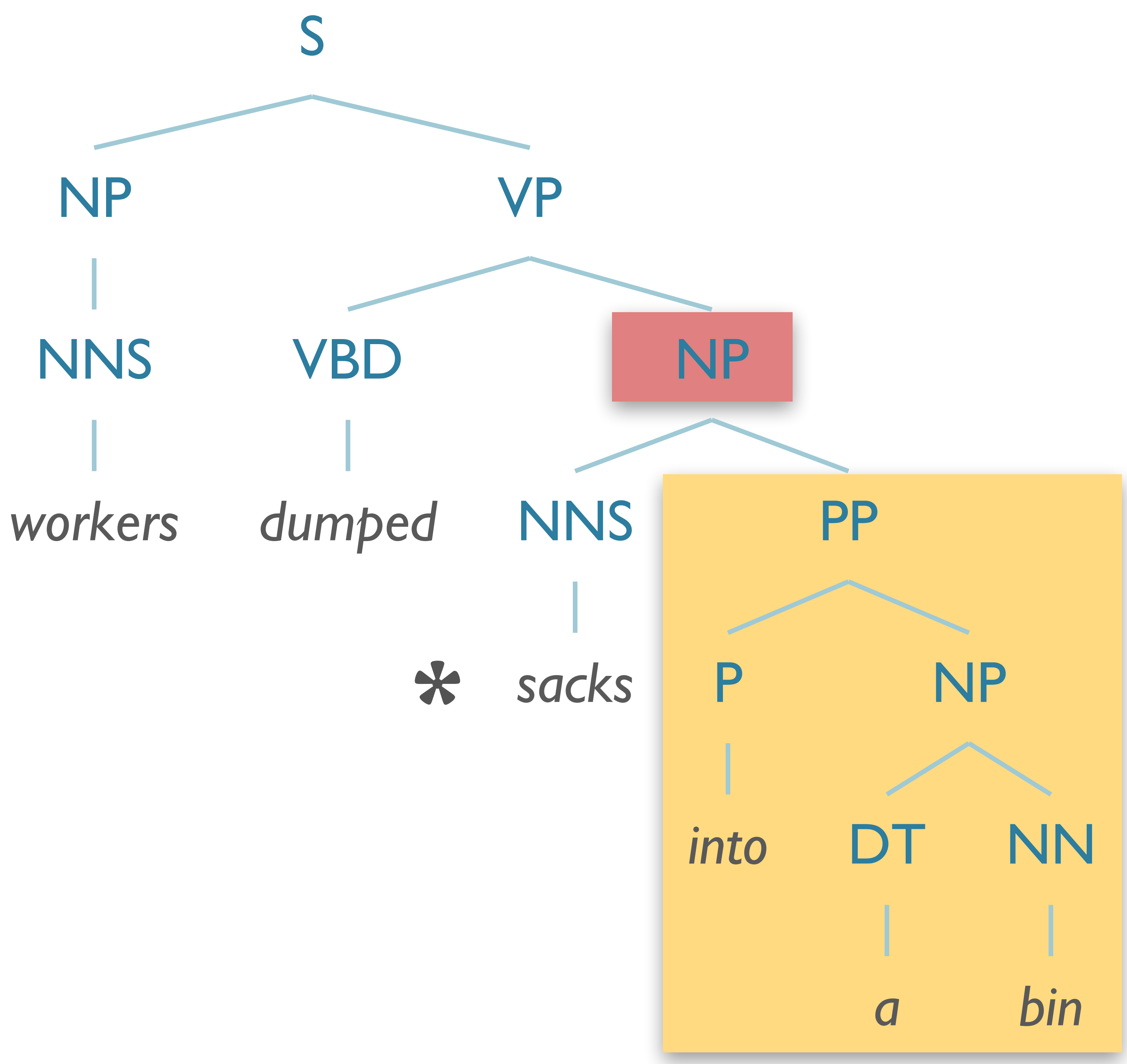

("into a bin" = location of sacks after dumping)
OK!

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

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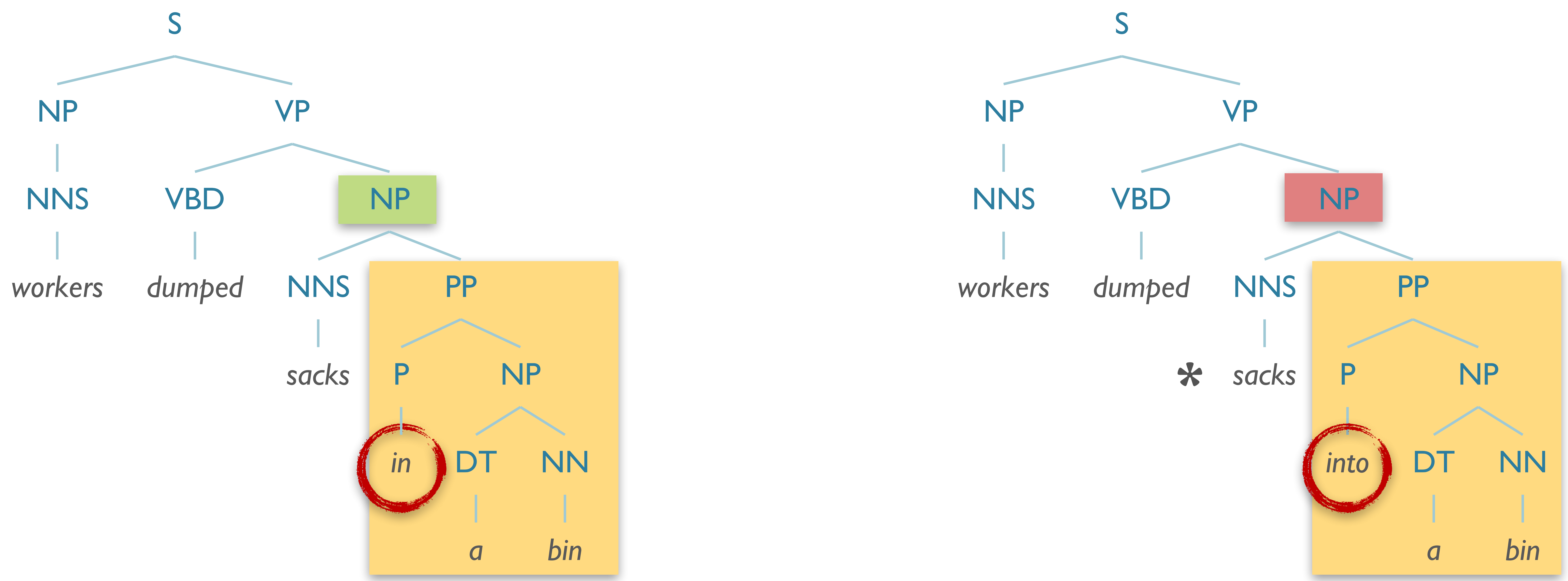

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OK!

("***into*** a bin" = *the sacks which were located ***in PP***)
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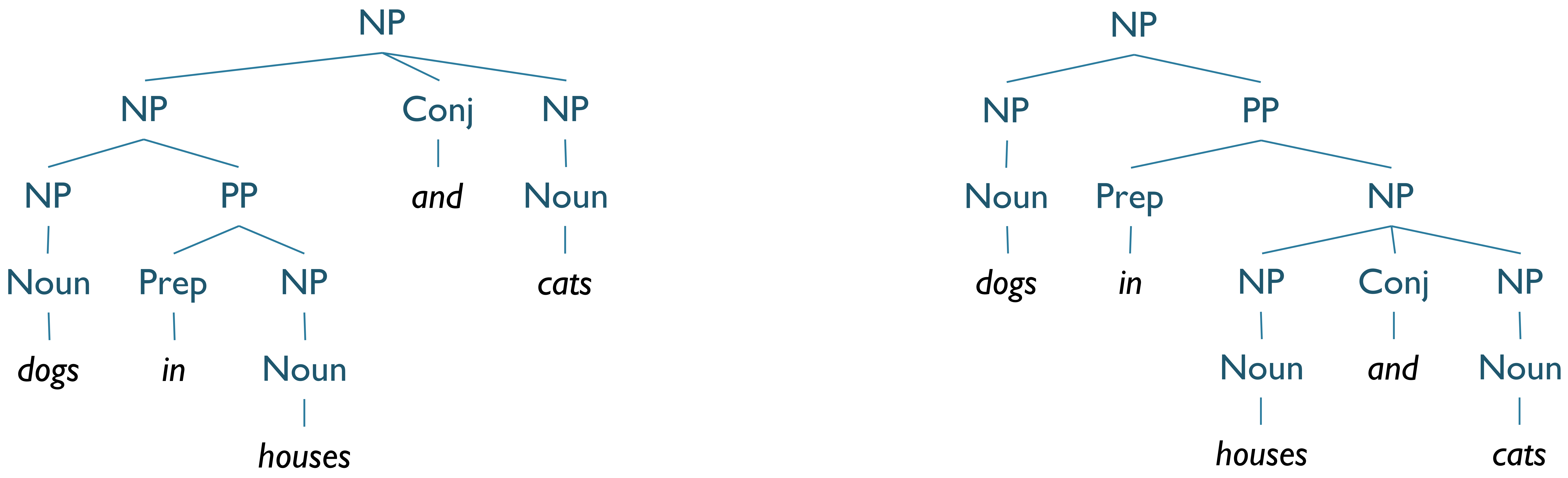
Issues with PCFGs: Lexical Conditioning

- *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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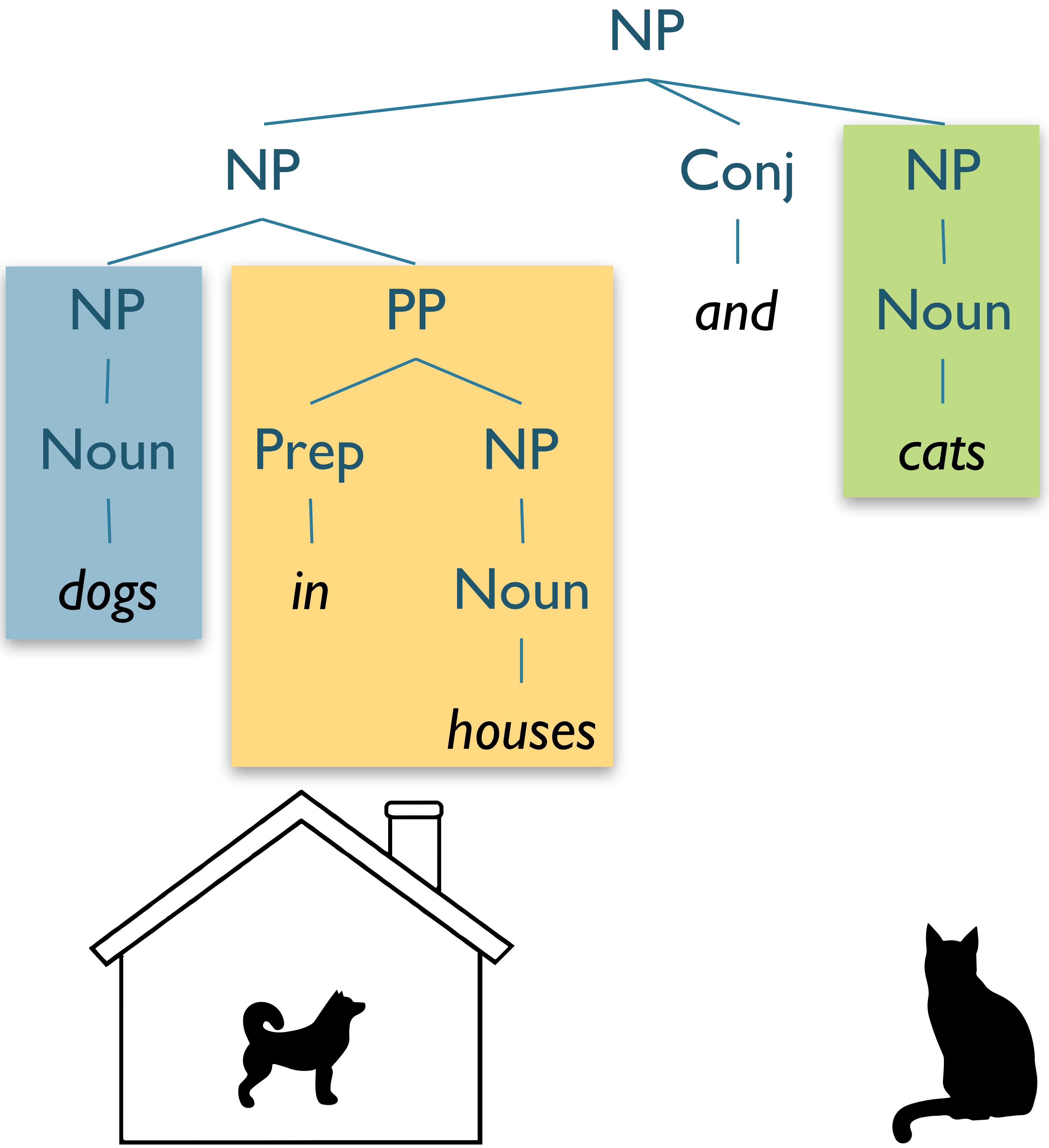

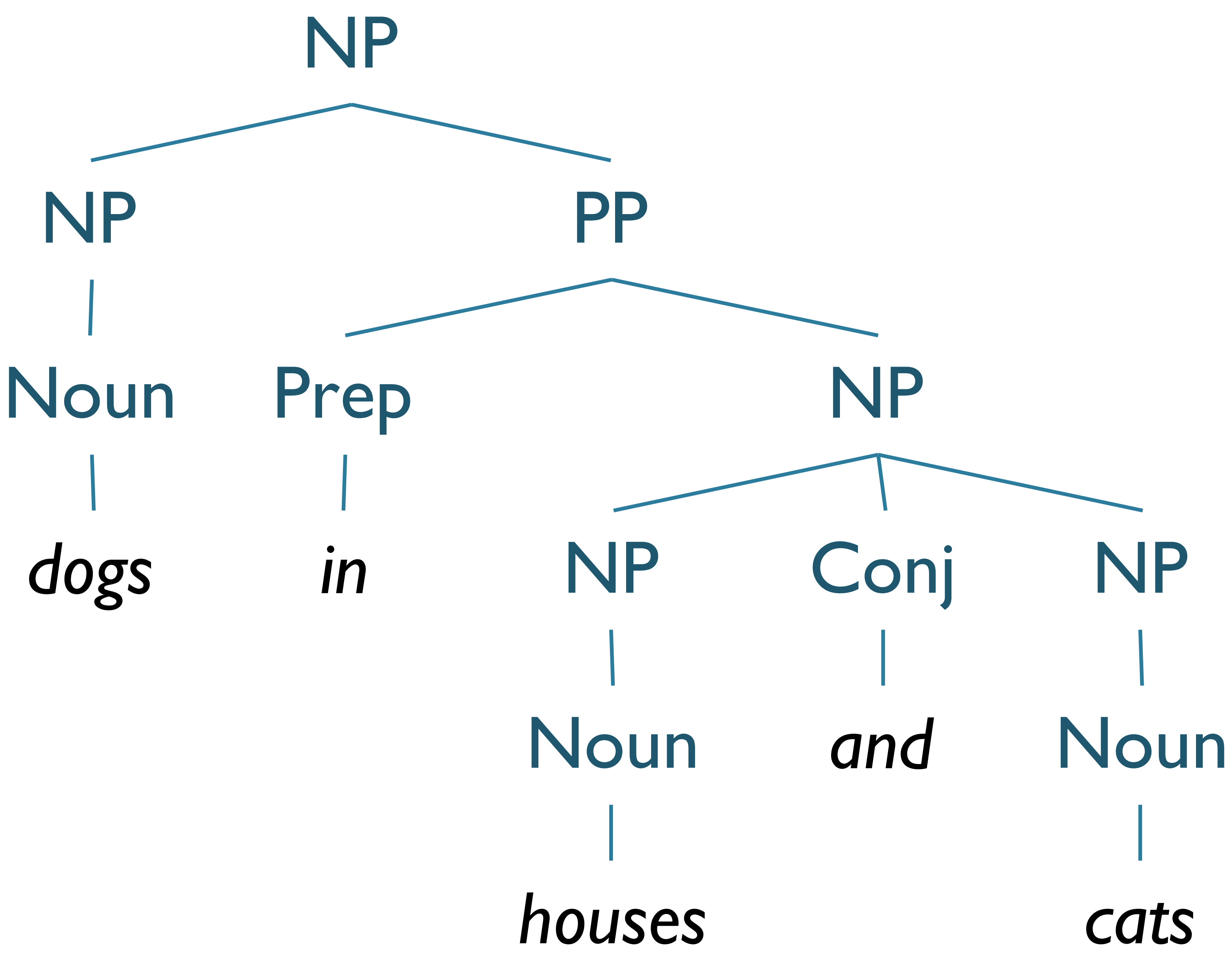

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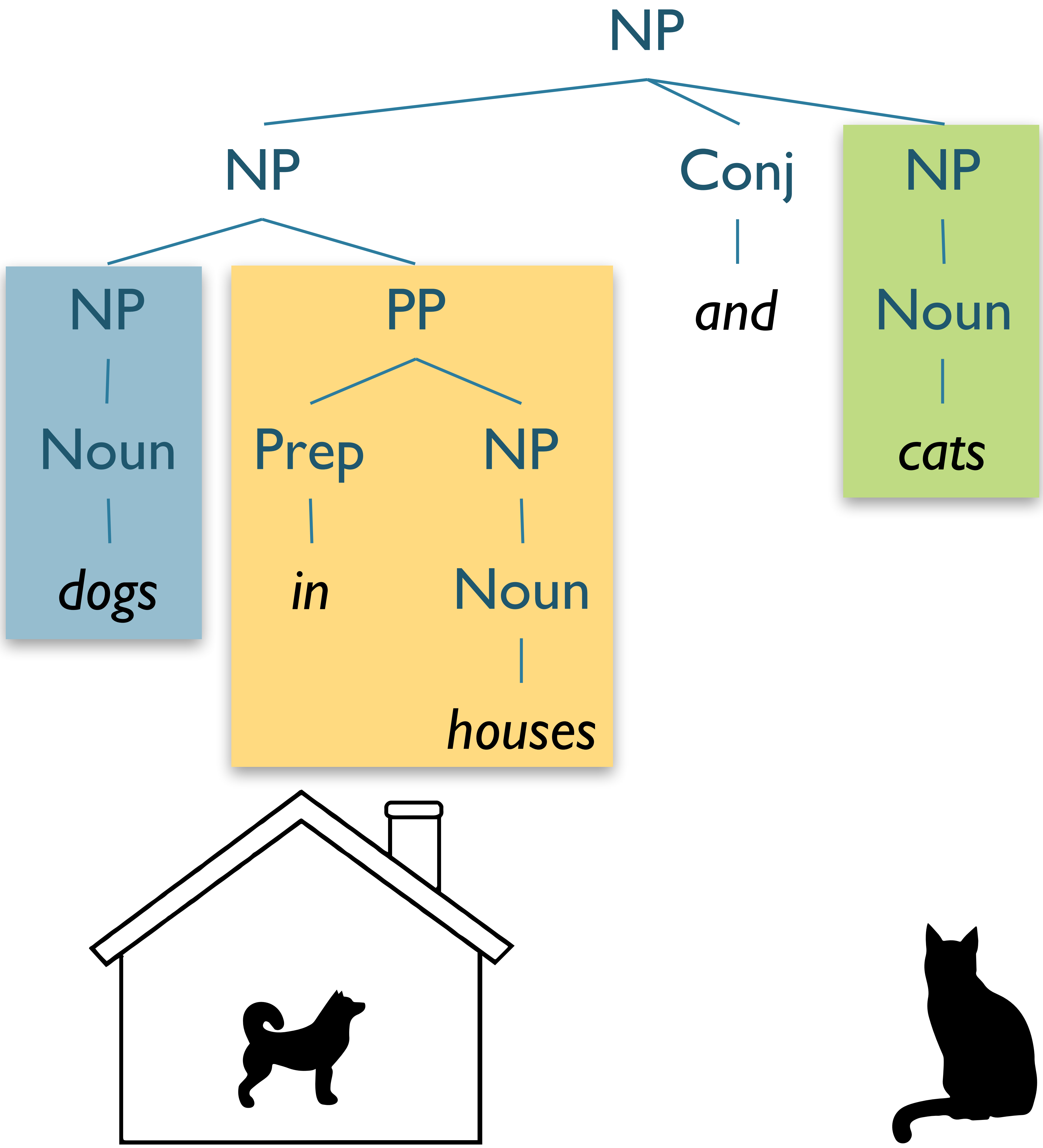

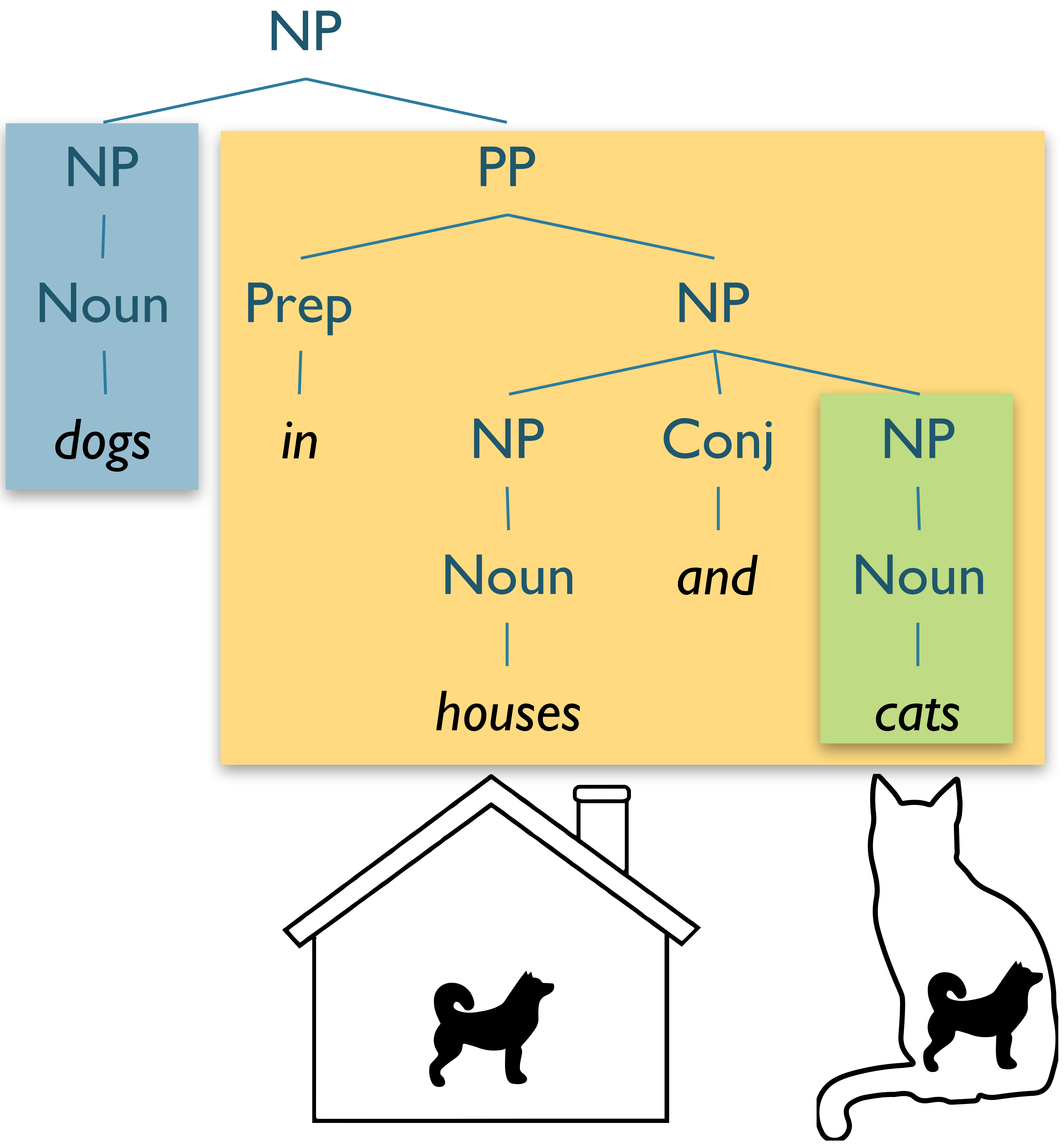

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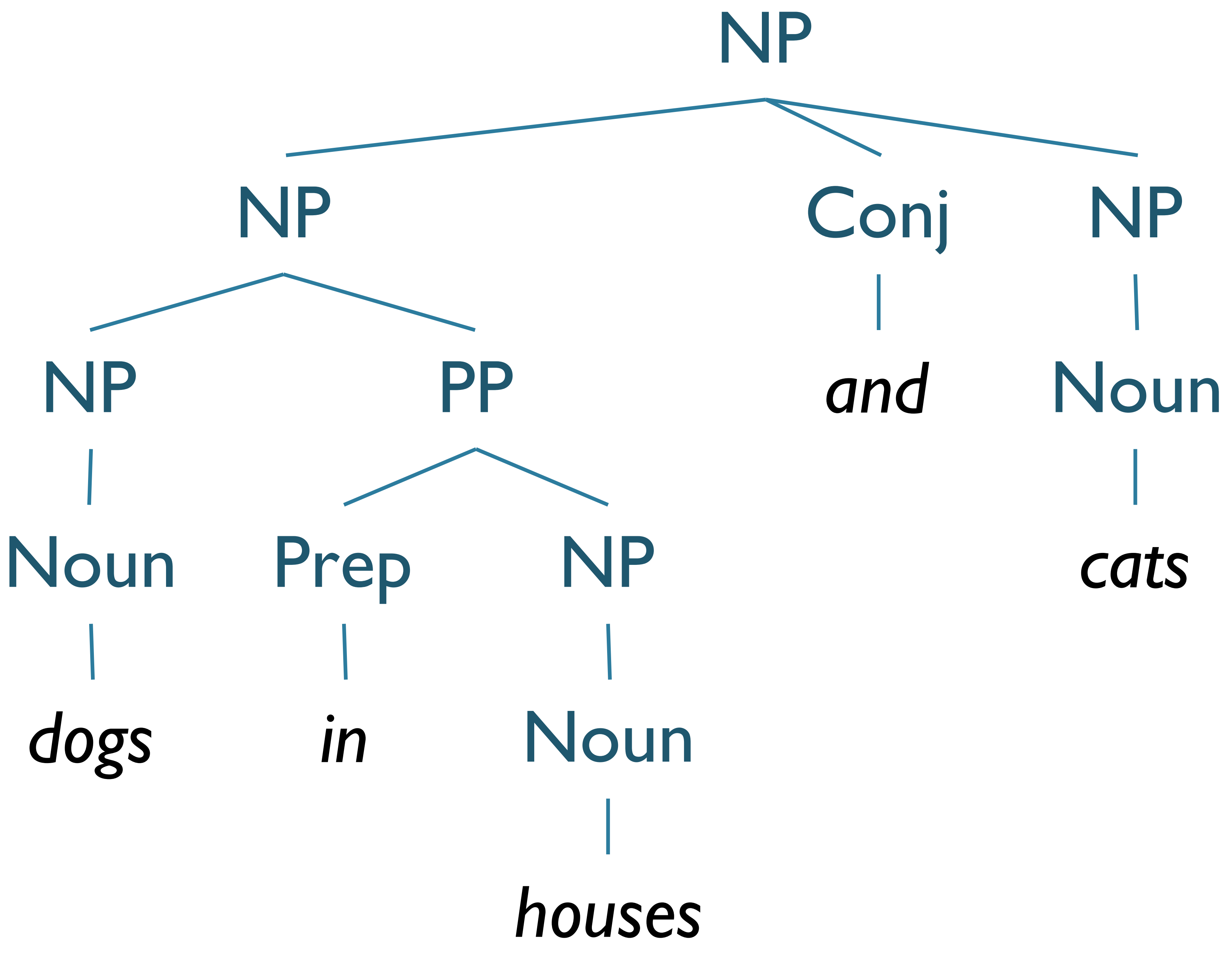

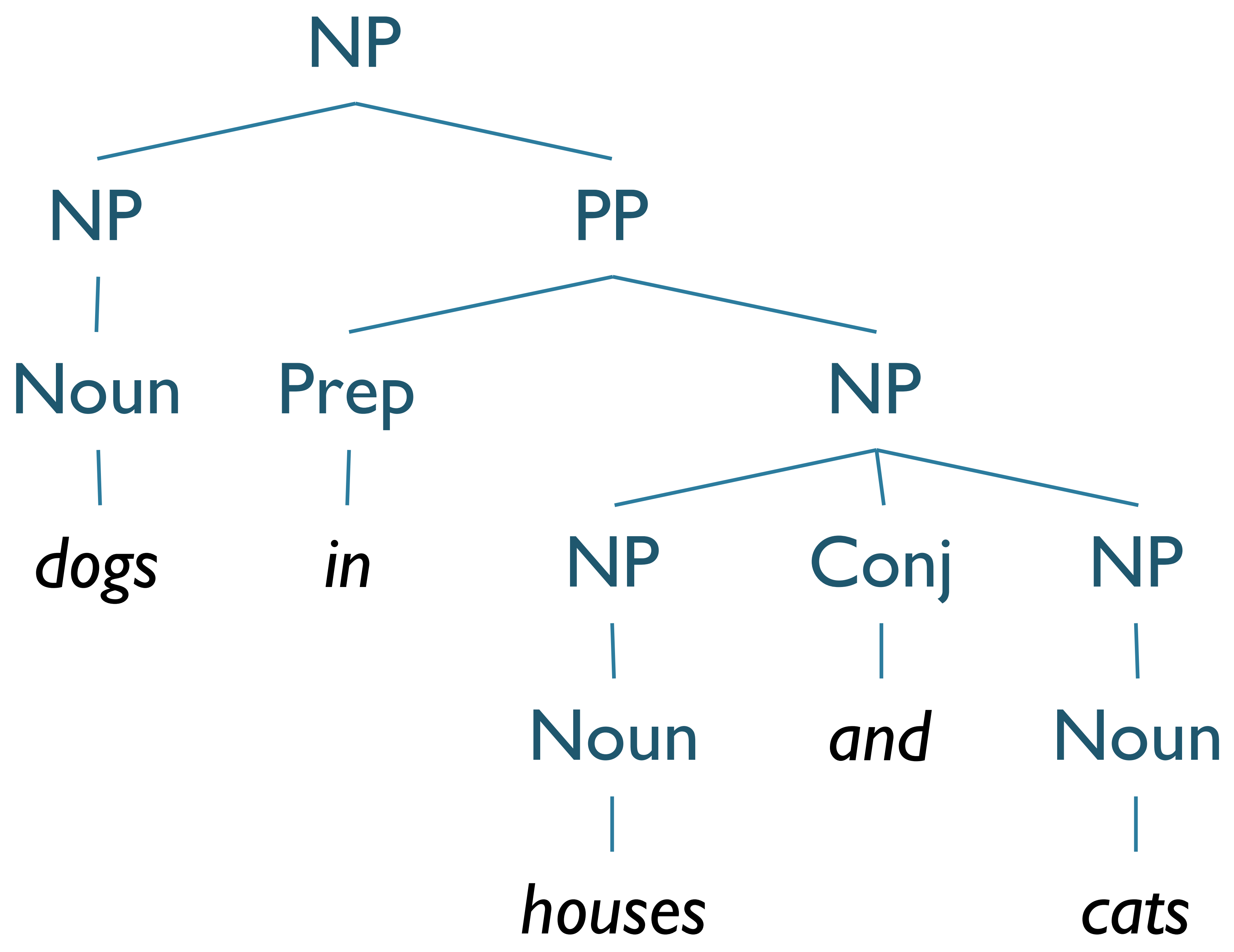

NP → NP Conj NP
NP → NP PP
Noun → "dogs"
PP → Prep NP
Prep → "in"
NP → Noun
Noun → "houses"
Conj → "and"
NP → Noun
Noun → "cats"

Same Rules!

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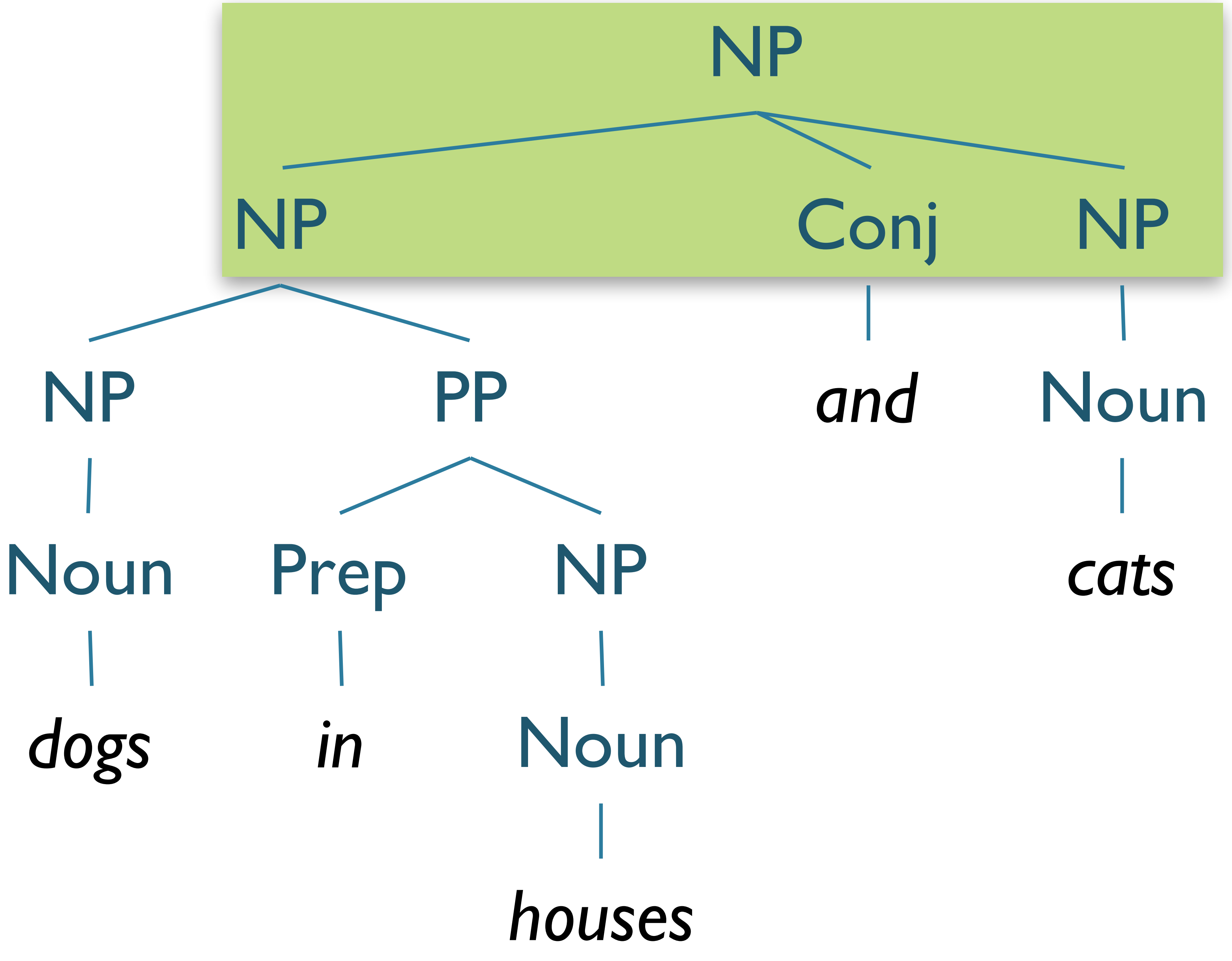

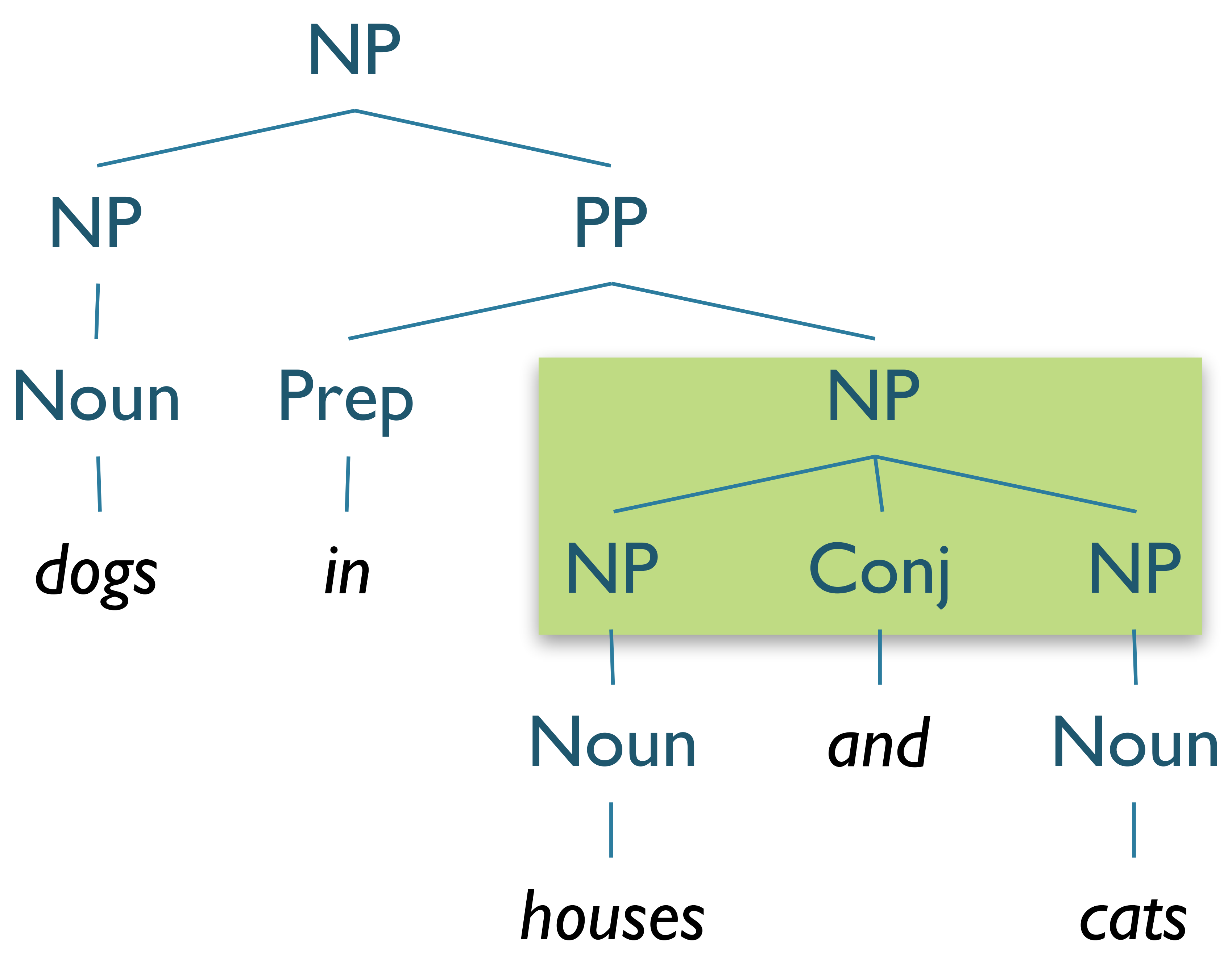

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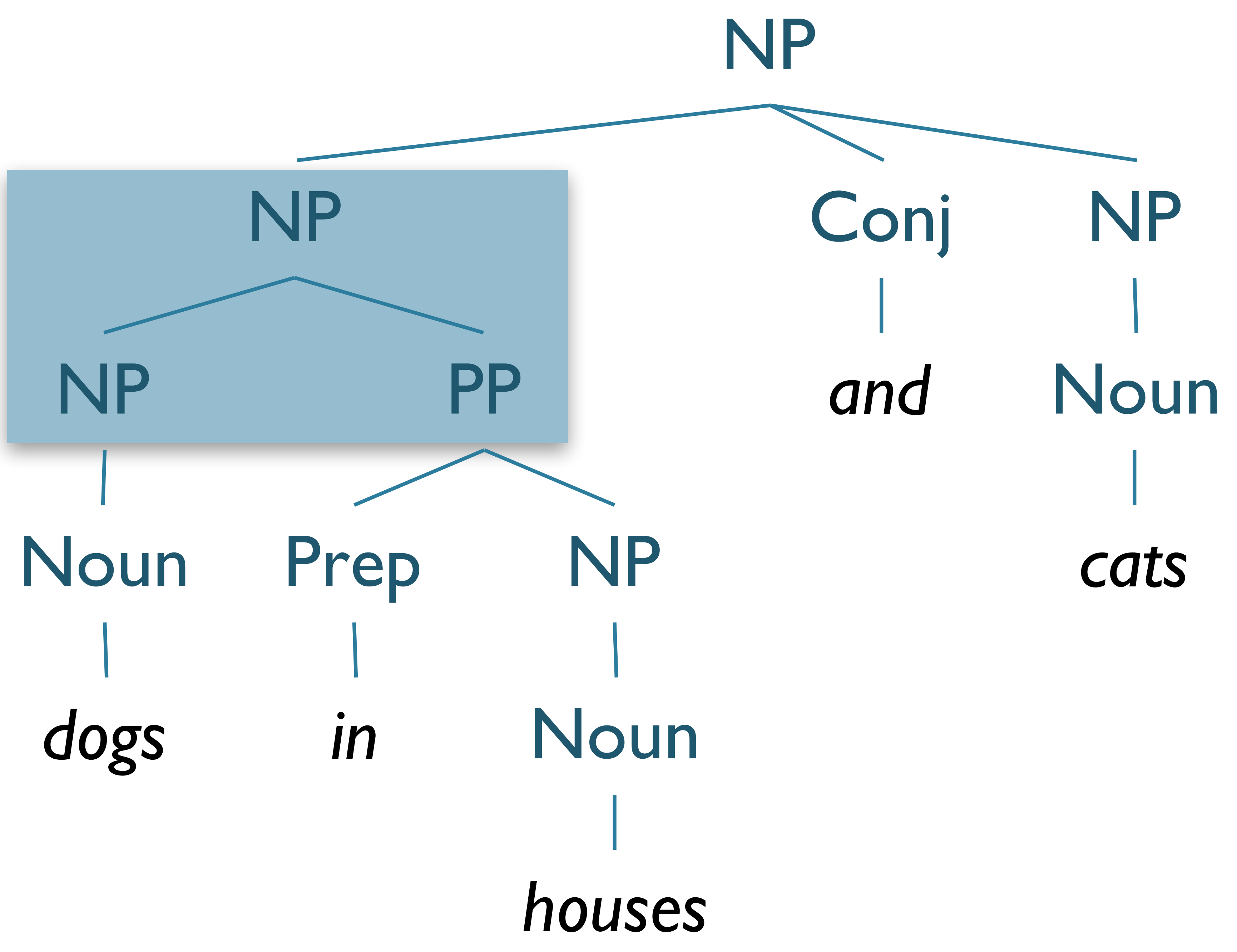

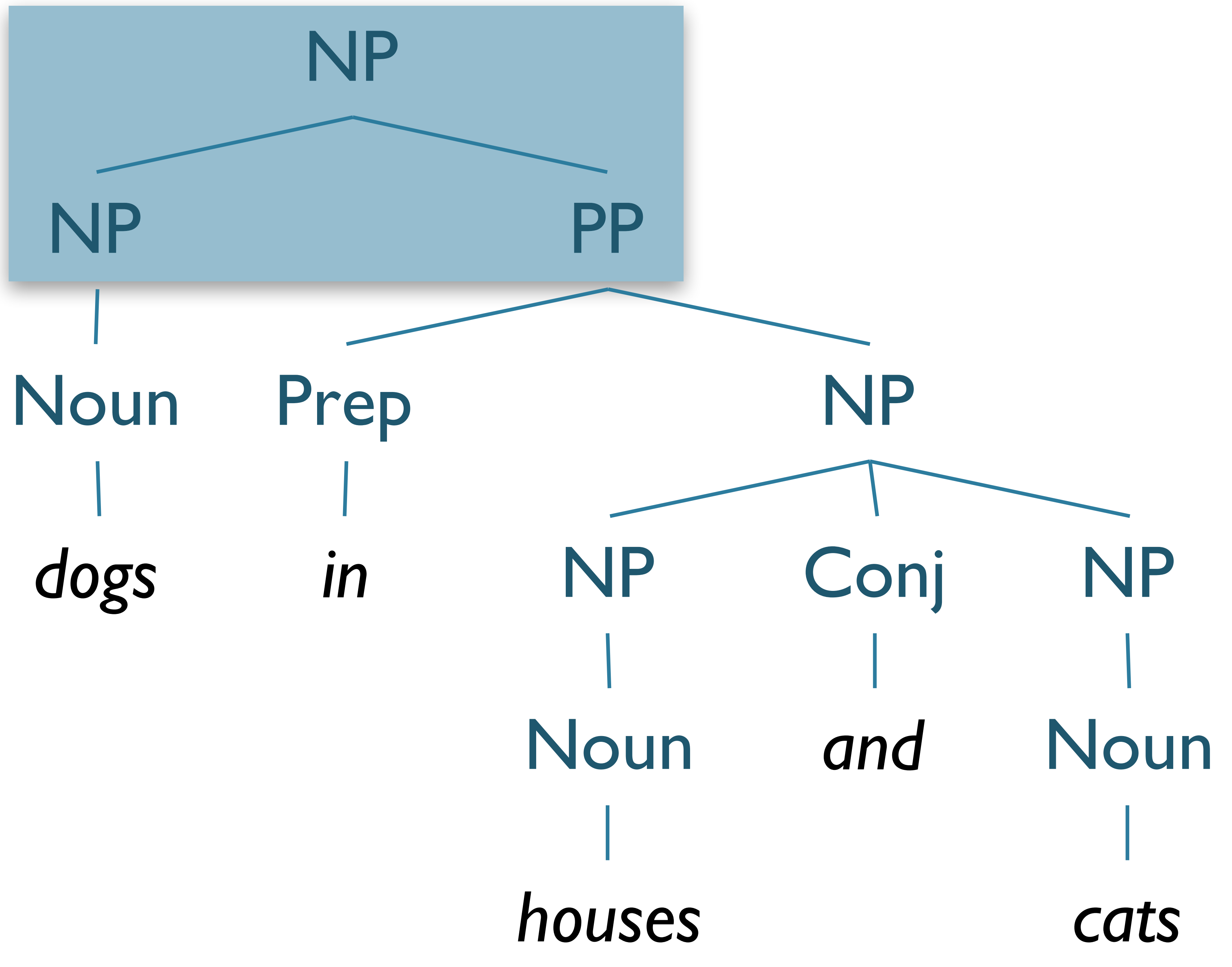

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Improving PCFGs

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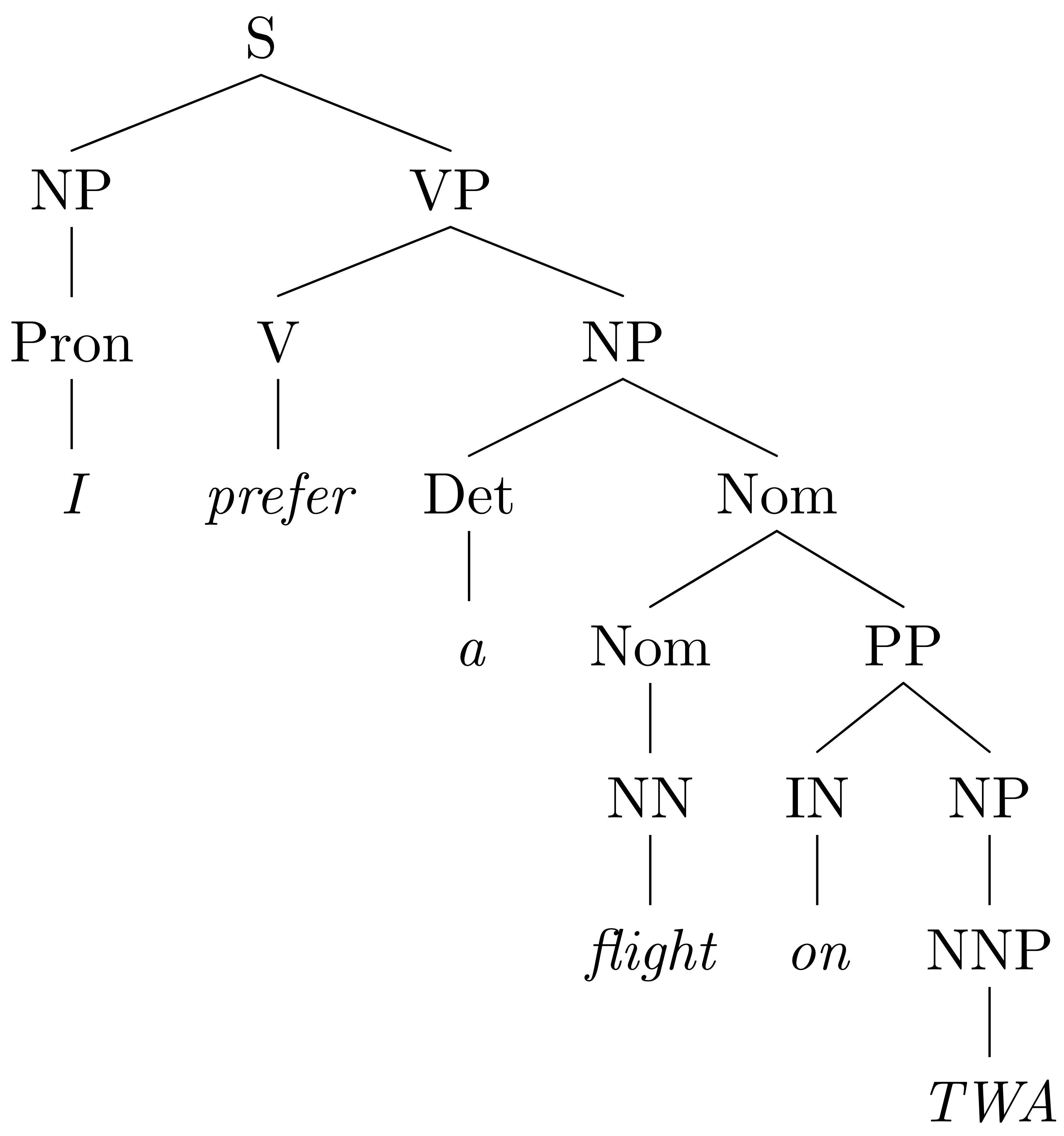
- **Parent Annotation**
- Lexicalization
- Markovization
- Reranking

Improving PCFGs: Parent Annotation

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



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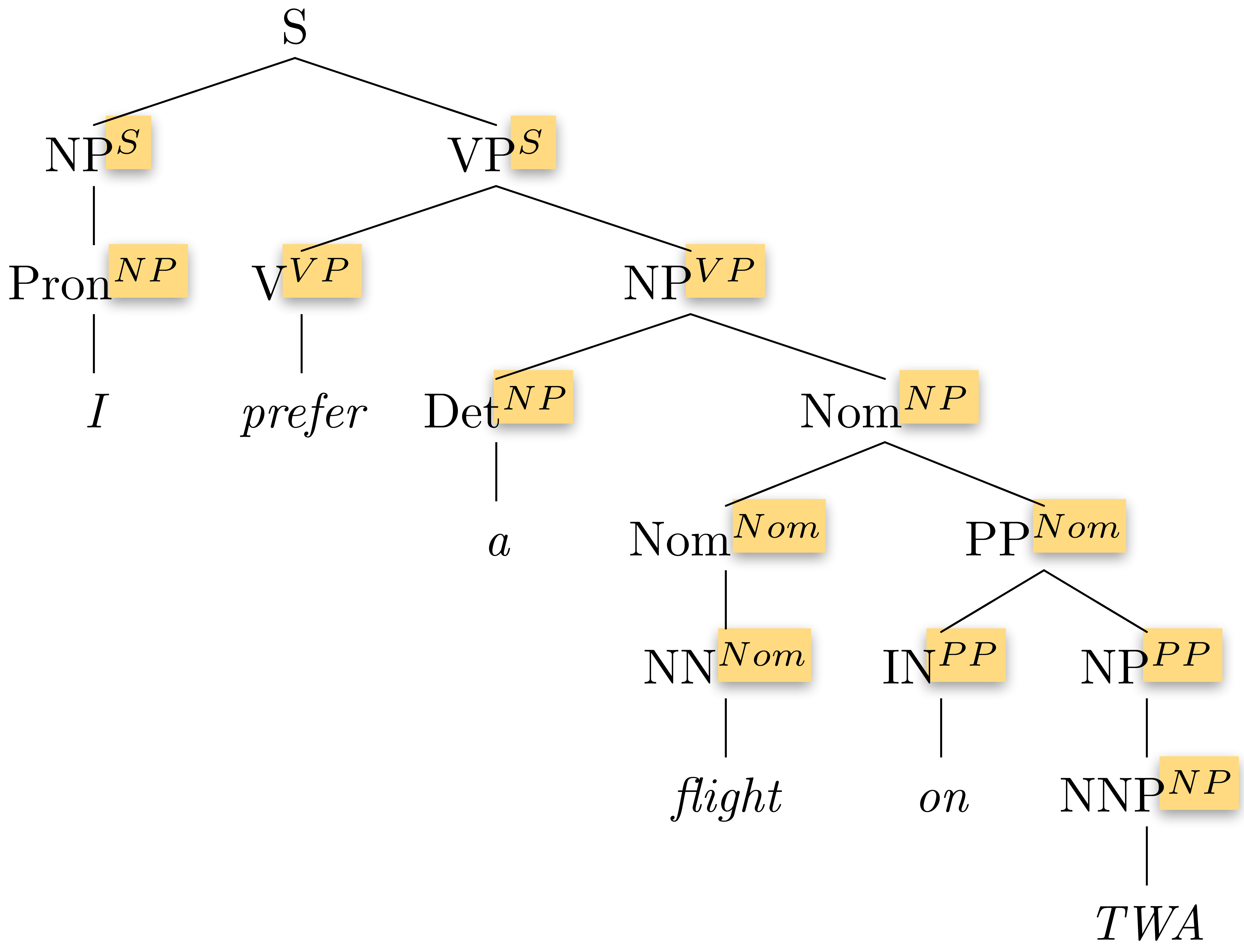

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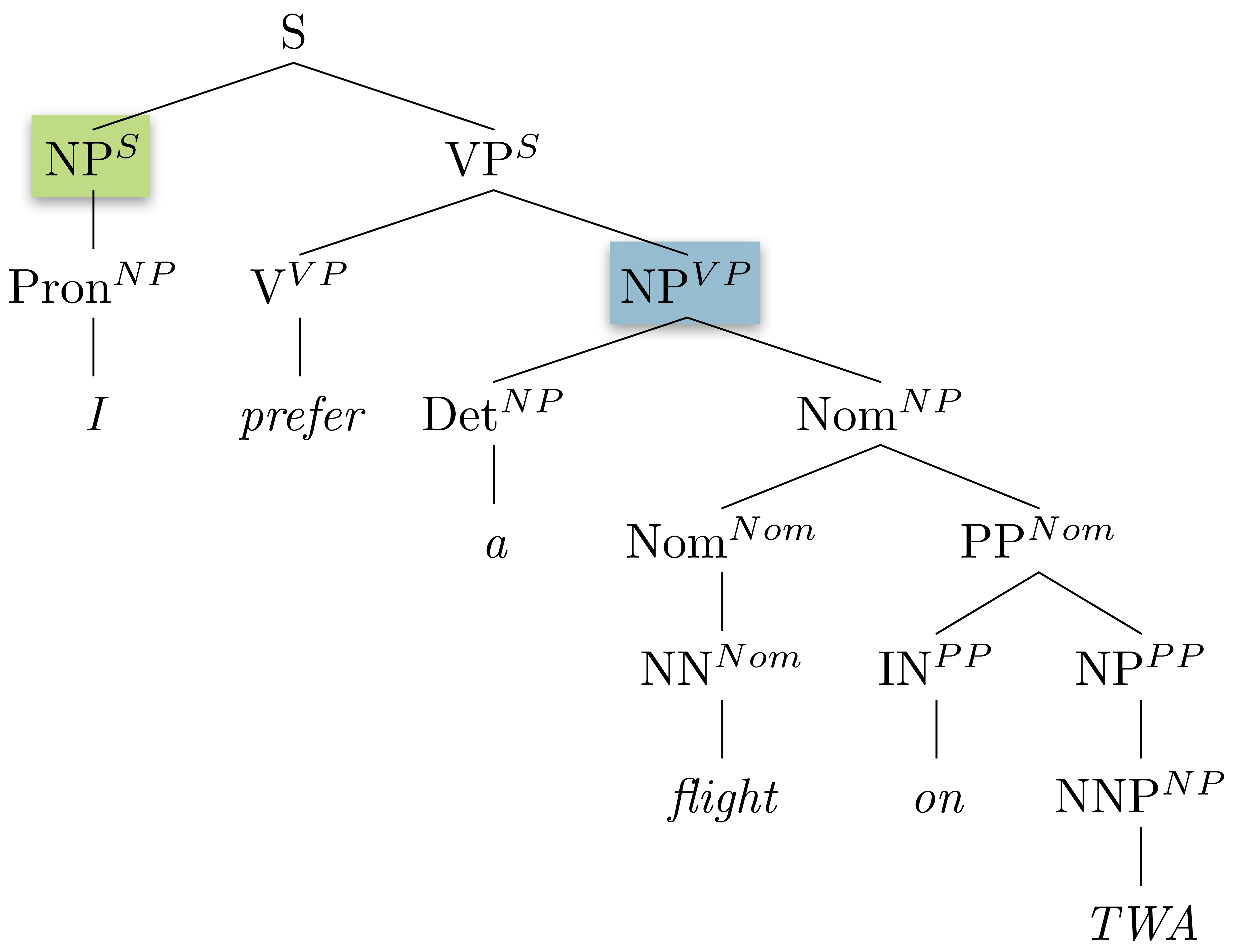

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- Advantages:
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- Disadvantages:
  - Explodes number of rules in grammar
    - Same problem with subcategorization
  - Results in sparsity problems
- Strategies to find an optimal number of splits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

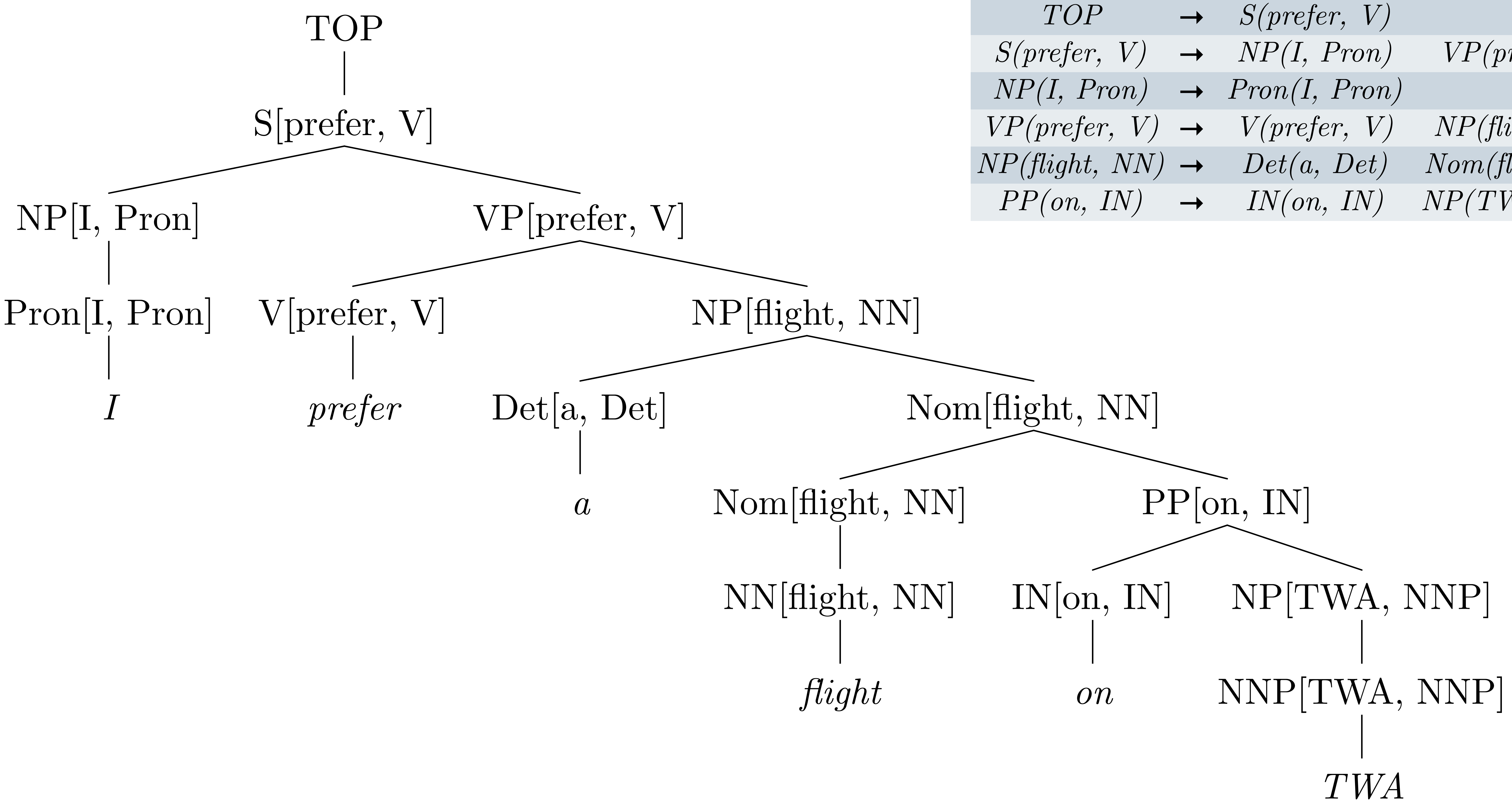
$$VP \rightarrow VBD\ NP\ PP$$

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

- **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

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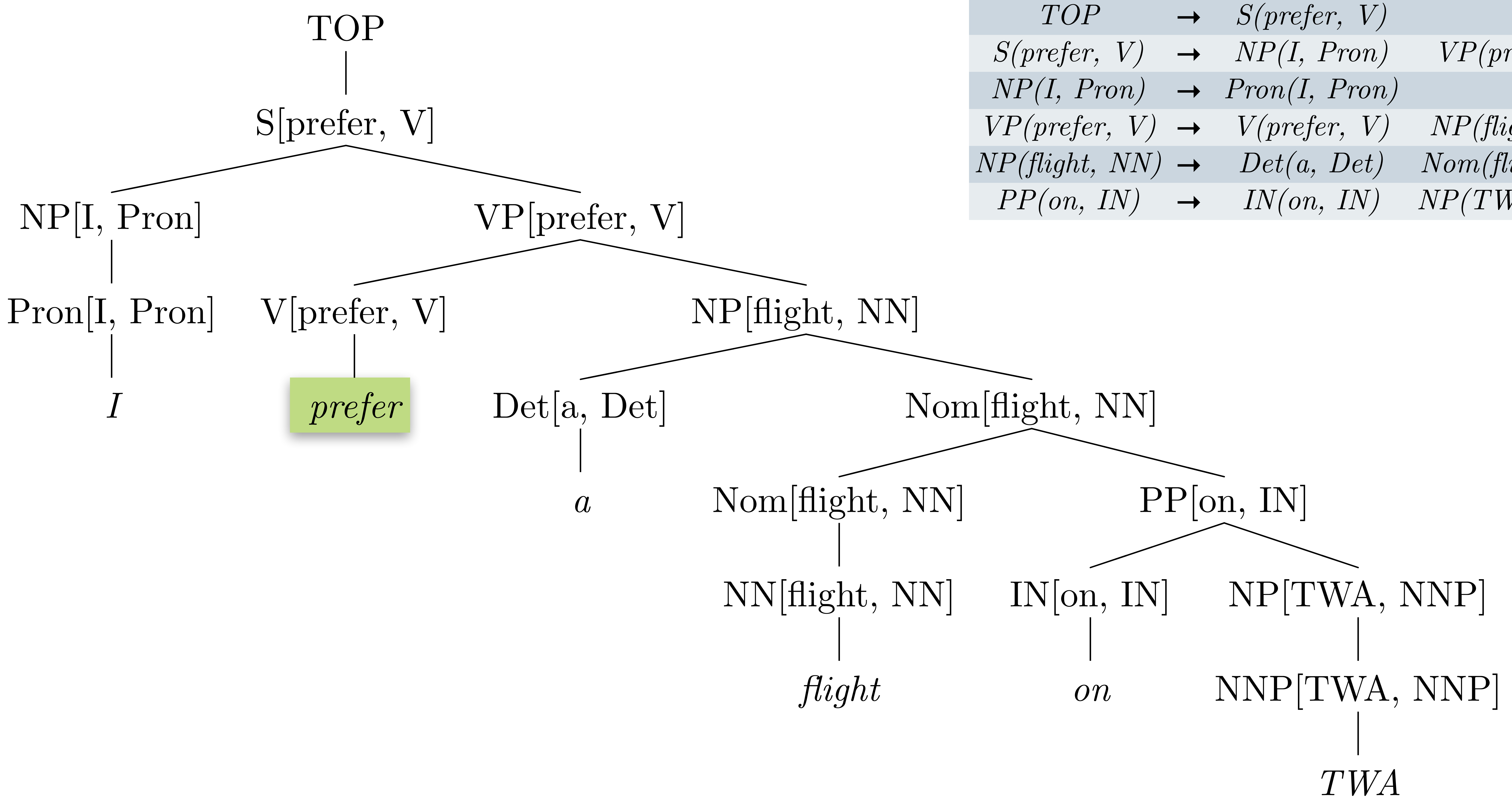

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NNP(NWA, NNP)	→	TWA

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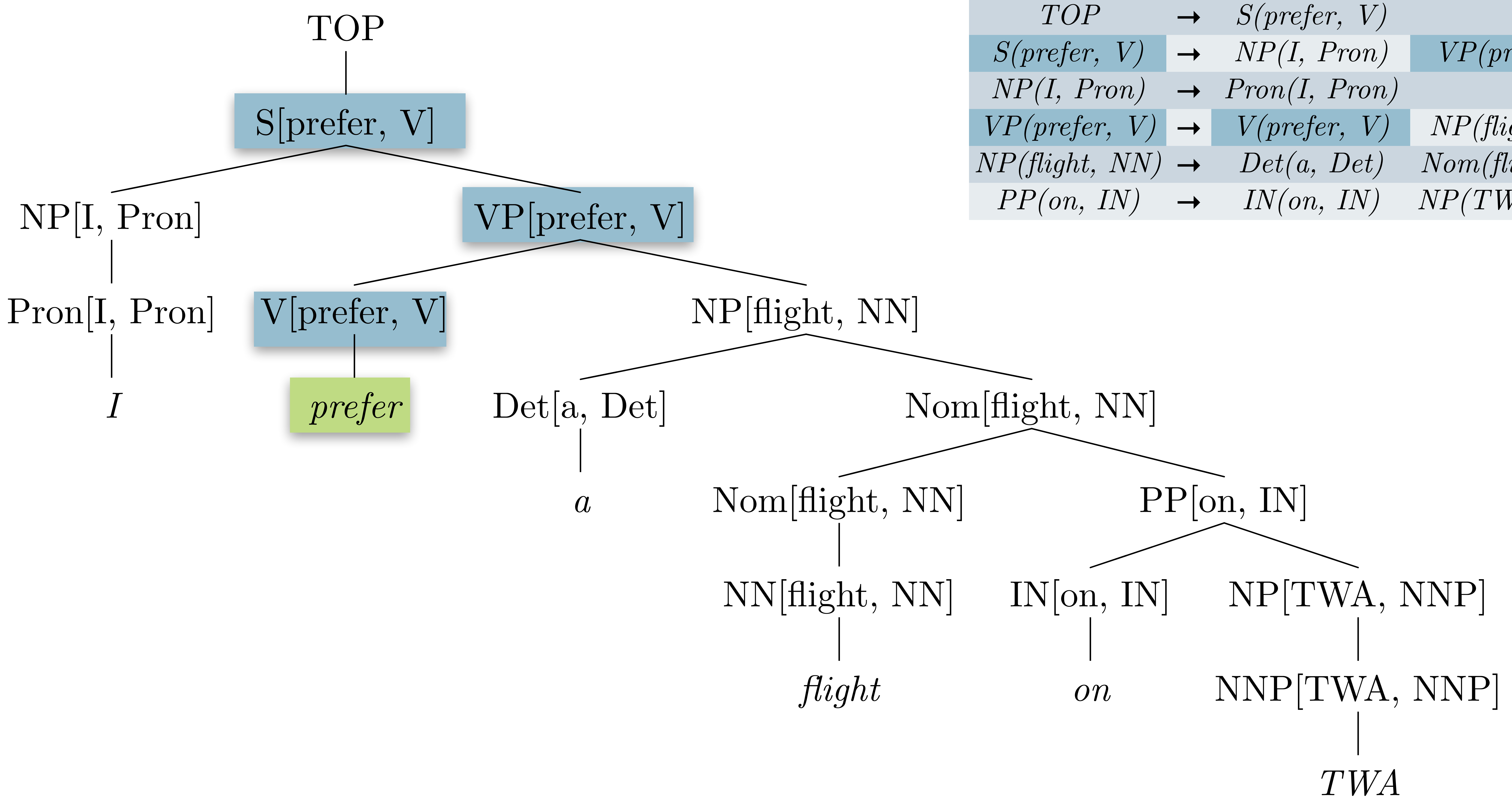

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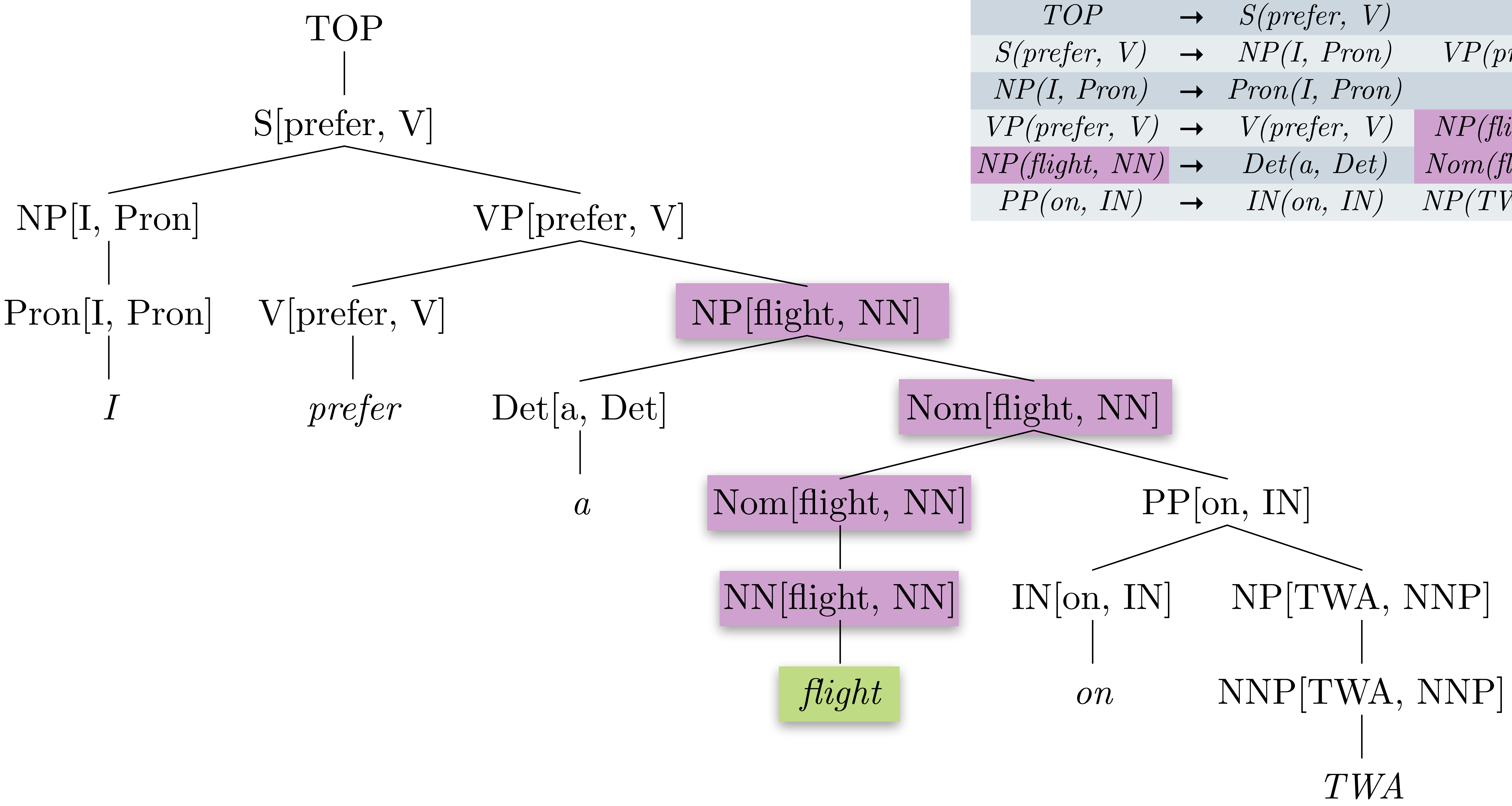
S(prefer, V)	→	*NP(I, Pron)*	*VP(prefer, V)*
NP(I, Pron)	→	*Pron(I, Pron)*	
VP(prefer, V)	→	*V(prefer, V)*	*NP(flight, NN)*
NP(flight, NN)	→	*Det(a, Det)*	*Nom(flight, NN)*
PP(on, IN)	→	*IN(on, IN)*	*NP(TWA, NNP)*

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



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)*
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Improving PCFGs: Lexical Dependencies

- Upshot: heads propagate up tree:

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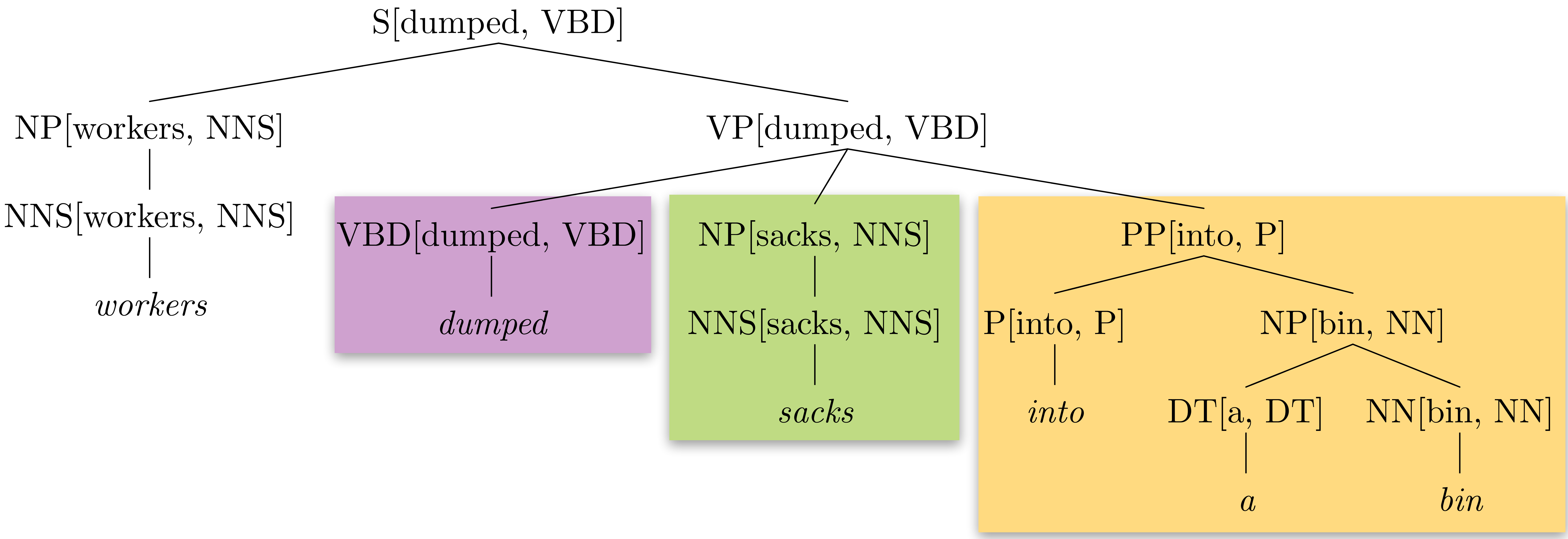


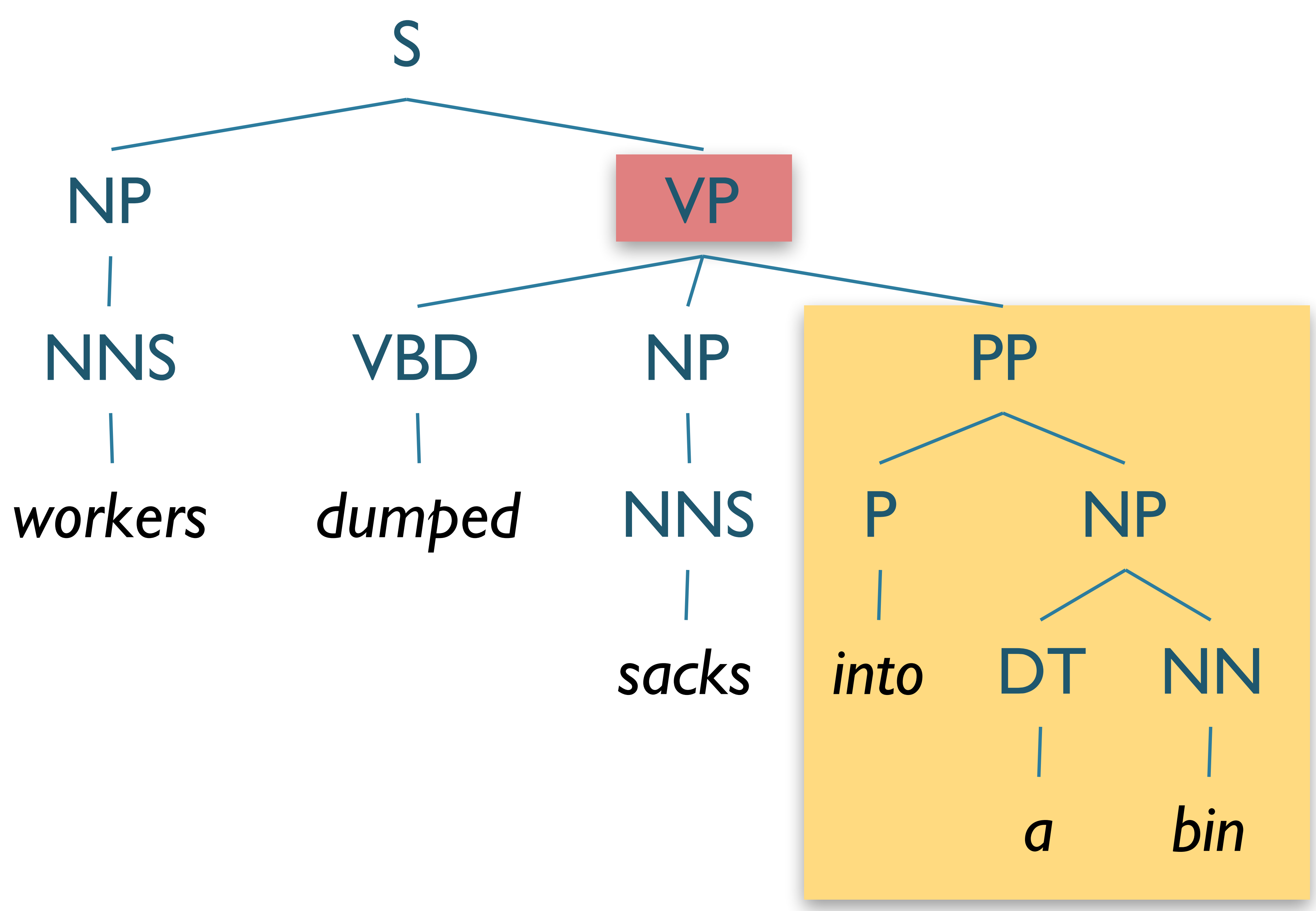
Improving PCFGs: Lexical Dependencies

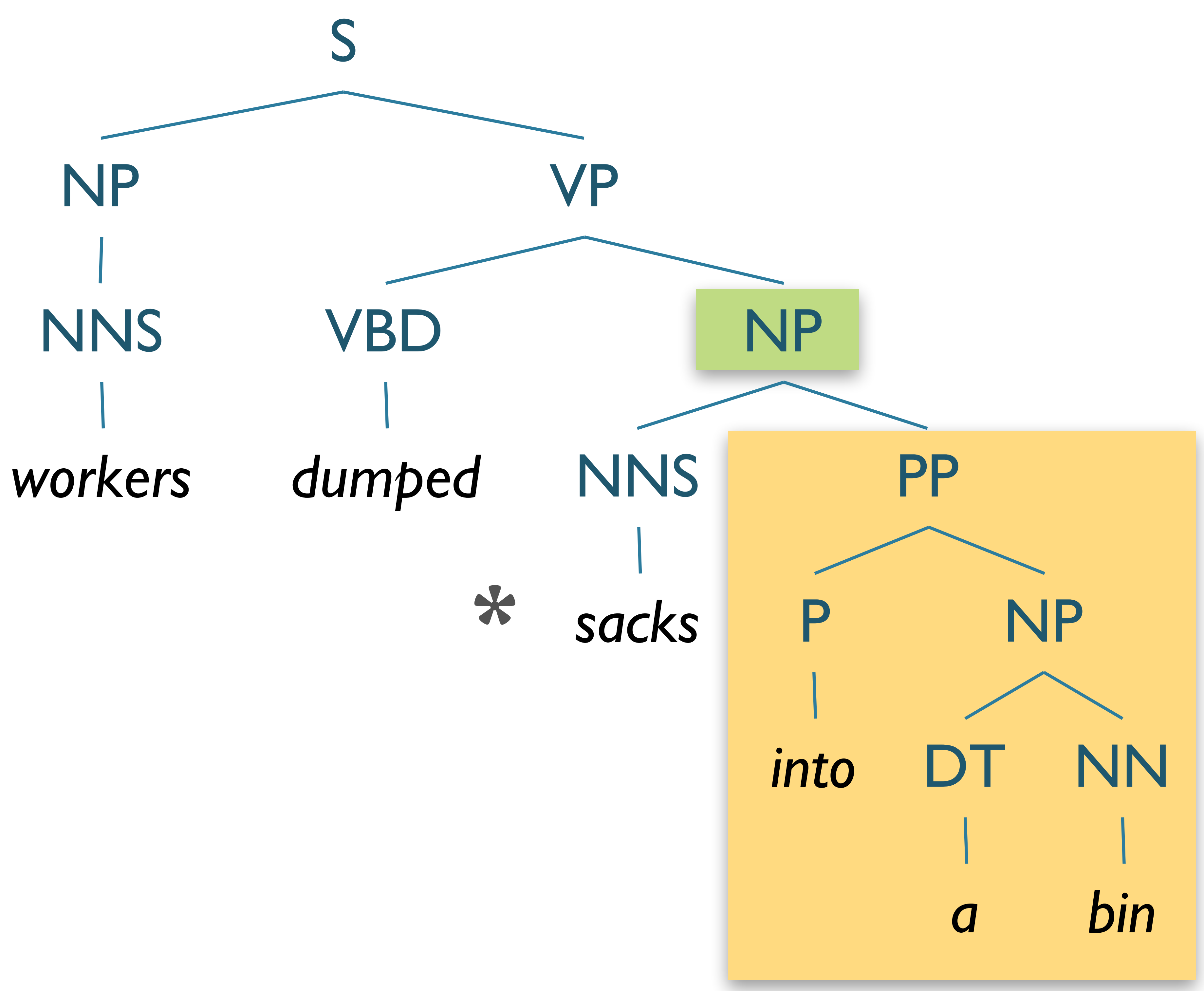
- Downside:
  - Rules far too specialized — will be sparse
- Solution:
  - Assume ***conditional*** independence
  - Create more rules

Improving PCFGs: Collins Parser

- Proposal:
  - $\boldsymbol{LHS} \rightarrow \boldsymbol{LeftOfHead} \ldots \quad \boldsymbol{Head} \quad \ldots \boldsymbol{RightOfHead}$
  - 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

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

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

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

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

Improving PCFGs

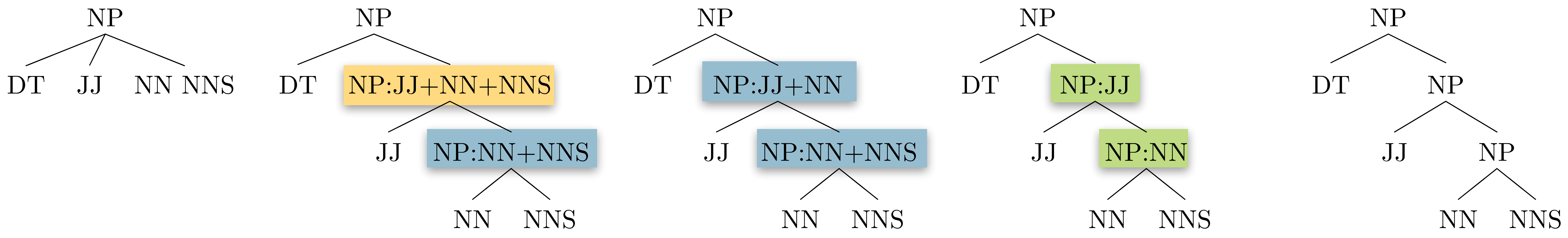
- Parent Annotation
- Lexicalization
- **Markovization**
- Reranking

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. $P(\boldsymbol{Y}) > 100 \times P(\boldsymbol{X})$