PCFGs: Parsing & Evaluation

LING 571 — Deep Processing Techniques for NLP
October 13, 2021
Shane Steinert-Threlkeld

Announcements

- HW2 due today at 11:59pm
  - readme.{txt|pdf}
    - Separate upload to Canvas
    - NOT in hw2.tar.gz
  - Run check_hw2.sh before submitting!
- Start symbol: either "%start S" *or* first nonterminal
  - NB: needs to be readable by nltk's grammar loading methods
- Condor job: runs conversion, but *not* parsing before/after; that can be done separately

Announcements

- Recording failed last time 😭 😭 😭
  - Uploaded last year’s lecture on Canvas; let me know if any questions arise
  - And please do let me know if you don’t see the red recording symbol on Zoom
- Re indigenous languages and NLP:
  - First Workshop on NLP for Indigenous Languages of the Americas (NAACL ’21)
  - http://turing.iimas.unam.mx/americasnlp/
  - Great papers, a shared task, excellent dataset made publicly available
    - [being used, e.g., by C.M. Downey for an unsupervised segmentation project]

Roadmap

- CKY + back-pointers
- PCFGs
- PCFG Parsing (PCKY)
- Inducing a PCFG
- Evaluation
- [Earley parsing]
- HW3 + collaboration

CKY Parsing: Backpointers

Backpointers

- Instead of list of possible nonterminals for that node, each cell should have:
  - Nonterminal for the node
  - Pointer to left and right children cells
    - Either direct pointer to cell, or indices

For example:

```
bp_2 = BackPointer()
bp_2.l_child = [X2, (1,4)]
bp_2.r_child = [PP, (4,6)]
```

CKY *Parser*

- Pair each nonterminal with back-pointer to cells from which it was derived
- Last step:
  - construct trees from back-pointers in $[\ 0,\ n\ ]$

NP, Pronoun [0,1]	S [0,2]	[0,3]	S [0,4]	[0,5]	
	Verb, VP, S [1,2]	[1,3]	VP, X2, S [1,4]	[1,5]	VP [1,6]
		Det [2,3]	NP [2,4]	[2,5]	NP [2,6]
			Noun, Nom [3,4]	[3,5]	Nom [3,6]
				Prep [4,5]	PP [4,6]
					NNP, NP [5,6]

$$VP \rightarrow VP\ PP$$

```
   bp_1 = BackPointer()
bp_1.l_child = [VP, (1,4)]
bp_1.r_child = [PP, (4,6)]
```

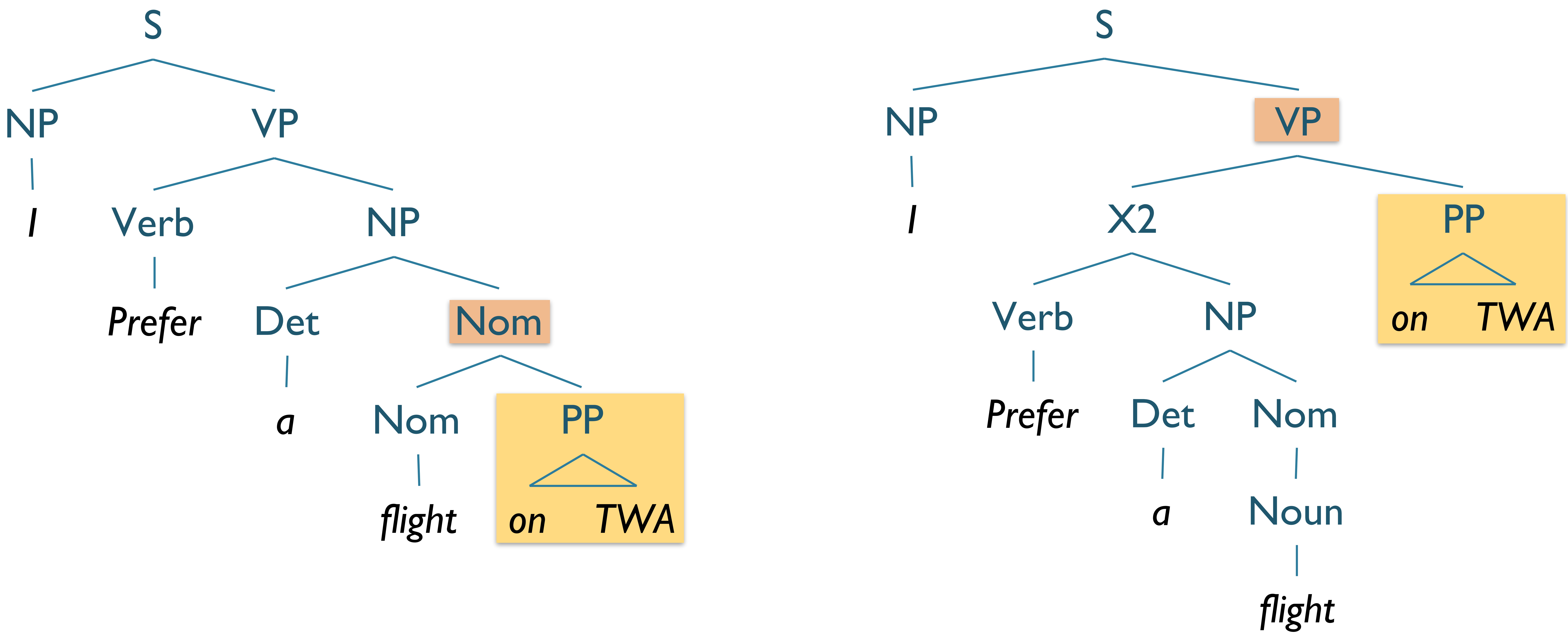
NP, Pronoun [0,1]	S [0,2]	[0,3]	S [0,4]	[0,5]	
	Verb, VP, S [1,2]	[1,3]	VP, X2, S [1,4]	[1,5]	VP [1,6]
		Det [2,3]	NP [2,4]	[2,5]	NP [2,6]
			Noun, Nom [3,4]	[3,5]	Nom [3,6]
				Prep [4,5]	PP [4,6]
					NNP, NP [5,6]

$VP \rightarrow X2\ PP$

```
   bp_2 = BackPointer()
bp_2.l_child = [X2, (1,4)]
bp_2.r_child = [PP, (4,6)]
```

NP, Pronoun [0,1]	S [0,2]	[0,3]	S [0,4]	[0,5]	
	Verb, VP, S [1,2]	[1,3]	VP, X2, S [1,4]	[1,5]	VP [1,6]
		Det [2,3]	NP [2,4]	[2,5]	NP [2,6]
			Noun, Nom [3,4]	[3,5]	Nom [3,6]
				Prep [4,5]	PP [4,6]
					NNP, NP [5,6]

Resulting Parses



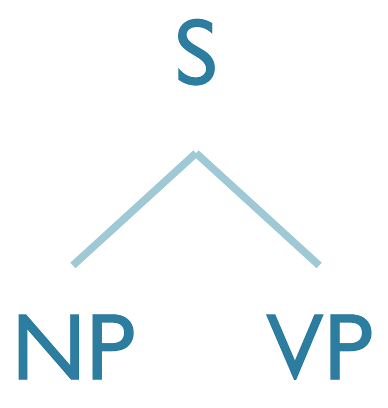
CKY Discussion

- Running time:
  - $O(n^3)$ where n is the length of the input string
  - Inner loop grows as square of # of non-terminals
- Expressiveness:
  - As implemented, requires CNF
    - Weak equivalence to original grammar
    - Doesn't capture full original structure
    - Back-conversion?
      - Can do binarization, terminal conversion
      - Unit productions requires change in CKY

CKY + Back-pointers Example

```
cky_table[0,6][S] = {(NP, (0,1)),
                      VP, (1,6))}
```

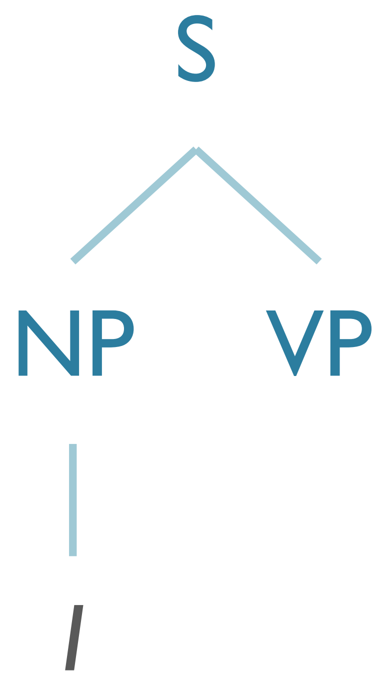
NP, Pronoun [0,1]	S [0,2]	[0,3]	S [0,4]	[0,5]	S [0,6]
	Verb, VP, S [1,2]	[1,3]	VP, X2, S [1,4]	[1,5]	VP, X2, S [1,6]
		Det [2,3]	NP [2,4]	[2,5]	NP [2,6]
			Noun, Nom [3,4]	[3,5]	Nom [3,6]
				Prep [4,5]	PP [4,6]
					NNP, NP [5,6]



I *prefer* *a* *flight* *on* *TWA*

```
cky_table[0,6][S] = {(NP, (0,1),
                       VP, (1,6))}
  cky_table[0,1][NP] = {('I')}
```

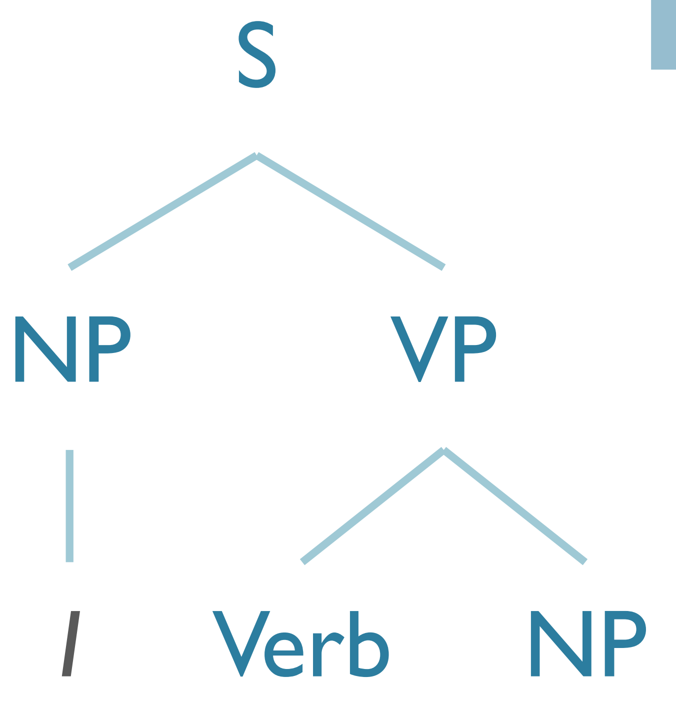
NP, Pronoun [0,1]	S [0,2]	[0,3]	S [0,4]	[0,5]	S [0,6]
	Verb, VP, S [1,2]	[1,3]	VP, X2, S [1,4]	[1,5]	VP, X2, S [1,6]
		Det [2,3]	NP [2,4]	[2,5]	NP [2,6]
			Noun, Nom [3,4]	[3,5]	Nom [3,6]
				Prep [4,5]	PP [4,6]
					NNP, NP [5,6]



I prefer a flight on TWA

```
cky_table[0,6][S] = {(NP, (0,1)),
                     VP, (1,6))}
cky_table[0,1][NP] = {('I')}
cky_table[1,6][VP] = {(Verb, (1,2)),
                      NP, (2,6)),
                      (X2, (1,4)),
                      PP, (4,6))}
```

NP, Pronoun [0,1]	S [0,2]	[0,3]	S [0,4]	[0,5]	S [0,6]
	Verb, VP, S [1,2]	[1,3]	VP, X2, S [1,4]	[1,5]	VP, X2, S [1,6]
		Det [2,3]	NP [2,4]	[2,5]	NP [2,6]
			Noun, Nom [3,4]	[3,5]	Nom [3,6]
				Prep [4,5]	PP [4,6]
					NNP, NP [5,6]

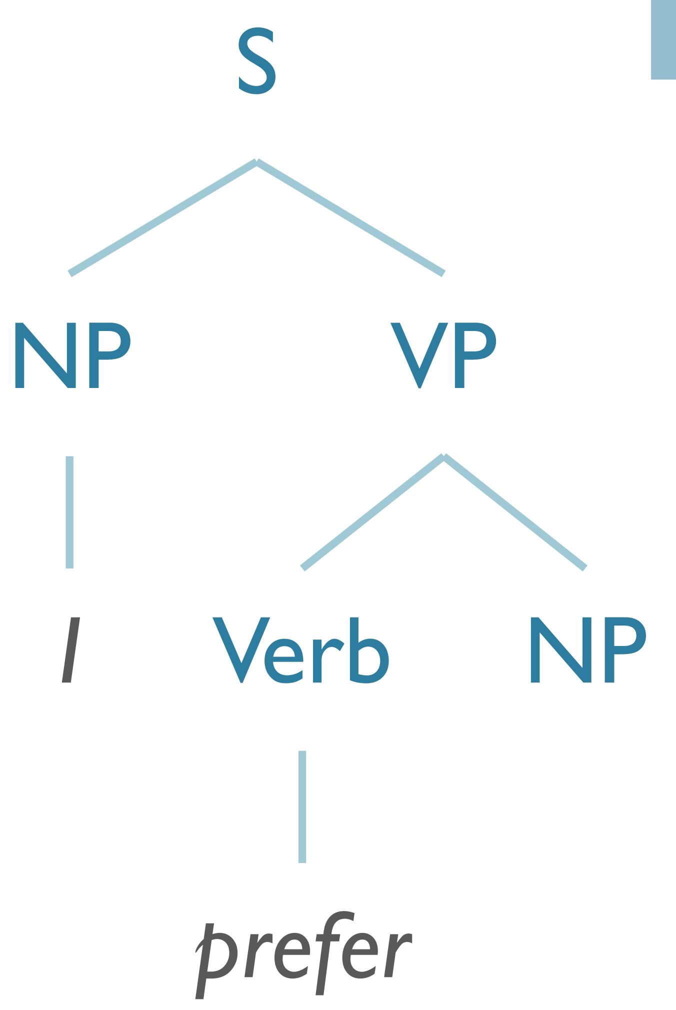


I *prefer* *a* *flight* *on* *TWA*

```
cky_table[0,6][S] = {(NP, (0,1)),
                     VP, (1,6))}
  cky_table[0,1][NP] = {('I')}
cky_table[1,6][VP] = {(Verb, (1,2)),
                      NP, (2,6)),
                      (X2, (1,4)),
                      PP, (4,6))}

cky_table[1,2][Verb] = {('prefer')}
```

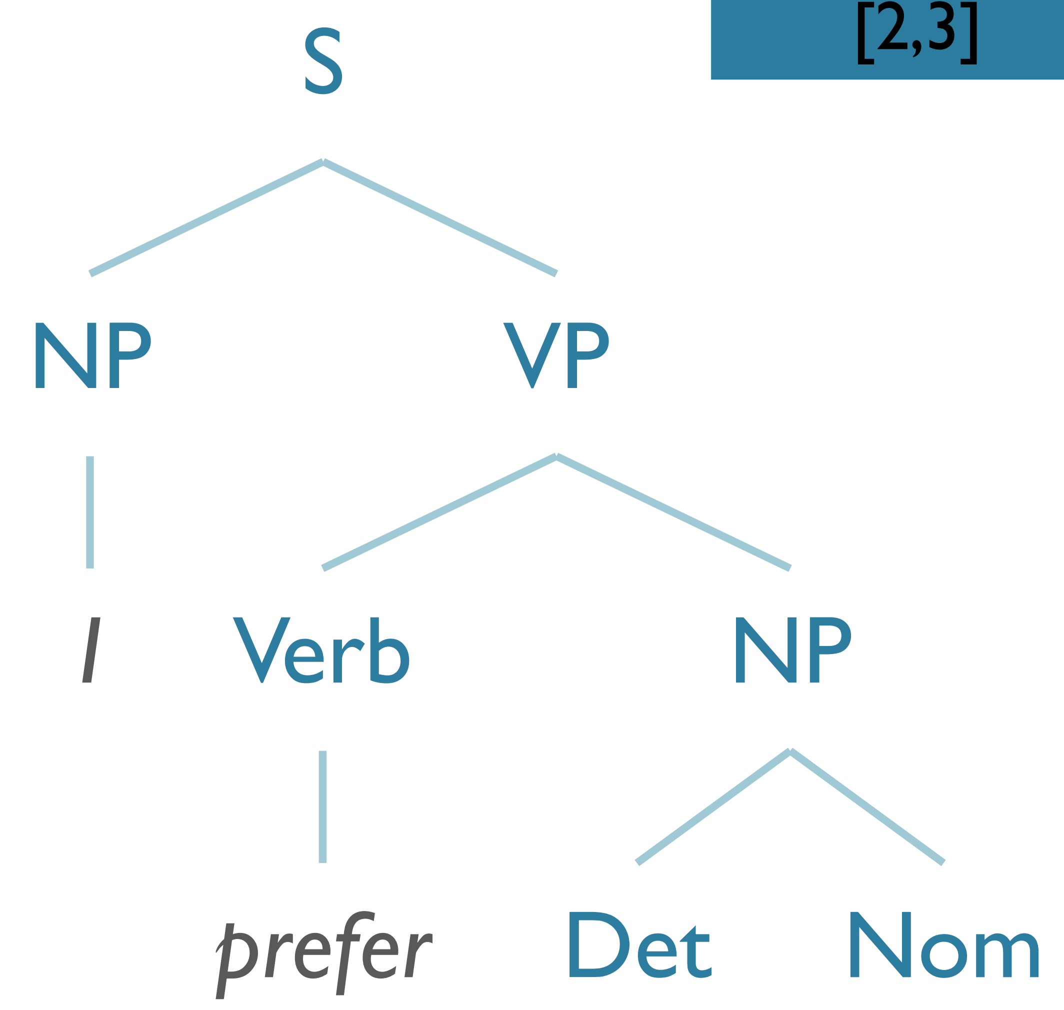
NP, Pronoun [0,1]	**S** [0,2]	[0,3]	**S** [0,4]	[0,5]	**S** [0,6]
	Verb, VP, S [1,2]	[1,3]	**VP, X2, S** [1,4]	[1,5]	**VP, X2, S** [1,6]
		Det [2,3]	**NP** [2,4]	[2,5]	**NP** [2,6]
			Noun, Nom [3,4]	[3,5]	**Nom** [3,6]
				Prep [4,5]	**PP** [4,6]
					NNP, NP [5,6]



I *prefer* *a* *flight* *on* *TWA*

```
cky_table[0,6][S] = {(NP, (0,1),
                      VP, (1,6))}
cky_table[0,1][NP] = {('I')}
cky_table[1,6][VP] = {(Verb, (1,2),
                       NP, (2,6)),
                      (X2, (1,4),
                       PP, (4,6))}
cky_table[1,2][Verb] = {('prefer')}
cky_table[2,6][NP] = {(Det, (2,3),
                       Nom, (3,6))}
```

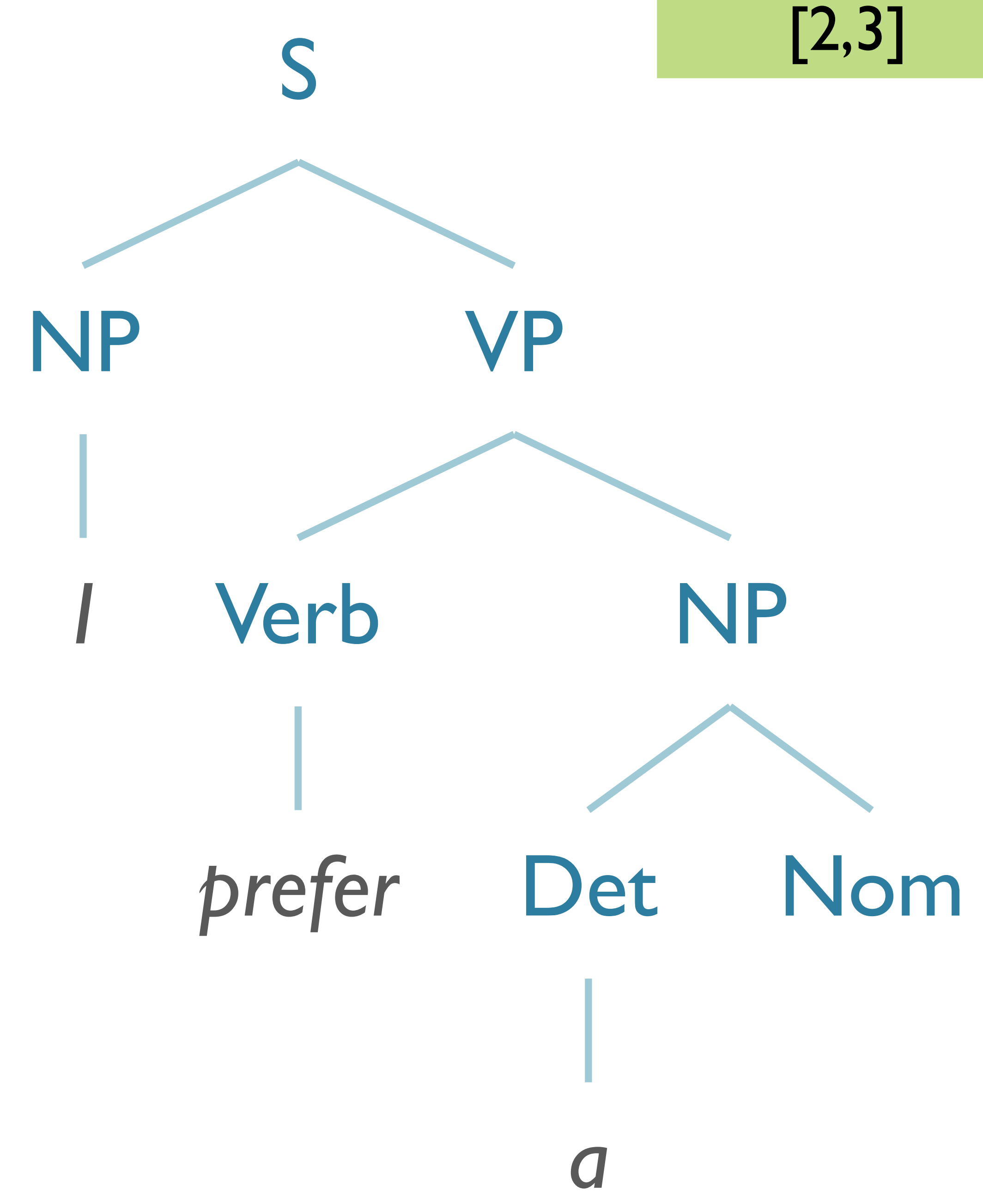
NP, Pronoun [0,1]	S [0,2]	[0,3]	S [0,4]	[0,5]	S [0,6]
	Verb, VP, S [1,2]	[1,3]	VP, X2, S [1,4]	[1,5]	VP, X2, S [1,6]
		Det [2,3]	NP [2,4]	[2,5]	NP [2,6]
			Noun, Nom [3,4]	[3,5]	Nom [3,6]
				Prep [4,5]	PP [4,6]
					NNP, NP [5,6]



I prefer a flight on TWA

```
cky_table[0,6][S] = {(NP, (0,1),
                      VP, (1,6))}
  cky_table[0,1][NP] = {('I')}
cky_table[1,6][VP] = {(Verb, (1,2),
                       NP, (2,6)),
                       (X2, (1,4),
                       PP, (4,6))}
cky_table[1,2][Verb] = {('prefer')}
 cky_table[2,6][NP] = {(Det, (2,3),
                        Nom, (3,6)}
   cky_table[2,3][Det] = {('a')}
```

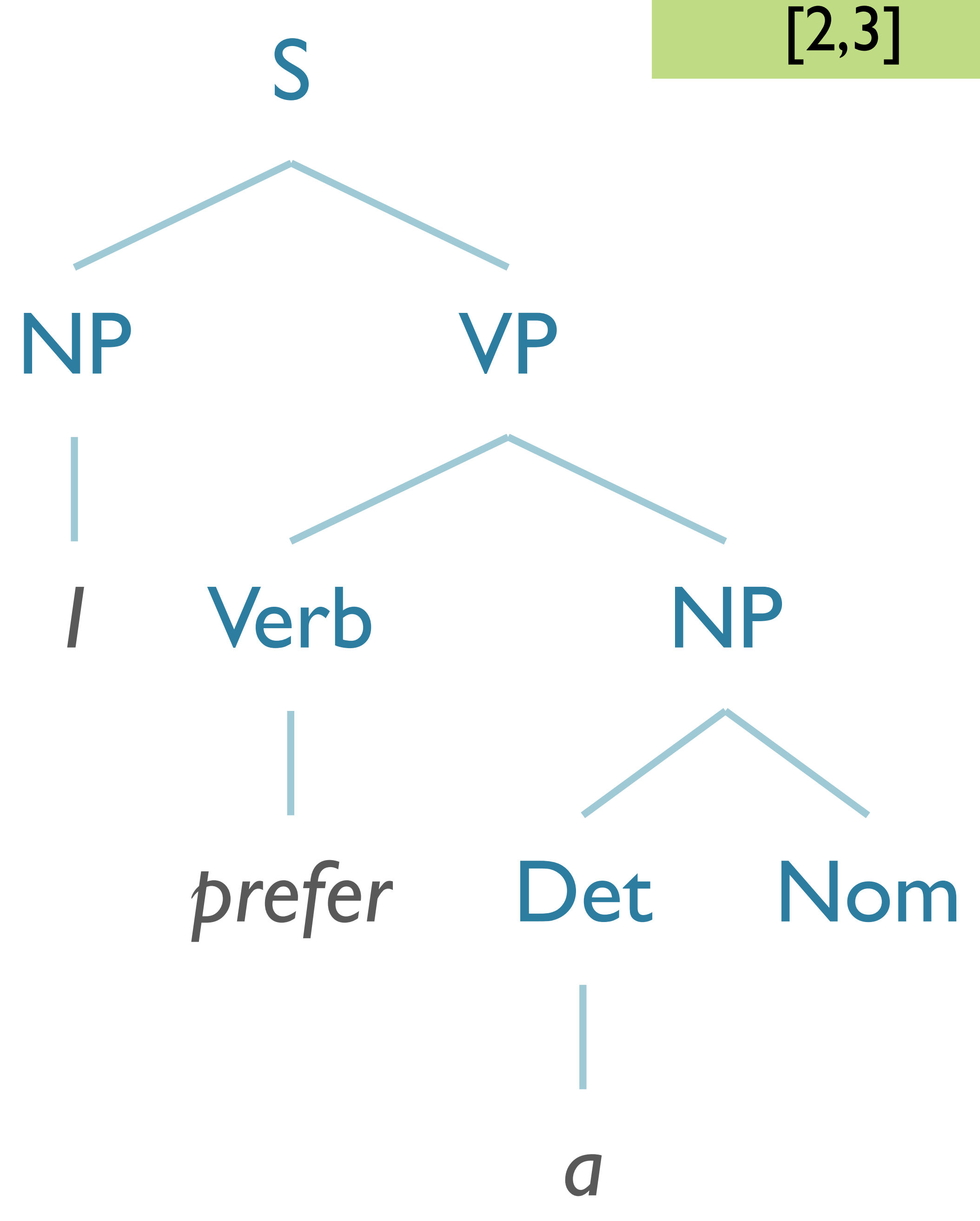
NP, Pronoun [0,1]	S [0,2]	[0,3]	S [0,4]	[0,5]	S [0,6]
	Verb, VP, S [1,2]	[1,3]	VP, X2, S [1,4]	[1,5]	VP, X2, S [1,6]
		Det [2,3]	NP [2,4]	[2,5]	NP [2,6]
			Noun, Nom [3,4]	[3,5]	Nom [3,6]
				Prep [4,5]	PP [4,6]
					NNP, NP [5,6]



I *prefer* *a* *flight* *on* *TWA*

```
cky_table[0,6][S] = {(NP, (0,1),
                      VP, (1,6))}
cky_table[0,1][NP] = {('I')}
cky_table[1,6][VP] = {(Verb, (1,2),
                       NP, (2,6)),
                      (X2, (1,4),
                       PP, (4,6))}
cky_table[1,2][Verb] = {('prefer')}
cky_table[2,6][NP] = {(Det, (2,3),
                       Nom, (3,6)}
cky_table[2,3][Det] = {('a')}
```

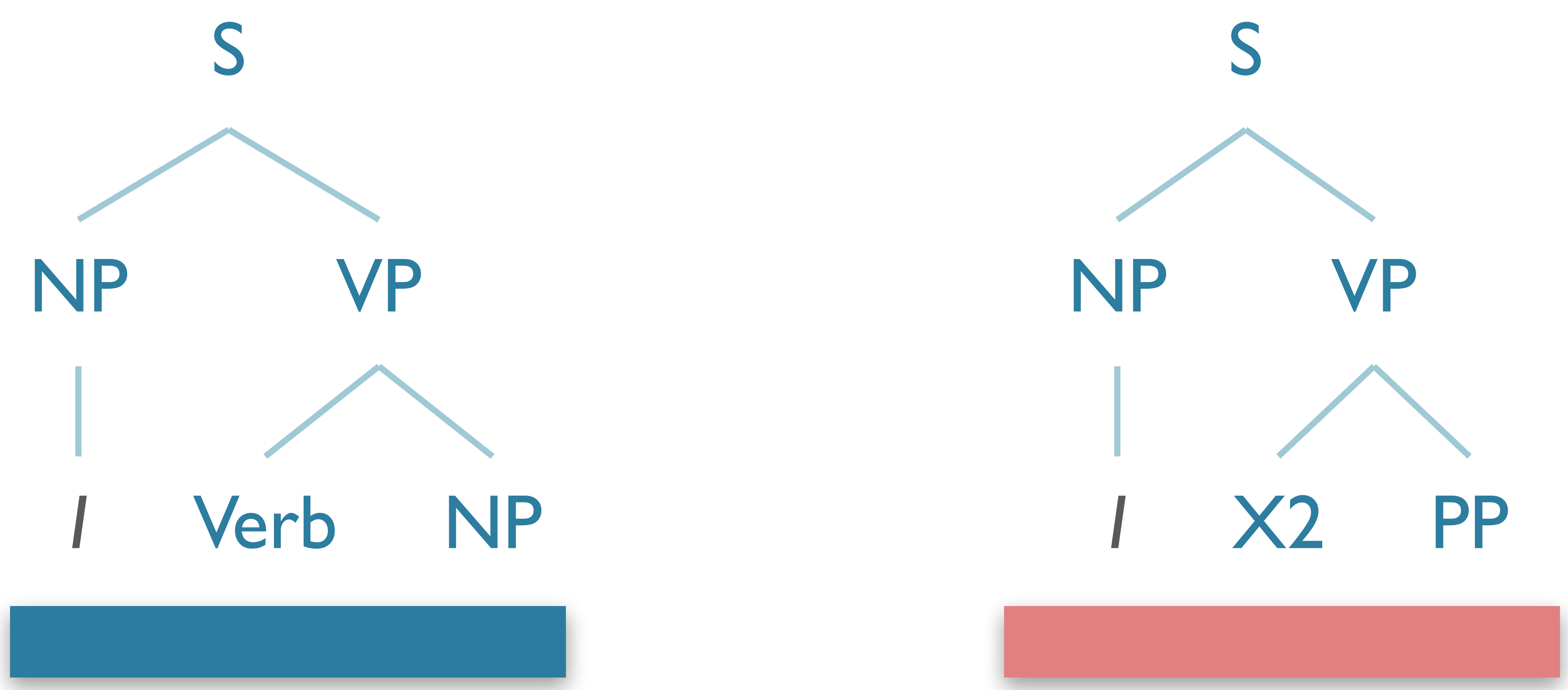
NP, Pronoun [0,1]	**S** [0,2]	[0,3]	**S** [0,4]	[0,5]	**S** [0,6]
	Verb, VP, S [1,2]	[1,3]	**VP, X2, S** [1,4]	[1,5]	**VP, X2, S** [1,6]
		Det [2,3]	**NP** [2,4]	[2,5]	**NP** [2,6]
			Noun, Nom [3,4]	[3,5]	**Nom** [3,6]
				Prep [4,5]	**PP** [4,6]
					NNP, NP [5,6]



I *prefer* *a* *flight* *on* *TWA*

```
cky_table[0,6][S] = {(NP, (0,1),
                      VP, (1,6))}
  cky_table[0,1][NP] = {('I')}
cky_table[1,6][VP] = {(Verb, (1,2),
                       NP, (2,6)),
                      (X2, (1,4),
                       PP, (4,6))}
```

NP, Pronoun [0,1]	**S** [0,2]	[0,3]	**S** [0,4]	[0,5]	**S** [0,6]
	Verb, VP, S [1,2]	[1,3]	**VP, X2, S** [1,4]	[1,5]	**VP, X2, S** [1,6]
		Det [2,3]	**NP** [2,4]	[2,5]	**NP** [2,6]
			Noun, Nom [3,4]	[3,5]	**Nom** [3,6]
				Prep [4,5]	**PP** [4,6]
					NNP, NP [5,6]



I *prefer* *a* *flight* *on* *TWA*

Probabilistic Context-Free Grammars

Probabilistic Context-free Grammars: Roadmap

Motivation: Ambiguity

Approach:

- Definition
- Disambiguation
- Parsing
- Evaluation
- Enhancements

Motivation

What about ambiguity?

Current algorithm can ***represent*** it

…can’t resolve it.

Probabilistic Parsing

- Provides strategy for solving disambiguation problem
  - Compute the probability of all analyses
  - Select the most probable

- Employed in language modeling for speech recognition
  - N-gram grammars predict words, constrain search
  - Also, constrain generation, translation

PCFGs: Formal Definition

N	a set of **non-terminal symbols** (or **variables**)

PCFGs: Formal Definition

N	a set of **non-terminal symbols** (or **variables**)
Σ	a set of **terminal symbols** (disjoint from N)

PCFGs: Formal Definition

N	a set of **non-terminal symbols** (or **variables**)
Σ	a set of **terminal symbols** (disjoint from N)
R	a set of rules of productions, each of the form $A \rightarrow \beta[p]$, where A is a non-terminal where A is a non-terminal, β is a string of symbols from the infinite set of strings $(\Sigma \cup N)*$ and p is a number between 0 and 1 expressing $P(\beta \mid A)$

PCFGs: Formal Definition

N	a set of **non-terminal symbols** (or **variables**)
Σ	a set of **terminal symbols** (disjoint from N)
R	a set of rules of productions, each of the form $A \rightarrow \beta[p]$, where A is a non-terminal where A is a non-terminal, β is a string of symbols from the infinite set of strings $(\Sigma \cup N)*$ and p is a number between 0 and 1 expressing $P(\beta\|A)$
S	a designated **start symbol**

PCFGs

- Augment each production with probability that LHS will be expanded as RHS
  - $P(A \rightarrow \beta)$
  - $P(A \rightarrow \beta | A)$
  - $P(\beta | A)$
  - $P(RHS \mid LHS)$
- NB: the first is often used; but the latter are what's really meant.

PCFGs

- Sum over all possible expansions is 1

$$\sum_{\beta} P(A \rightarrow \beta) = 1$$

- A PCFG is ***consistent*** if sum of probabilities of all sentences in language is 1
  - Recursive rules often yield inconsistent grammars *([Booth & Thompson, 1973](#))*

Example PCFG: Augmented $\mathscr{L}_1$

Grammar		Lexicon
$S \rightarrow NP\ VP$	[.80]	$Det \rightarrow that$ [.10] | a [.30] | the [.60]
$S \rightarrow Aux\ NP\ VP$	[.15]	$Noun \rightarrow book$ [.10] | $flight$ [.30] | $meal$ [.15] | $money$ [0.5]
$S \rightarrow VP$	[.05]	| $flights$ [0.40] | $dinner$ [.10]
$NP \rightarrow Pronoun$	[.35]	$Verb \rightarrow book$ [.30] | $include$ [.30] | $prefer$ [.40]
$NP \rightarrow Proper\text{-}Noun$	[.30]	$Pronoun \rightarrow I$ [.40] | she [.05] | me [.15] | you [.40]
$NP \rightarrow Det\ Nominal$	[.20]	$Proper\text{-}Noun \rightarrow Houston$ [.60] | NWA [.40]
$NP \rightarrow Nominal$	[.15]	$Aux \rightarrow does$ [.60] | can [.40]
$Nominal \rightarrow Noun$	[.75]	$Preposition \rightarrow from$ [.30] | to [.30] | on [.20] | $near$ [.15]
$Nominal \rightarrow Nominal\ Noun$	[.20]	| $through$ [.05]
$Nominal \rightarrow Nominal\ PP$	[.05]	
$VP \rightarrow Verb$	[.35]	
$VP \rightarrow Verb\ NP$	[.20]	
$VP \rightarrow Verb\ NP\ PP$	[.10]	
$VP \rightarrow Verb\ PP$	[.15]	
$VP \rightarrow Verb\ NP\ NP$	[.05]	
$VP \rightarrow VP\ PP$	[.15]	
$PP \rightarrow Preposition\ NP$	[1.0]	

Example PCFG: Augmented $\mathscr{L}_1$

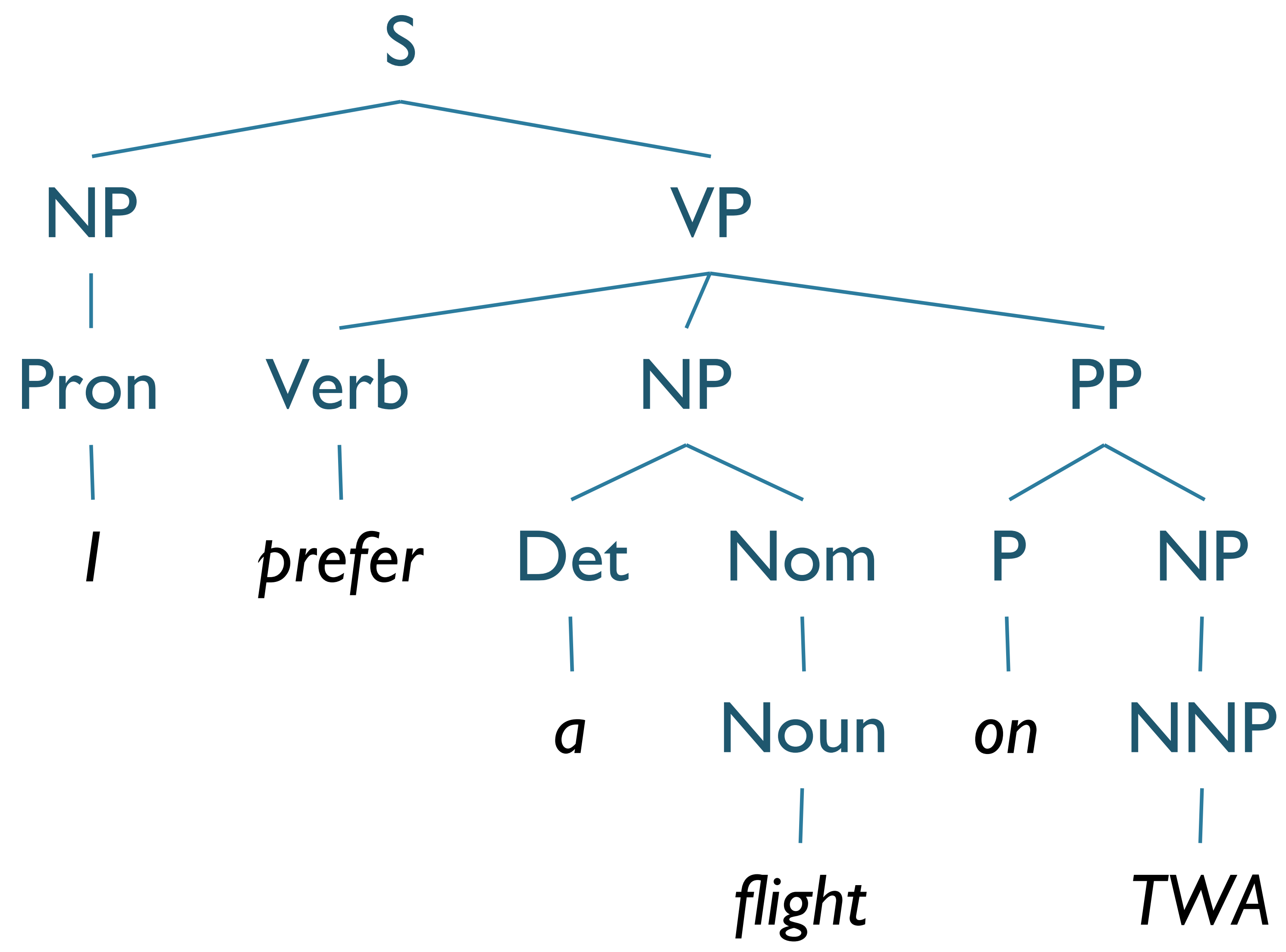
Grammar		Lexicon
$S \rightarrow NP\ VP$	[.80]	$Det \rightarrow that$ [.10] | a [.30] | the [.60]
$S \rightarrow Aux\ NP\ VP$	[.15]	$Noun \rightarrow book$ [.10] | $flight$ [.30] | $meal$ [.15] | $money$ [0.5]
$S \rightarrow VP$	[.05]	| $flights$ [0.40] | $dinner$ [.10]
$NP \rightarrow Pronoun$	[.35]	$Verb \rightarrow book$ [.30] | $include$ [.30] | $prefer$ [.40]
$NP \rightarrow Proper\text{-}Noun$	[.30]	$Pronoun \rightarrow I$ [.40] | she [.05] | me [.15] | you [.40]
$NP \rightarrow Det\ Nominal$	[.20]	$Proper\text{-}Noun \rightarrow Houston$ [.60] | NWA [.40]
$NP \rightarrow Nominal$	[.15]	$Aux \rightarrow does$ [.60] | can [.40]
$Nominal \rightarrow Noun$	[.75]	$Preposition \rightarrow from$ [.30] | to [.30] | on [.20] | $near$ [.15]
$Nominal \rightarrow Nominal\ Noun$	[.20]	| $through$ [.05]
$Nominal \rightarrow Nominal\ PP$	[.05]	
$VP \rightarrow Verb$	[.35]	
$VP \rightarrow Verb\ NP$	[.20]	
$VP \rightarrow Verb\ NP\ PP$	[.10]	
$VP \rightarrow Verb\ PP$	[.15]	
$VP \rightarrow Verb\ NP\ NP$	[.05]	
$VP \rightarrow VP\ PP$	[.15]	
$PP \rightarrow Preposition\ NP$	[1.0]	

Disambiguation

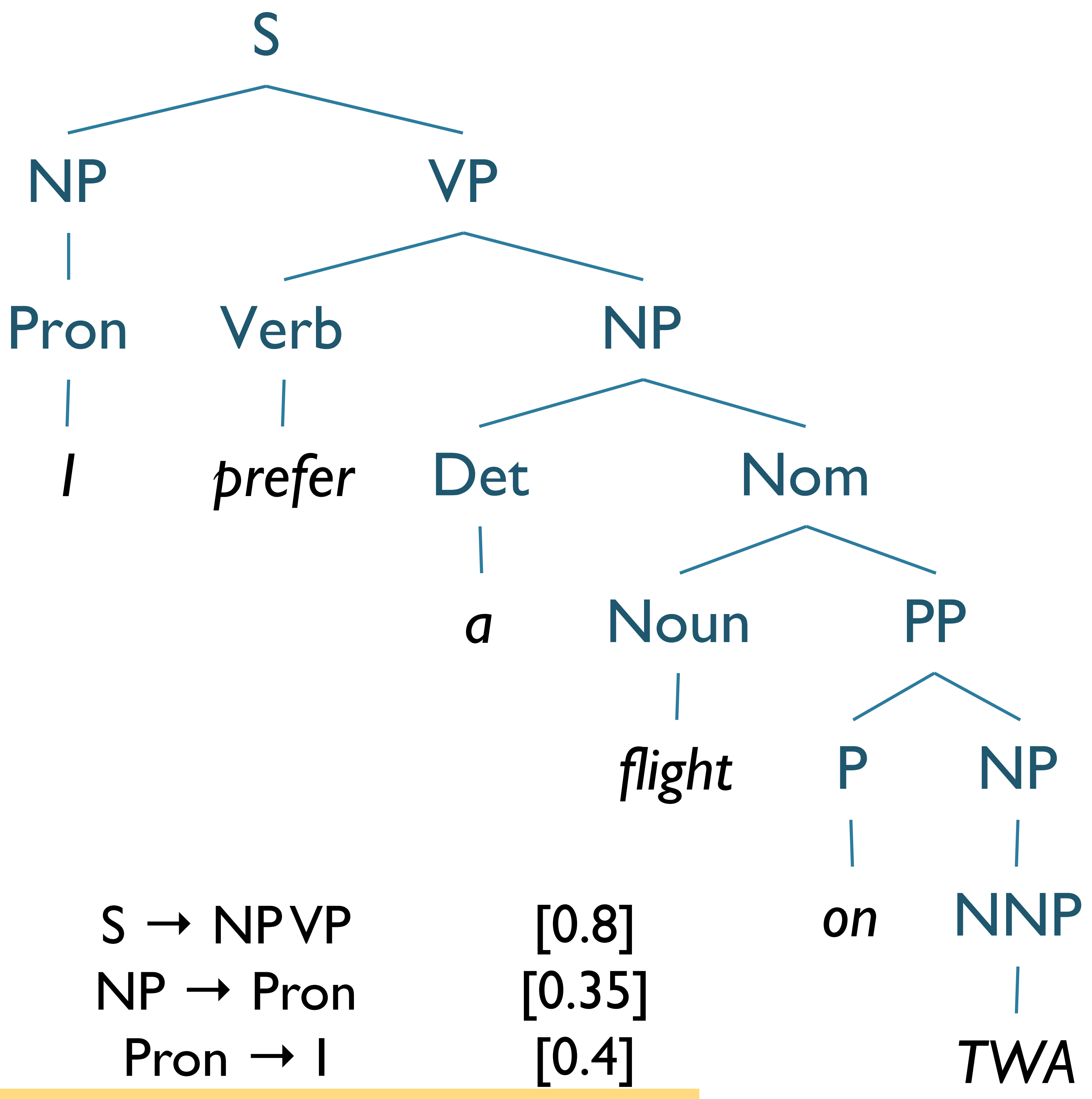
- A PCFG assigns probability to each parse tree T for input S
- Probability of T: product of all rules used to derive T

$$P(T,S) = \prod_{i=1}^{n} P(RHS_i \mid LHS_i)$$

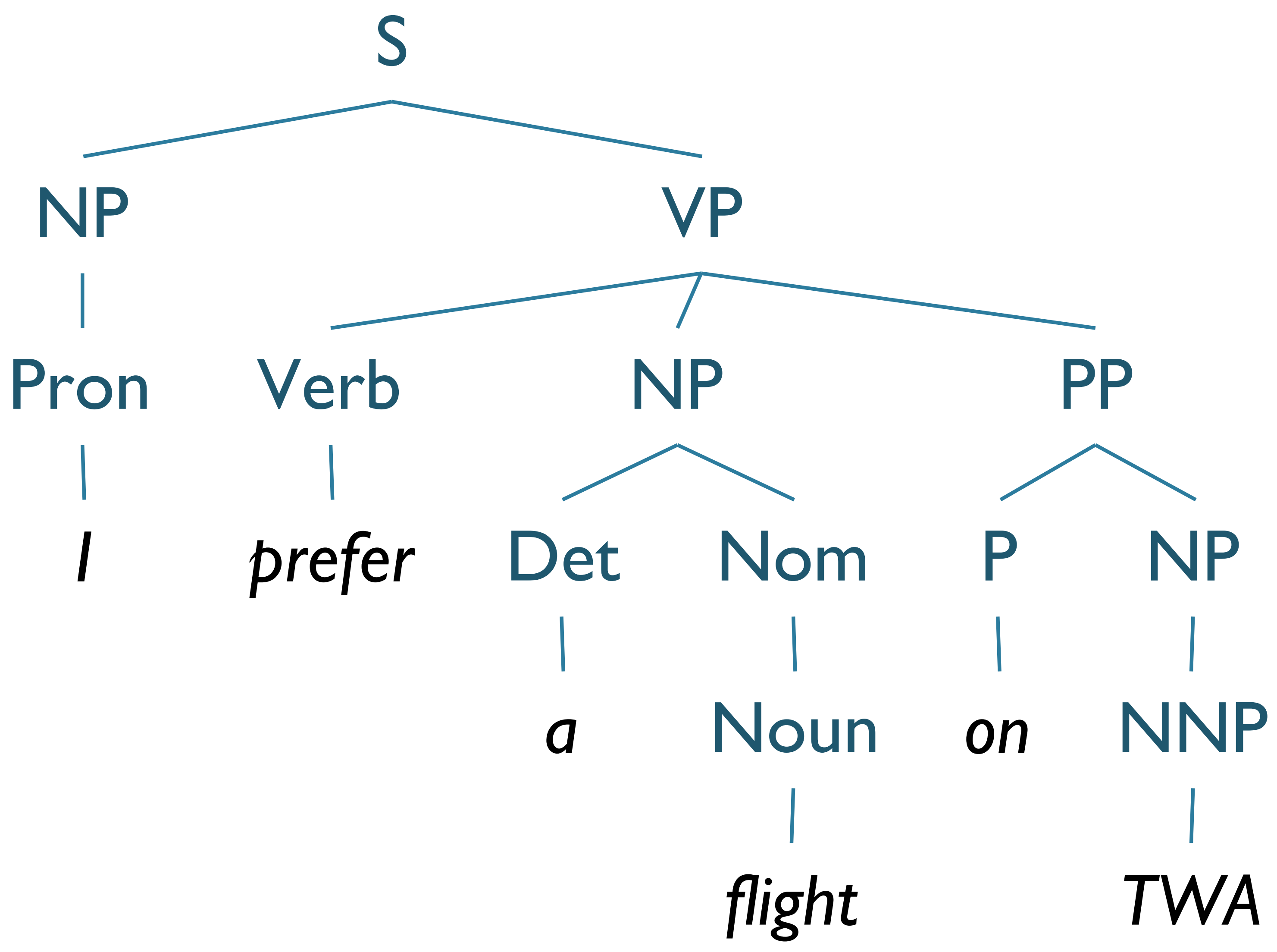
$$P(T,S) = P(T)P(S \mid T) = P(T)$$



S → NP VP	[0.8]
NP → Pron	[0.35]
Pron → I	[0.4]
VP → V NP PP	[0.1]
V → prefer	[0.4]
NP → Det Nom	[0.2]
Det → a	[0.3]
Nom → N	[0.75]
N → flight	[0.3]
PP → P NP	[1.0]
P → on	[0.2]
NP → NNP	[0.3]
NNP → NWA	[0.4]

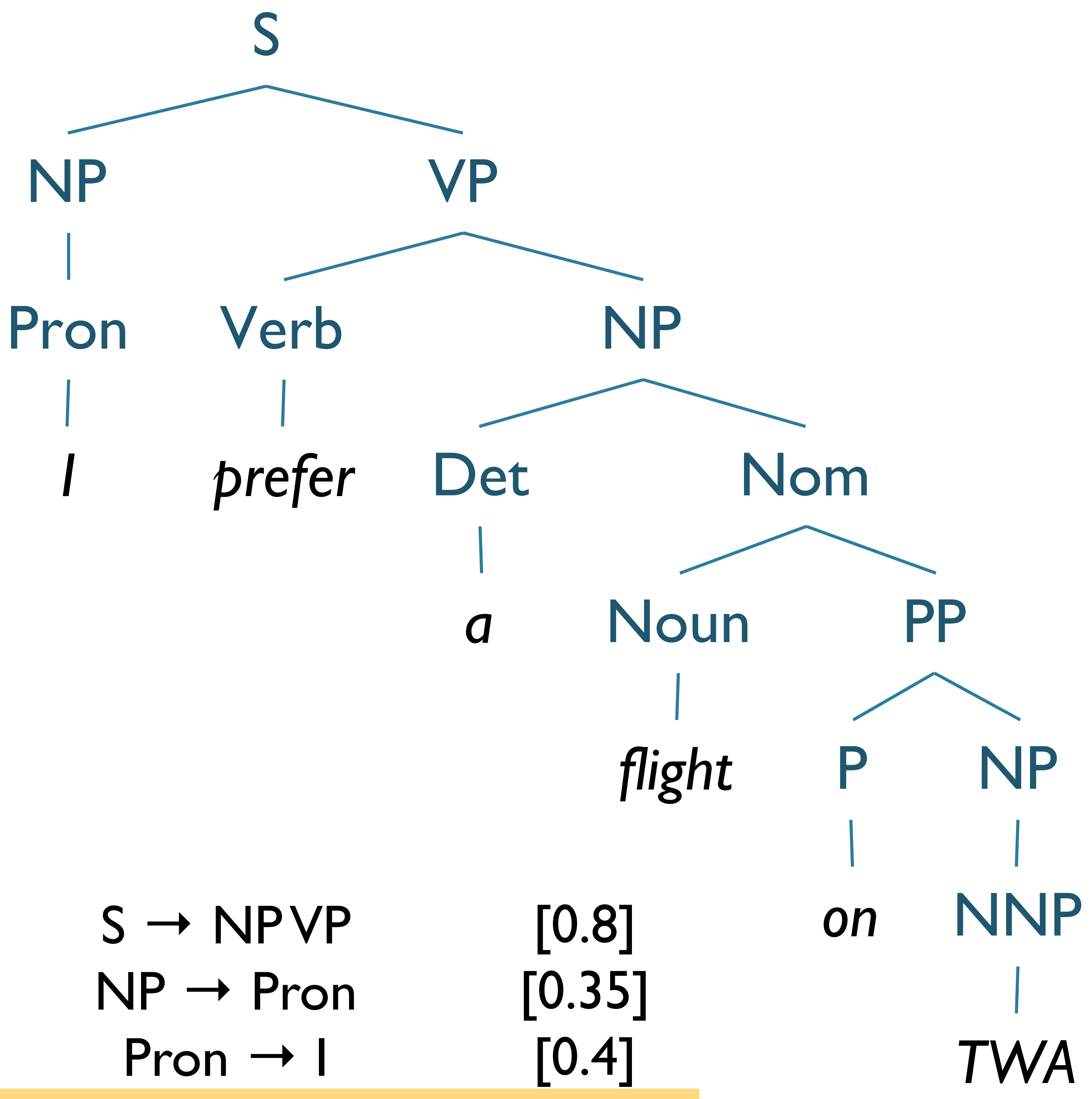


S → NP VP	[0.8]
NP → Pron	[0.35]
Pron → I	[0.4]
VP → V NP	[0.2]
V → prefer	[0.4]
NP → Det Nom	[0.2]
Det → a	[0.3]
Nom → Nom PP	[0.05]
Nom → N	[0.75]
N → flight	[0.3]
PP → P NP	[1.0]
P → on	[0.2]
NP → NNP	[0.3]
NNP → NWA	[0.4]



S → NP VP	[0.8]
NP → Pron	[0.35]
Pron → I	[0.4]
VP → V NP PP	[0.1]
V → prefer	[0.4]
NP → Det Nom	[0.2]
Det → a	[0.3]
Nom → N	[0.75]
N → flight	[0.3]
PP → P NP	[1.0]
P → on	[0.2]
NP → NNP	[0.3]
NNP → NWA	[0.4]

~1.452×10^{-6}



S → NP VP	[0.8]
NP → Pron	[0.35]
Pron → I	[0.4]
VP → V NP	[0.2]
V → prefer	[0.4]
NP → Det Nom	[0.2]
Det → a	[0.3]
Nom → Nom PP	[0.05]
Nom → N	[0.75]
N → flight	[0.3]
PP → P NP	[1.0]
P → on	[0.2]
NP → NNP	[0.3]
NNP → NWA	[0.4]

~1.452×10^{-7}

Parsing Problem for PCFGs

- Select T such that $(s.t.)$

$$\hat{T}(S) = \underset{T\ s.t.\ S=yield(T)}{\operatorname{argmax}} P(T)$$

- String of words S is $yield$ of parse tree
- Select the tree $\hat{T}$ that maximizes the probability of the parse

Application: Language Modeling

- *n*-grams helpful for modeling the probability of a string

Application: Language Modeling

- *n*-grams helpful for modeling the probability of a string
- To model a whole sentence with *n-grams* either:

Application:
Language Modeling

- *n*-grams helpful for modeling the probability of a string
- To model a whole sentence with *n-grams* either:
  - Must use 10+-grams… too sparse

Application: Language Modeling

- *n*-grams helpful for modeling the probability of a string
- To model a whole sentence with *n-grams* either:
  - Must use 10+-grams… too sparse
  - Approximate using conditioning on limited context: $P(w_i \mid w_{i-1}) = \dfrac{P(w_{i-1}, w_i)}{P(w_{i-1})}$

Application: Language Modeling

- *n*-grams helpful for modeling the probability of a string
- To model a whole sentence with *n-grams* either:
  - Must use 10+-grams… too sparse
  - Approximate using conditioning on limited context: $P(w_i \mid w_{i-1}) = \dfrac{P(w_{i-1}, w_i)}{P(w_{i-1})}$
- PCFGs are able to give probability of entire string without as bad sparsity

Application: Language Modeling

- *n*-grams helpful for modeling the probability of a string
- To model a whole sentence with *n-grams* either:
  - Must use 10+-grams… too sparse
  - Approximate using conditioning on limited context: $P(w_i \mid w_{i-1}) = \frac{P(w_{i-1}, w_i)}{P(w_{i-1})}$
- PCFGs are able to give probability of entire string without as bad sparsity
- Model probability of *syntactically valid* sentences

Application: Language Modeling

- *n*-grams helpful for modeling the probability of a string
- To model a whole sentence with *n-grams* either:
  - Must use 10+-grams… too sparse
  - Approximate using conditioning on limited context: $P(w_i \mid w_{i-1}) = \dfrac{P(w_{i-1}, w_i)}{P(w_{i-1})}$
- PCFGs are able to give probability of entire string without as bad sparsity
- Model probability of *syntactically valid* sentences
  - Not just probability of sequence of words

PCFGs: Parsing

Probabilistic CKY (PCKY)

- Like regular CKY
  - Assumes grammar in Chomsky Normal Form (CNF)
    - $A \rightarrow B\ C$
    - $A \rightarrow \mathrm{w}$
  - Represent input with indices b/t words:
    - $_0$ Book $_1$ that $_2$ flight $_3$ through $_4$ Houston $_5$

Probabilistic CKY (PCKY)

- For input string length n and non-terminals V
  - Cell [i, j, A] in (n+1) × (n+1) × V matrix
  - Contains probability that A spans $[i, j]$

PCKY Algorithm

function PROBABILISTIC-CKY-PARSE($words$, $grammar$) **returns** most probable parse and its probability

for j ← **from** 1 to LENGTH($words$) **do**

for all { A | A → $words[j]$ ∈ $grammar$ }

$table[\ j–1,\ j,\ A\ ] \leftarrow P(A \rightarrow words[j])$

for $i \leftarrow$ **from** $j–2$ **downto** 0 **do**

for $k \leftarrow i + 1$ **to** $j–1$ **do**

for all { A | A → B C ∈ $grammar$,

and $table[i,\ k,\ B] > 0$ **and** $table[\ k,\ j,\ C\ ] > 0$ }

if $(table[\ i,\ j,\ A\ ] < P(A \rightarrow BC\ )\times table[\ i,\ k,\ B\ ]\times table[\ k,j,C\ ])$ **then**

$table[\ i,\ j,\ A\ ] \leftarrow P(A \rightarrow BC\ )\times table[i,k,B]\times table[k,j,C]$

$back[\ i,\ j,\ A\ ] \leftarrow \{\ k,\ B,\ C\ \}$

return BUILD_TREE($back$[1, LENGTH($words$), S]), $table$[1,LENGTH($words$), S]

PCKY Algorithm

```
function PROBABILISTIC-CKY-PARSE(words, grammar) returns most probable parse and its probability
for j ← from 1 to LENGTH(words) do
 for all { A | A → words[j] ∈ grammar }
     table[ j–1, j, A ] ← P(A → words[j])
 for i ← from j–2 downto 0 do
  for k ← i + 1 to j–1 do
  for all { A | A → B C ∈ grammar,
        and table[i, k, B] > 0 and table[ k, j, C ] > 0 }
  if (table[ i, j, A ] < P(A → BC )×table[ i, k, B ]×table[ k,j,C ]) then
     table[ i, j, A ] ← P(A → BC )×table[i,k,B]×table[k,j,C]
     back[ i, j, A ] ← { k, B, C }
  return BUILD_TREE(back[ 1, LENGTH(words), S ]), table[ 1,LENGTH(words), S ]
```

PCKY Algorithm

function PROBABILISTIC-CKY-PARSE($words$, $grammar$) **returns** most probable parse and its probability

for j ← **from** 1 to LENGTH($words$) **do**

for all { A | A → $words[j]$ ∈ $grammar$ }

$table[j\!-\!1, j, A] \leftarrow P(A \rightarrow words[j])$

for i ← **from** $j\!-\!2$ **downto** 0 **do**

for $k \leftarrow i+1$ **to** $j\!-\!1$ **do**

for all { A | $A \rightarrow B\ C \in grammar$,

and $table[i, k, B] > 0$ **and** $table[k, j, C] > 0$ }

if $(table[i, j, A] < P(A \rightarrow BC) \times table[i, k, B] \times table[k,j,C])$ **then**

$table[i, j, A] \leftarrow P(A \rightarrow BC) \times table[i,k,B] \times table[k,j,C]$

$back[i, j, A] \leftarrow \{k, B, C\}$

return BUILD_TREE($back$[1, LENGTH($words$), S]), $table$[1,LENGTH($words$), S]

PCKY Algorithm

function PROBABILISTIC-CKY-PARSE(*words*, *grammar*) **returns** most probable parse and its probability

for j ← **from** 1 to LENGTH(*words*) **do**

  for all { A | A → *words[j]* ∈ *grammar* }

    table[j–1, j, A] ← P(A → *words[j]*)

  for i ← **from** j–2 **downto** 0 **do**

   for k ← $i + 1$ **to** j–1 **do**

   for all { A | A → B C ∈ *grammar*,

     and *table*[i, k, B] $>$ 0 **and** *table*[k, j, C] $>$ 0 }

   if (*table*[i, j, A] $<$ P(A → BC)×*table*[i, k, B]×*table*[k,j,C]) **then**

    table[i, j, A] ← P(A → BC)×*table*[i,k,B]×*table*[k,j,C]

    back[i, j, A] ← { k, B, C }

   return BUILD_TREE(*back*[1, LENGTH(*words*), S]), *table*[1,LENGTH(*words*), S]

PCKY Algorithm

function PROBABILISTIC-CKY-PARSE($words$, $grammar$) **returns** most probable parse and its probability

for j ← **from** 1 to LENGTH($words$) **do**

  for all { A | A → $words[j]$ ∈ $grammar$ }

    $table$[j–1, j, A] ← P(A → $words[j]$)

  for i ← **from** j–2 **downto** 0 **do**

   for k ← i + 1 **to** j–1 **do**

   for all { A | A → B C ∈ $grammar$,

     and $table$[i, k, B] > 0 **and** $table$[k, j, C] > 0 }

   if ($table$[i, j, A] < P(A → BC)×$table$[i, k, B]×$table$[k,j,C]) **then**

    $table$[i, j, A] ← P(A → BC)×$table$[i,k,B]×$table$[k,j,C]

    $back$[i, j, A] ← { k, B, C }

   return BUILD_TREE($back$[1, LENGTH($words$), S]), $table$[1,LENGTH($words$), S]

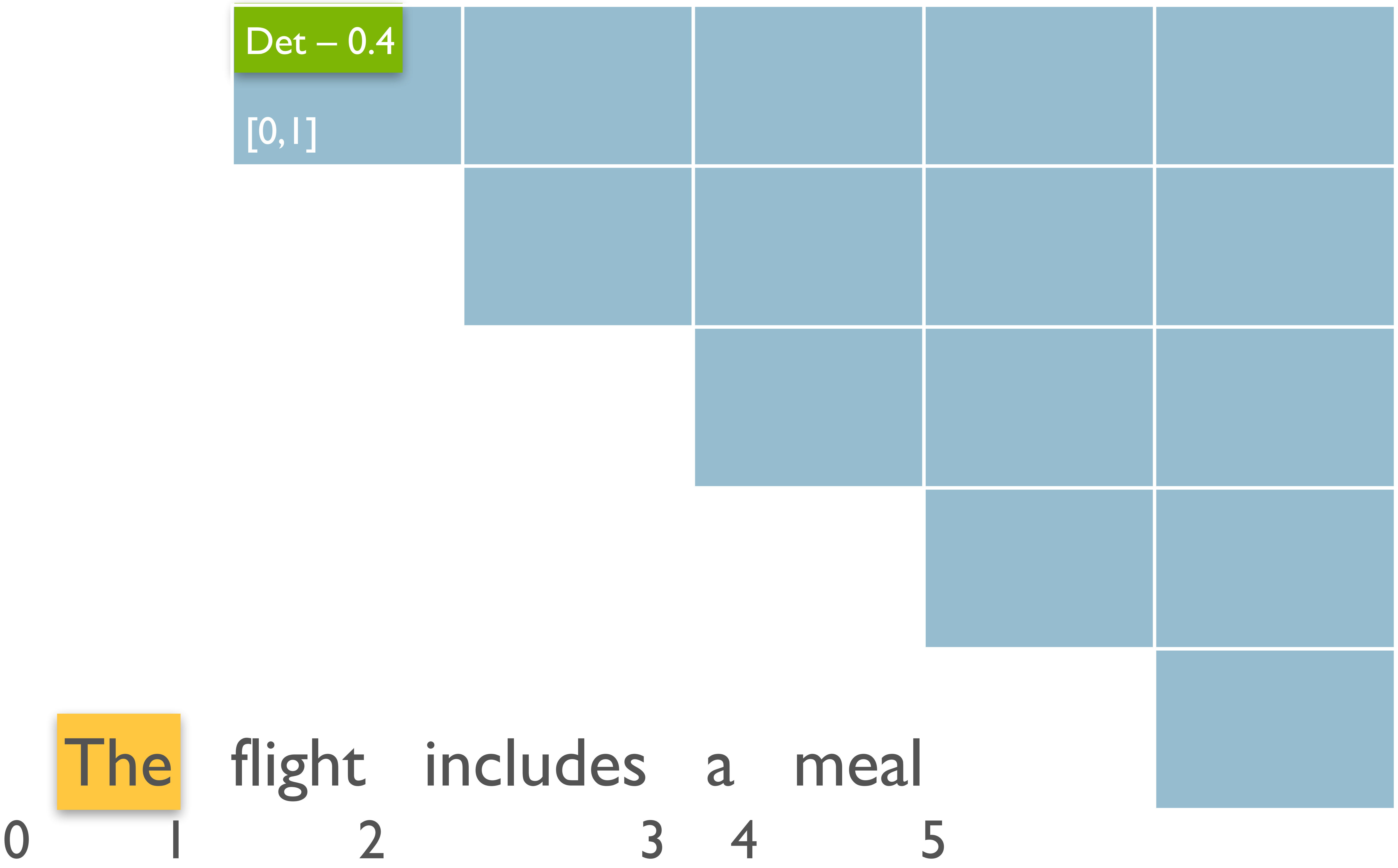
PCKY Grammar Segment

$S \rightarrow NP\ VP$	[0.80]	$Det \rightarrow$ the	[0.40]
$NP \rightarrow Det\ N$	[0.30]	$Det \rightarrow$ a	[0.40]
$VP \rightarrow V\ NP$	[0.20]	$V \rightarrow$ includes	[0.05]
		$N \rightarrow$ meal	[0.01]
		$N \rightarrow$ flight	[0.02]

PCKY Matrix

$S \rightarrow NP\ VP$ [0.80]
$NP \rightarrow Det\ N$ [0.30]
$VP \rightarrow V\ NP$ [0.20]

$Det \rightarrow$ the [0.40]
$Det \rightarrow$ a [0.40]
$V \rightarrow$ includes [0.05]
$N \rightarrow$ meal [0.01]
$N \rightarrow$ flight [0.02]



PCKY Matrix

$S \rightarrow NP\ VP \quad [0.80]$

$NP \rightarrow Det\ N \quad [0.30]$

$VP \rightarrow V\ NP \quad [0.20]$

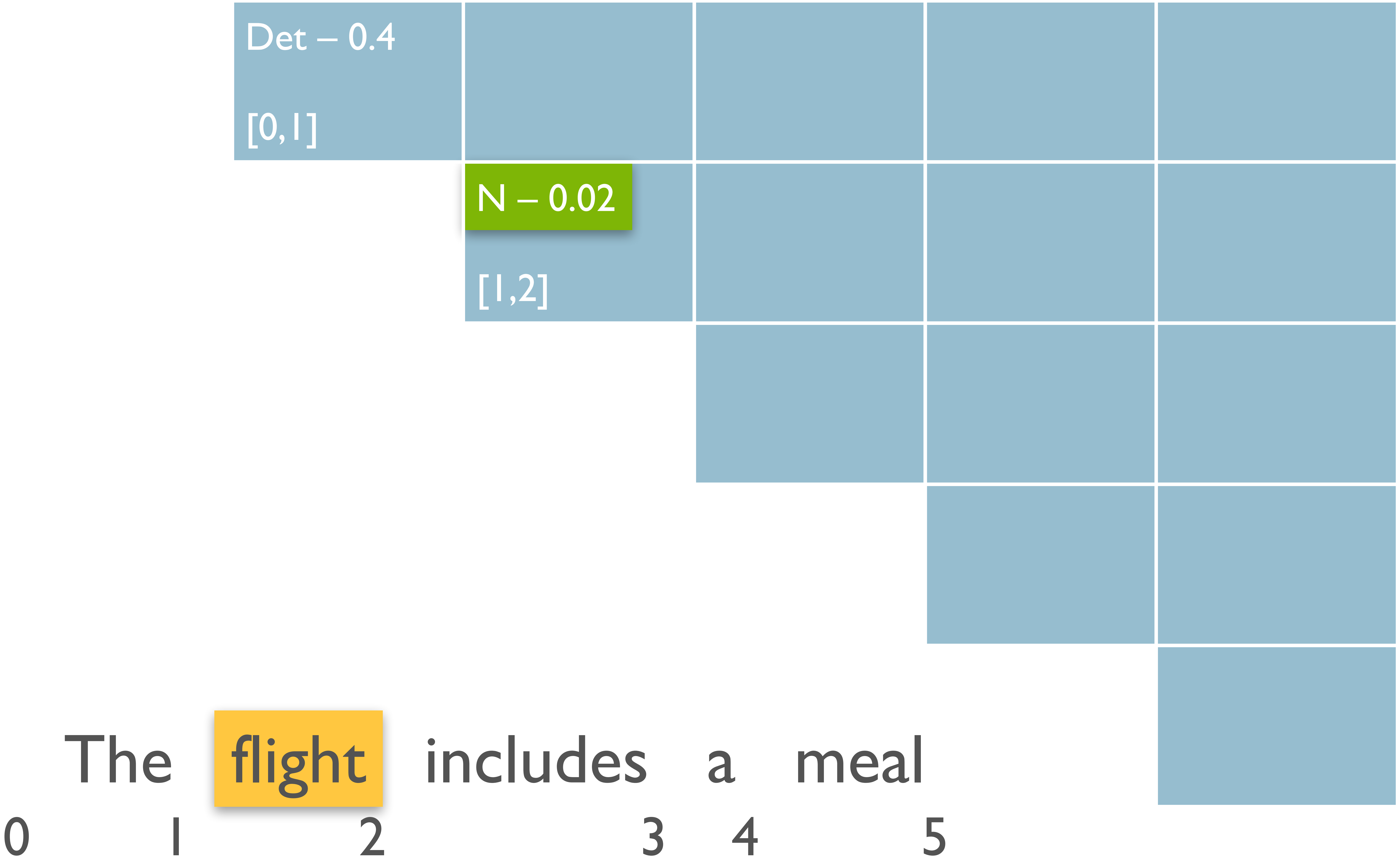
$Det \rightarrow \text{the} \quad [0.40]$

$Det \rightarrow \text{a} \quad [0.40]$

$V \rightarrow \text{includes} \quad [0.05]$

$N \rightarrow \text{meal} \quad [0.01]$

$N \rightarrow \text{flight} \quad [0.02]$



PCKY Matrix

$S \rightarrow NP\ VP \quad [0.80]$

$NP \rightarrow Det\ N \quad [0.30]$

$VP \rightarrow V\ NP \quad [0.20]$

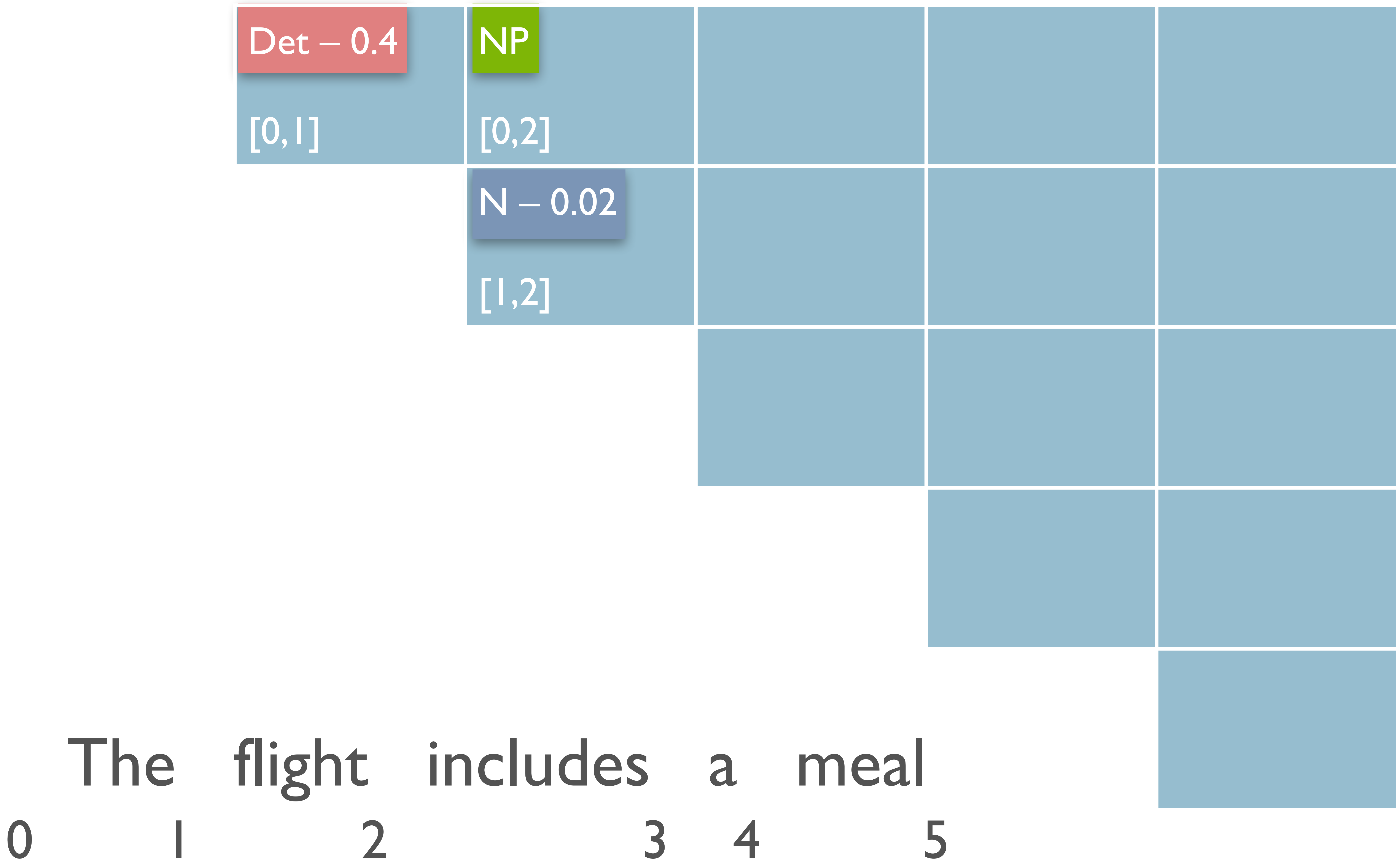
$Det \rightarrow \text{the} \quad [0.40]$

$Det \rightarrow \text{a} \quad [0.40]$

$V \rightarrow \text{includes} \quad [0.05]$

$N \rightarrow \text{meal} \quad [0.01]$

$N \rightarrow \text{flight} \quad [0.02]$



PCKY Matrix

$S \rightarrow NP\ VP \quad [0.80]$

$NP \rightarrow Det\ N \quad [0.30]$

$VP \rightarrow V\ NP \quad [0.20]$

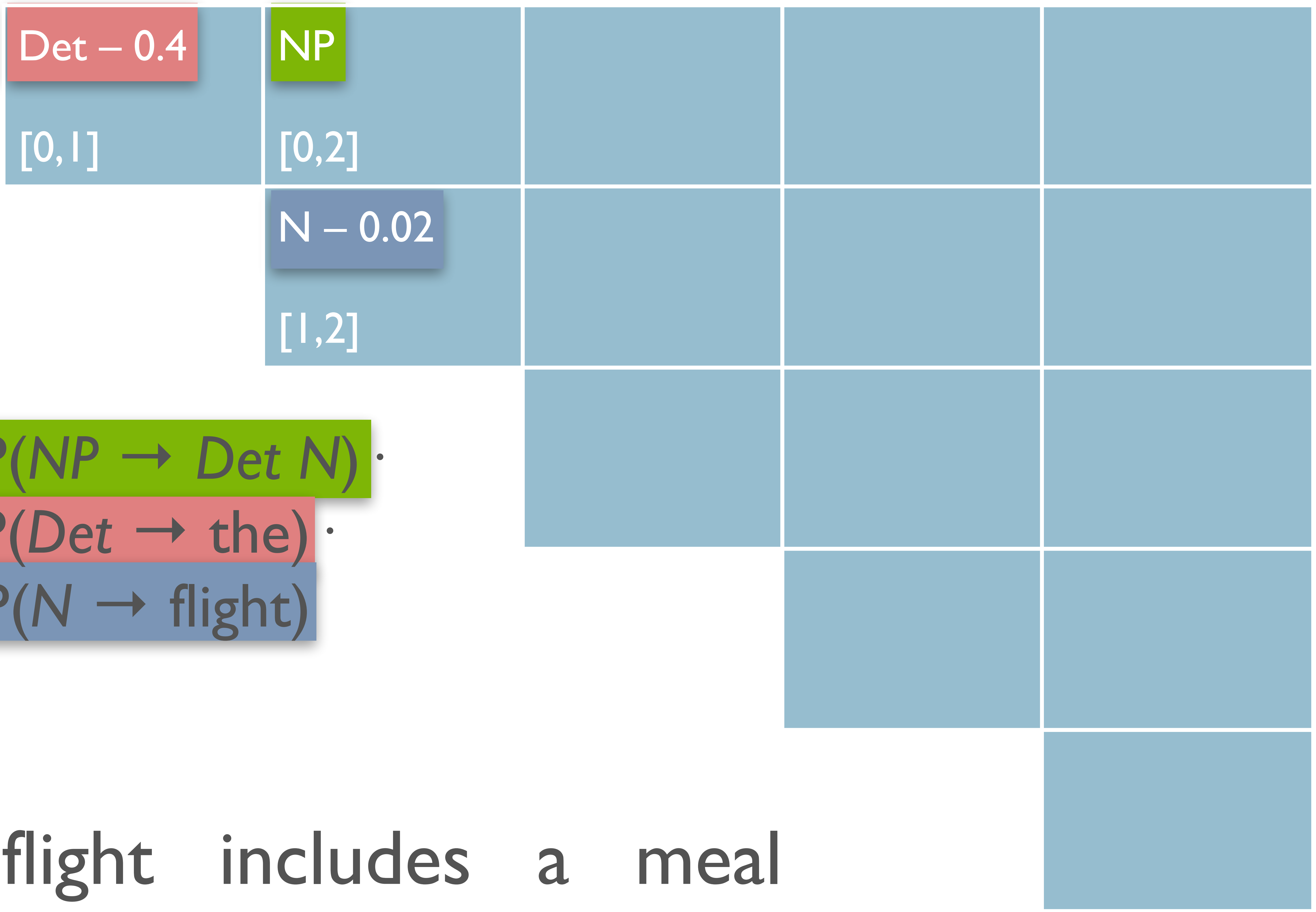
$Det \rightarrow \text{the} \quad [0.40]$

$Det \rightarrow \text{a} \quad [0.40]$

$V \rightarrow \text{includes} \quad [0.05]$

$N \rightarrow \text{meal} \quad [0.01]$

$N \rightarrow \text{flight} \quad [0.02]$



P = $P(NP \rightarrow Det\ N) \cdot P(Det \rightarrow \text{the}) \cdot P(N \rightarrow \text{flight})$

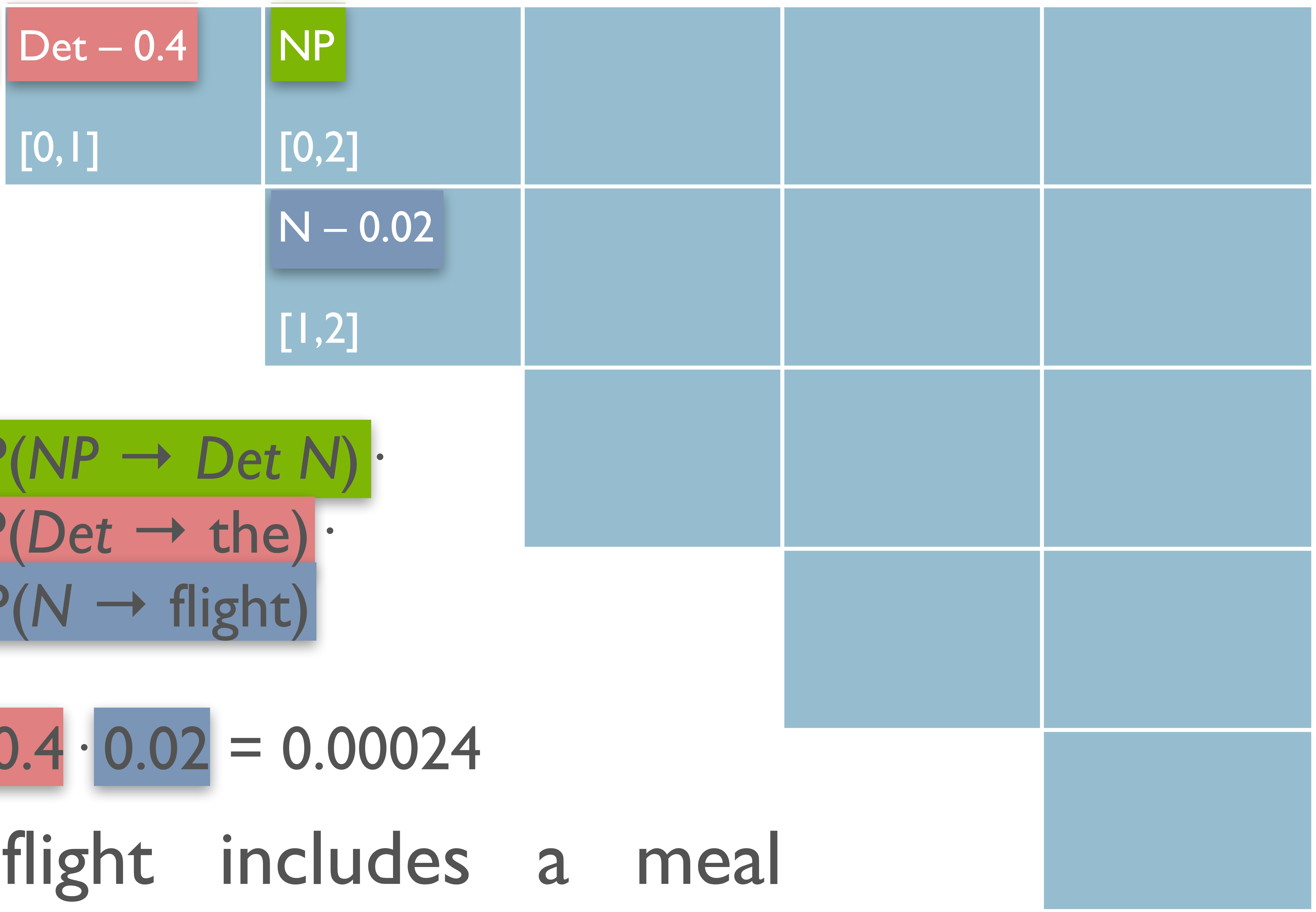
The flight includes a meal

0 1 2 3 4 5

PCKY Matrix

$S \rightarrow NP\ VP$	[0.80]
$NP \rightarrow Det\ N$	[0.30]
$VP \rightarrow V\ NP$	[0.20]

$Det \rightarrow$ the	[0.40]
$Det \rightarrow$ a	[0.40]
$V \rightarrow$ includes	[0.05]
$N \rightarrow$ meal	[0.01]
$N \rightarrow$ flight	[0.02]



P = P($NP \rightarrow Det\ N$) ·
P($Det \rightarrow$ the) ·
P($N \rightarrow$ flight)

P = 0.3 · 0.4 · 0.02 = 0.00024

The flight includes a meal

0 1 2 3 4 5

PCKY Matrix

$S \rightarrow NP\ VP \quad [0.80]$

$NP \rightarrow Det\ N \quad [0.30]$

$VP \rightarrow V\ NP \quad [0.20]$

$Det \rightarrow$ the $\quad [0.40]$

$Det \rightarrow$ a $\quad [0.40]$

$V \rightarrow$ includes $\quad [0.05]$

$N \rightarrow$ meal $\quad [0.01]$

$N \rightarrow$ flight $\quad [0.02]$

Det – 0.4 [0,1]	NP – 0.0024 [0,2]			
	N – 0.02 [1,2]			

P = P($NP \rightarrow Det\ N$) ·
P($Det \rightarrow$ a) ·
P($N \rightarrow$ flight)

P = 0.3 · 0.4 · 0.02 = 0.00024

The flight includes a meal

0 1 2 3 4 5

PCKY Matrix

$S \rightarrow NP\ VP$ [0.80]
$NP \rightarrow Det\ N$ [0.30]
$VP \rightarrow V\ NP$ [0.20]

$Det \rightarrow \text{the}$ [0.40]
$Det \rightarrow \text{a}$ [0.40]
$V \rightarrow \text{includes}$ [0.05]
$N \rightarrow \text{meal}$ [0.01]
$N \rightarrow \text{flight}$ [0.02]

Det – 0.4 [0,1]	NP – 0.0024 [0,2]	[0,3]	[0,4]	S – 2.304×10^{-8} [0,5]
	N – 0.02 [1,2]	[1,3]	[1,4]	[1,5]
		V – 0.05 [2,3]	[2,4]	VP – 1.2×10^{-5} [2,5]
			Det – 0.4 [3,4]	NP – 0.0012 [3,5]
				N – 0.01 [4,5]

The flight includes a meal
0 1 2 3 4 5

Inducing a PCFG

Learning Probabilities

- Simplest way:
  - Use treebank of parsed sentences

Learning Probabilities

- Simplest way:
  - Use treebank of parsed sentences
  - To compute probability of a rule, count:

Learning Probabilities

- Simplest way:
  - Use treebank of parsed sentences
  - To compute probability of a rule, count:
    - Number of times a nonterminal is expanded: $\Sigma_\gamma \; Count(\alpha \rightarrow \gamma)$

Learning Probabilities

- Simplest way:
  - Use treebank of parsed sentences
  - To compute probability of a rule, count:
    - Number of times a nonterminal is expanded: $\Sigma_\gamma \; Count(\alpha \rightarrow \gamma)$
    - Number of times a nonterminal is expanded by a given rule: $Count(\alpha \rightarrow \beta)$

Learning Probabilities

- Simplest way:
  - Use treebank of parsed sentences
  - To compute probability of a rule, count:
    - Number of times a nonterminal is expanded: $\Sigma_\gamma \; Count(\alpha \rightarrow \gamma)$
    - Number of times a nonterminal is expanded by a given rule: $Count(\alpha \rightarrow \beta)$

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

Learning Probabilities

- Simplest way:
  - Use treebank of parsed sentences
  - To compute probability of a rule, count:
    - Number of times a nonterminal is expanded: $\Sigma_\gamma\ Count(\alpha \rightarrow \gamma)$
    - Number of times a nonterminal is expanded by a given rule: $Count(\alpha \rightarrow \beta)$

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

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

Probabilistic Parser Development Paradigm

	Train	Dev	Test
Size	Large (eg. WSJ 2–21, 39,830 sentences)	Small (e.g. WSJ 22)	Small/Med (e.g. WSJ, 23, 2,416 sentences)
Usage	Estimate rule probabilities	Tuning/Verification, Check for Overfit	Held Out, Final Evaluation

Parser Evaluation

Parser Evaluation

- Assume a 'gold standard' set of parses for test set

Parser Evaluation

- Assume a ‘gold standard’ set of parses for test set
- How can we tell how good the parser is?

Parser Evaluation

- Assume a 'gold standard' set of parses for test set
- How can we tell how good the parser is?
- How can we tell how good a parse is?

Parser Evaluation

- Assume a ‘gold standard’ set of parses for test set
- How can we tell how good the parser is?
- How can we tell how good a parse is?
  - Maximally strict: identical to ‘gold standard’

Parser Evaluation

- Assume a 'gold standard' set of parses for test set
- How can we tell how good the parser is?
- How can we tell how good a parse is?
  - Maximally strict: identical to 'gold standard'
  - Partial credit:

Parser Evaluation

- Assume a ‘gold standard’ set of parses for test set
- How can we tell how good the parser is?
- How can we tell how good a parse is?
  - Maximally strict: identical to ‘gold standard’
  - Partial credit:
    - Constituents in output match those in reference

Parser Evaluation

- Assume a ‘gold standard’ set of parses for test set
- How can we tell how good the parser is?
- How can we tell how good a parse is?
  - Maximally strict: identical to ‘gold standard’
  - Partial credit:
    - Constituents in output match those in reference
      - Same start point, end point, non-terminal symbol

Parseval

- How can we compute parse score from constituents?
- Multiple Measures:

$$\text{Labeled Recall (LR)} = \frac{\text{\# of } \textbf{correct} \text{ constituents in } \textbf{hypothetical} \text{ parse}}{\text{\# of } \textbf{total} \text{ constituents in } \textbf{reference} \text{ parse}}$$

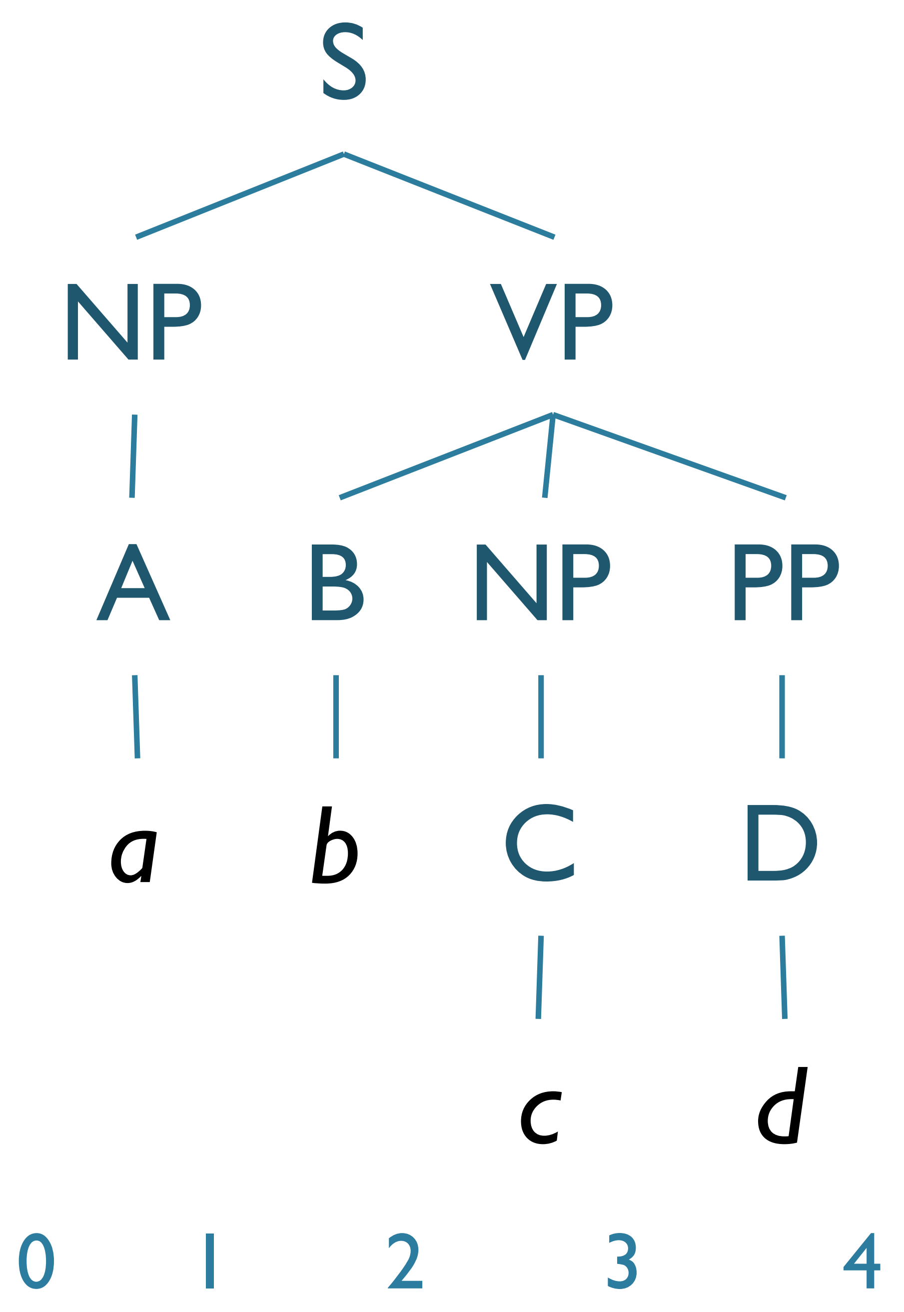
$$\text{Labeled Precision (LP)} = \frac{\text{\# of } \textbf{correct} \text{ constituents in } \textbf{hypothetical} \text{ parse}}{\text{\# of } \textbf{total} \text{ consituents in } \textbf{hypothetical} \text{ parse}}$$

Parseval

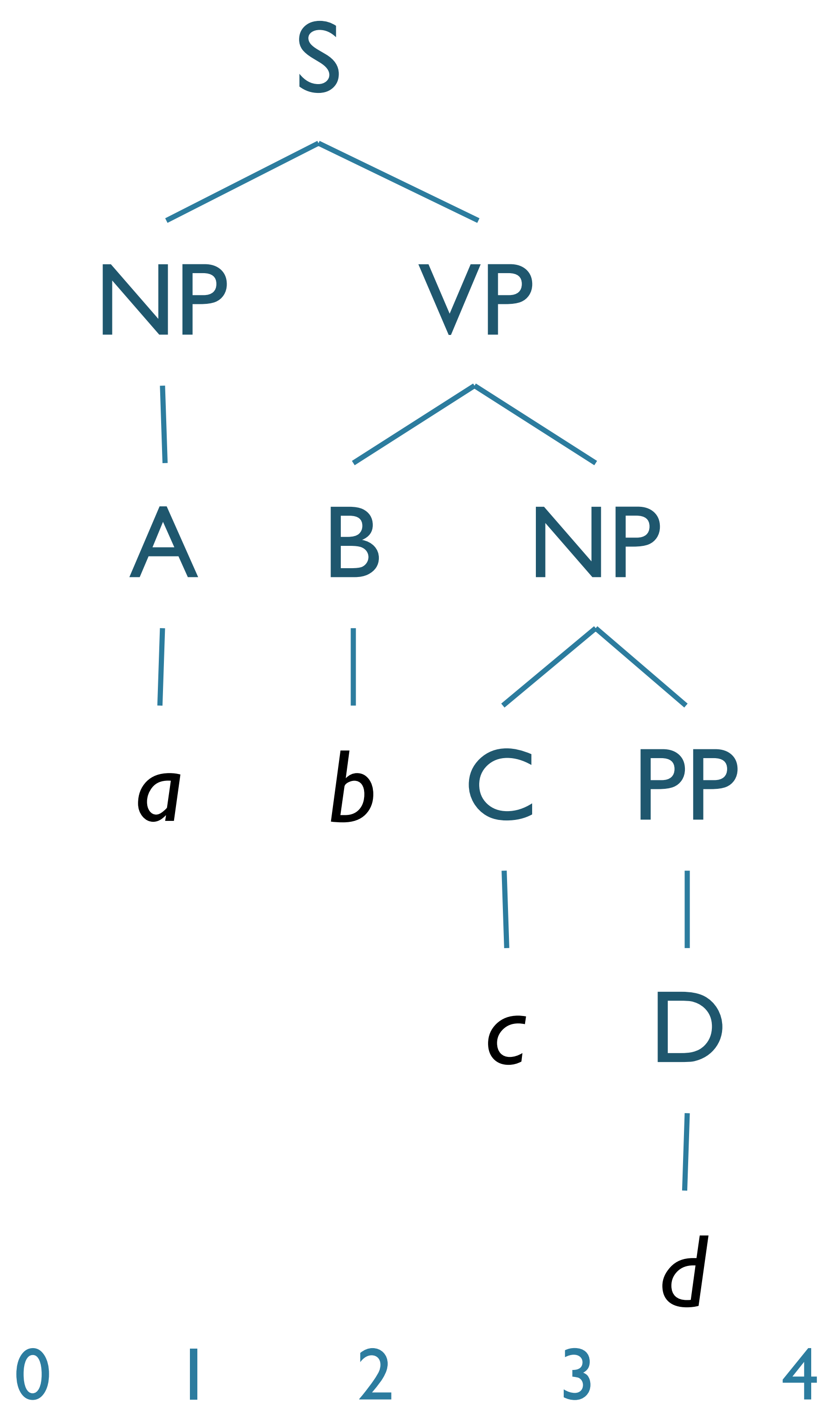
- **F-measure:**
  - Combines precision and recall
  - Let $\beta \in \mathbb{R}$, $\beta > 0$ that adjusts *P* vs. *R* s.t. $\beta \propto \frac{R}{P}$
  - F_β -measure is then: $F_\beta = (1+\beta^2) \cdot \frac{P \cdot R}{\beta^2 \cdot P + R}$
  - With F1-measure as $F_1 = \frac{2PR}{P+R}$

Evaluation: Example

Reference

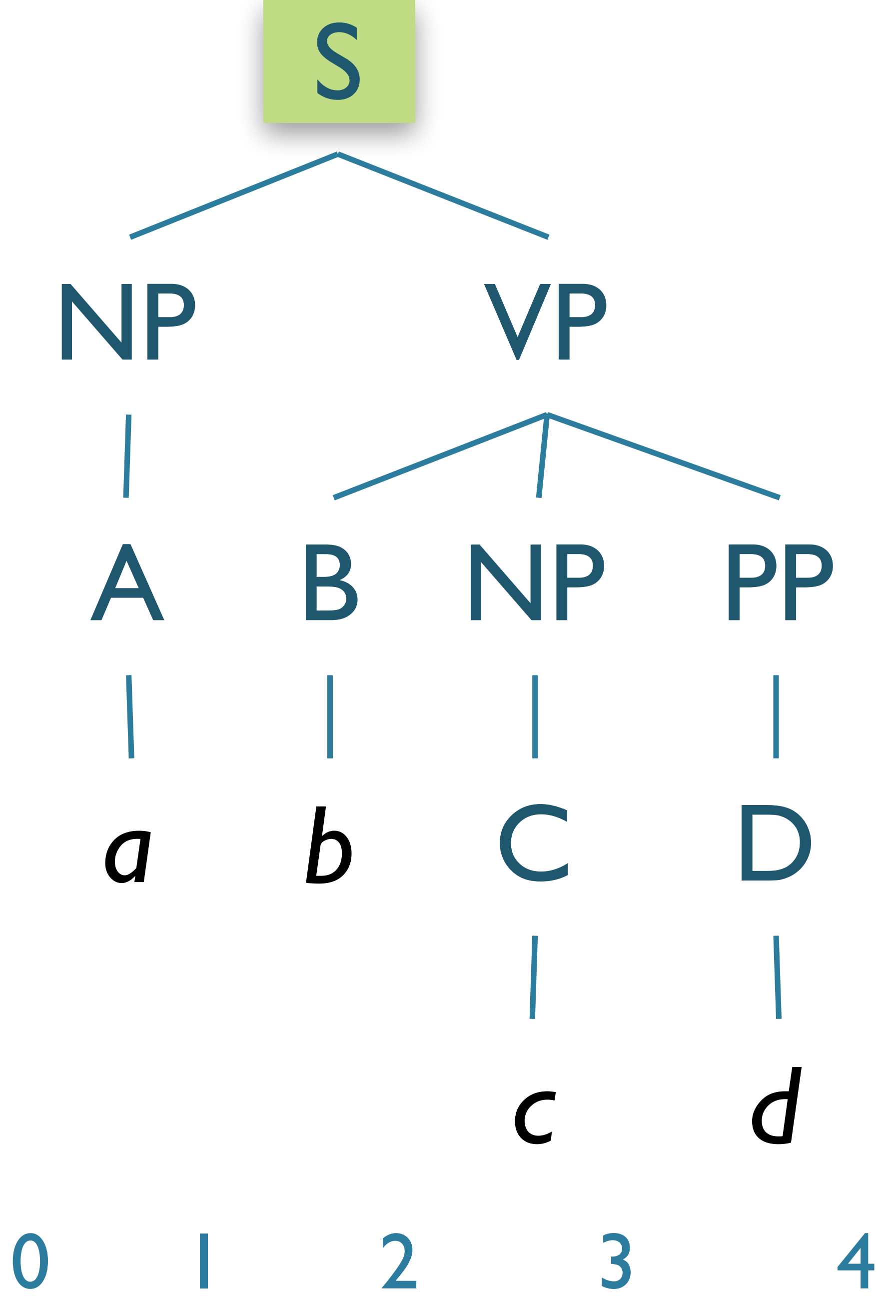


Hypothesis



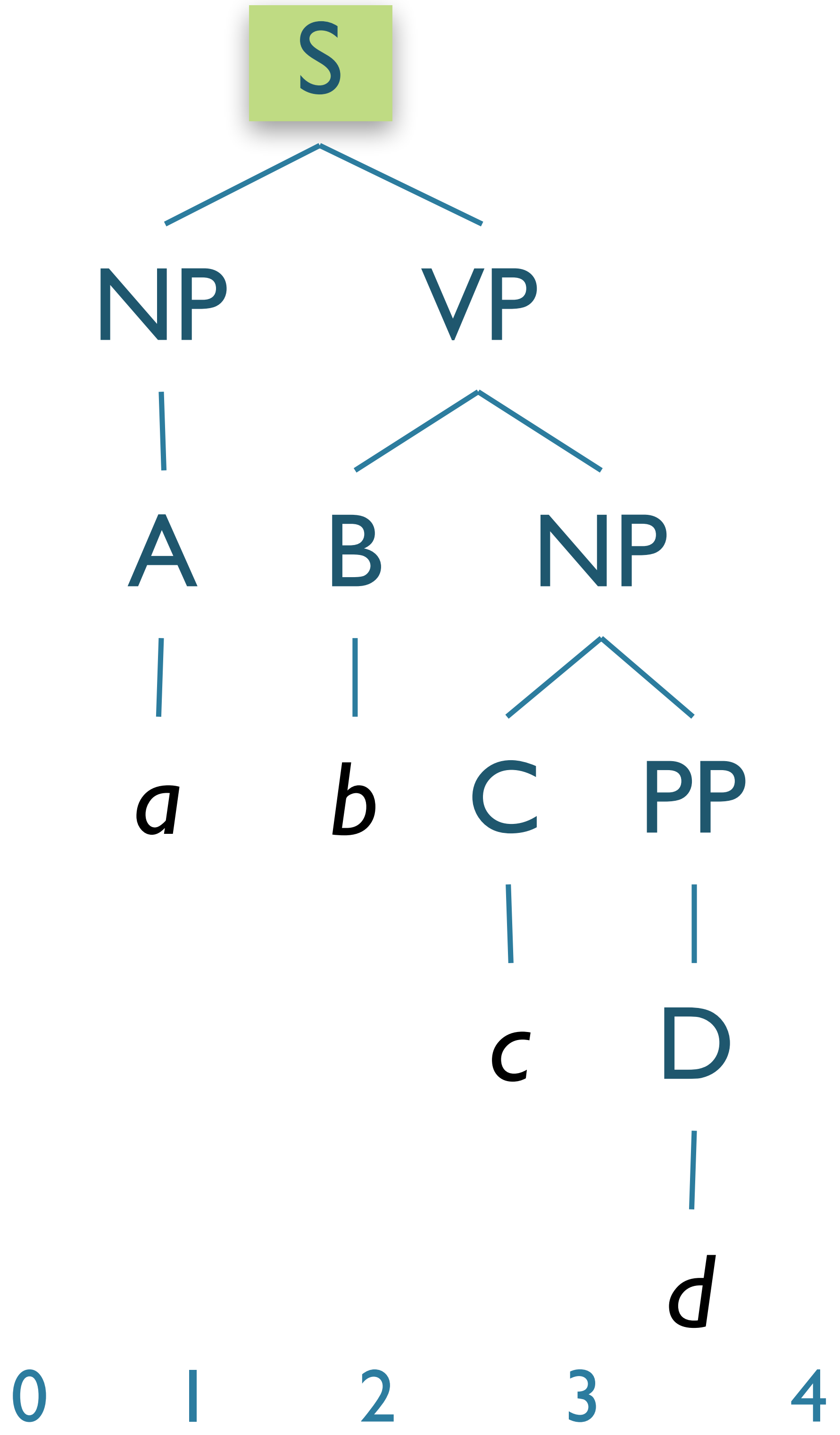
Evaluation: Example

Reference



S(0,4)

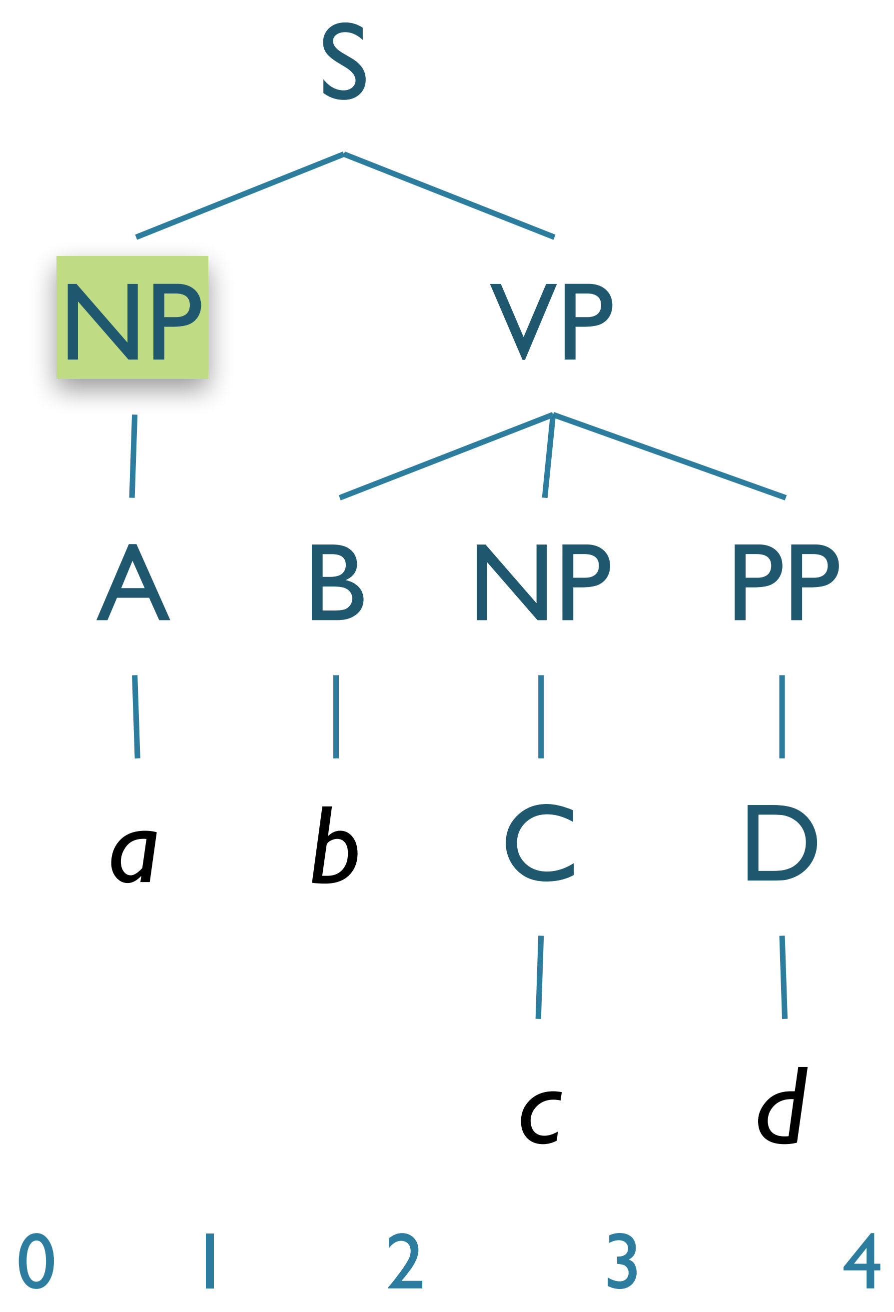
Hypothesis



S(0,4)

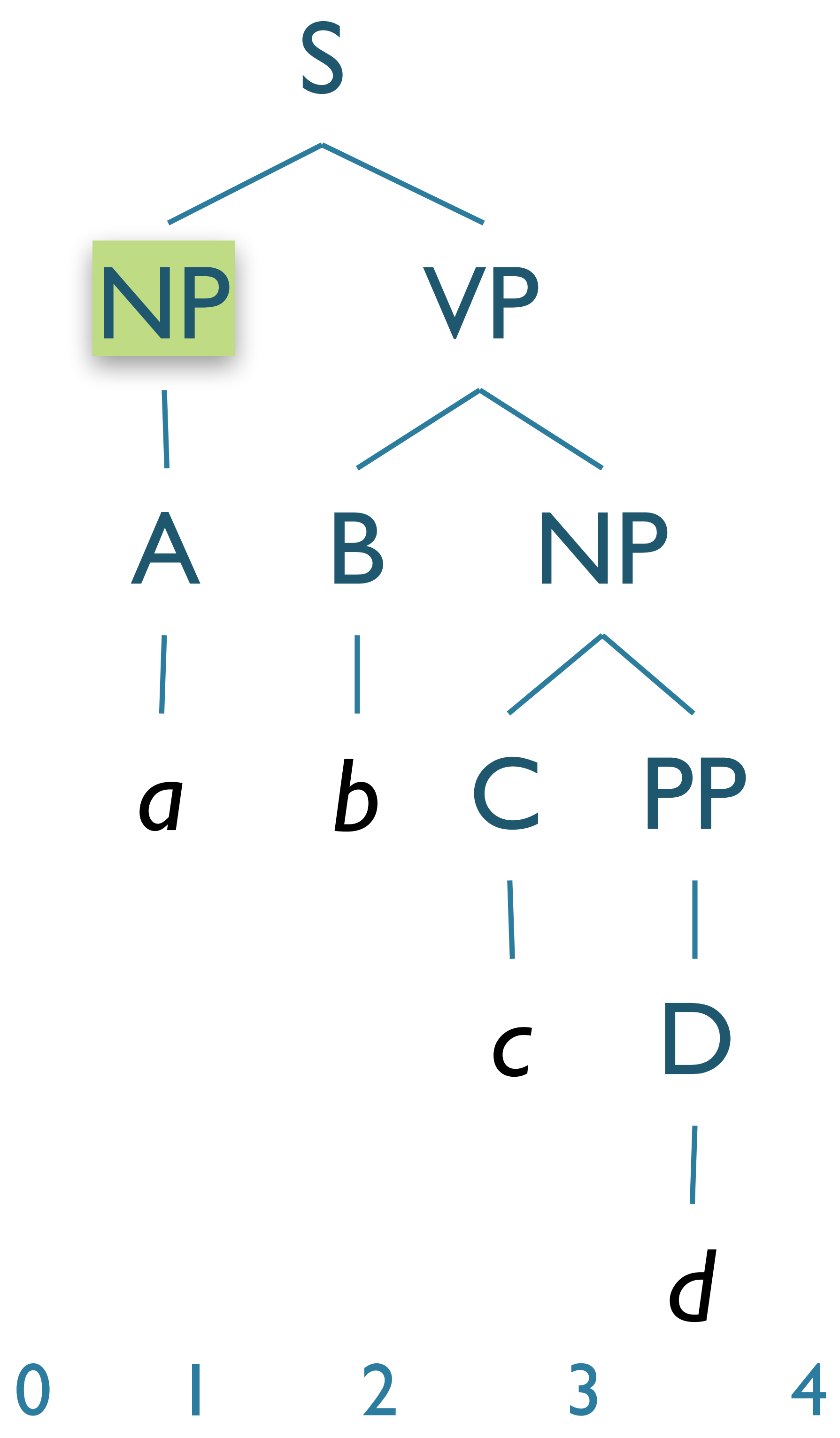
Evaluation: Example

Reference



S(0,4)
NP(0,1)

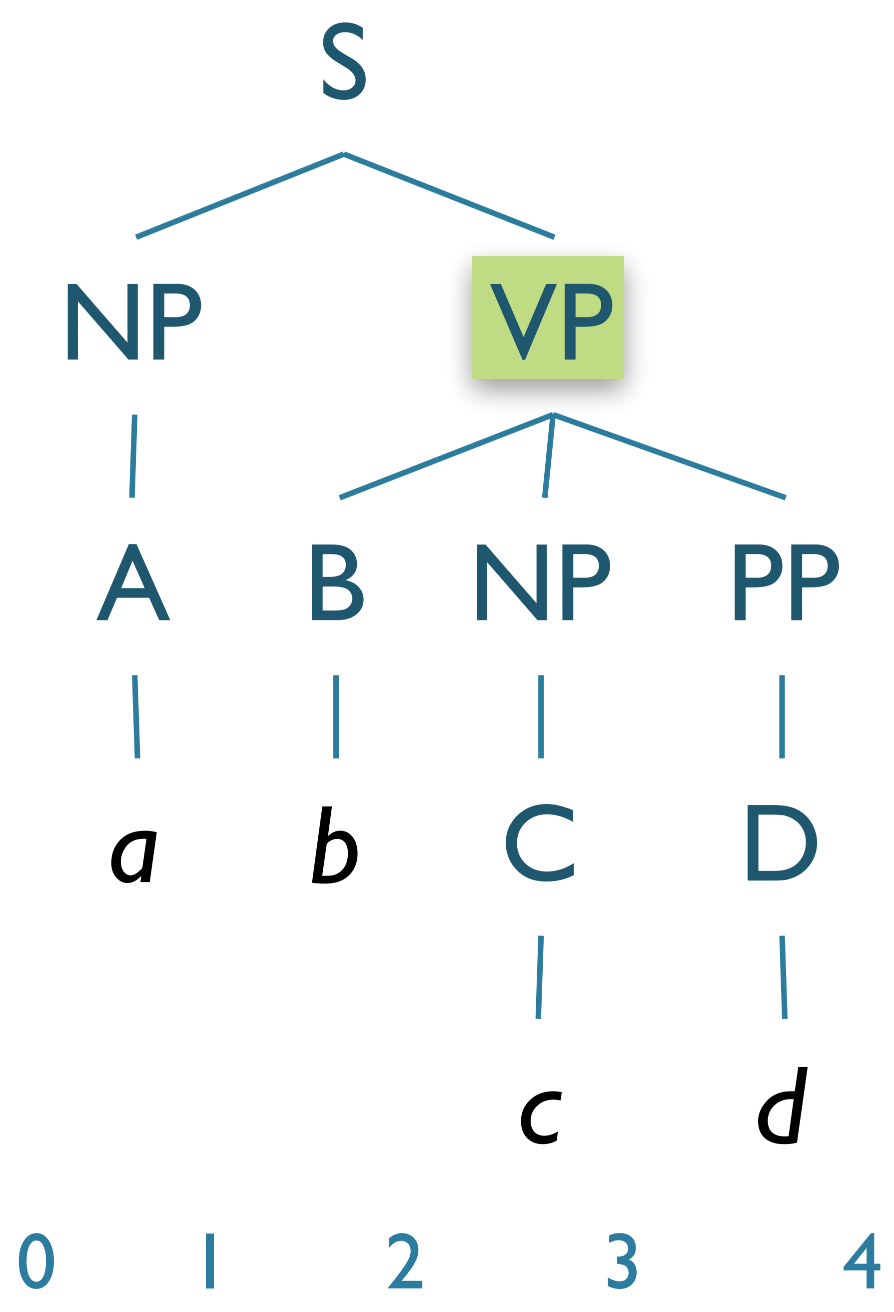
Hypothesis



S(0,4)
NP(0,1)

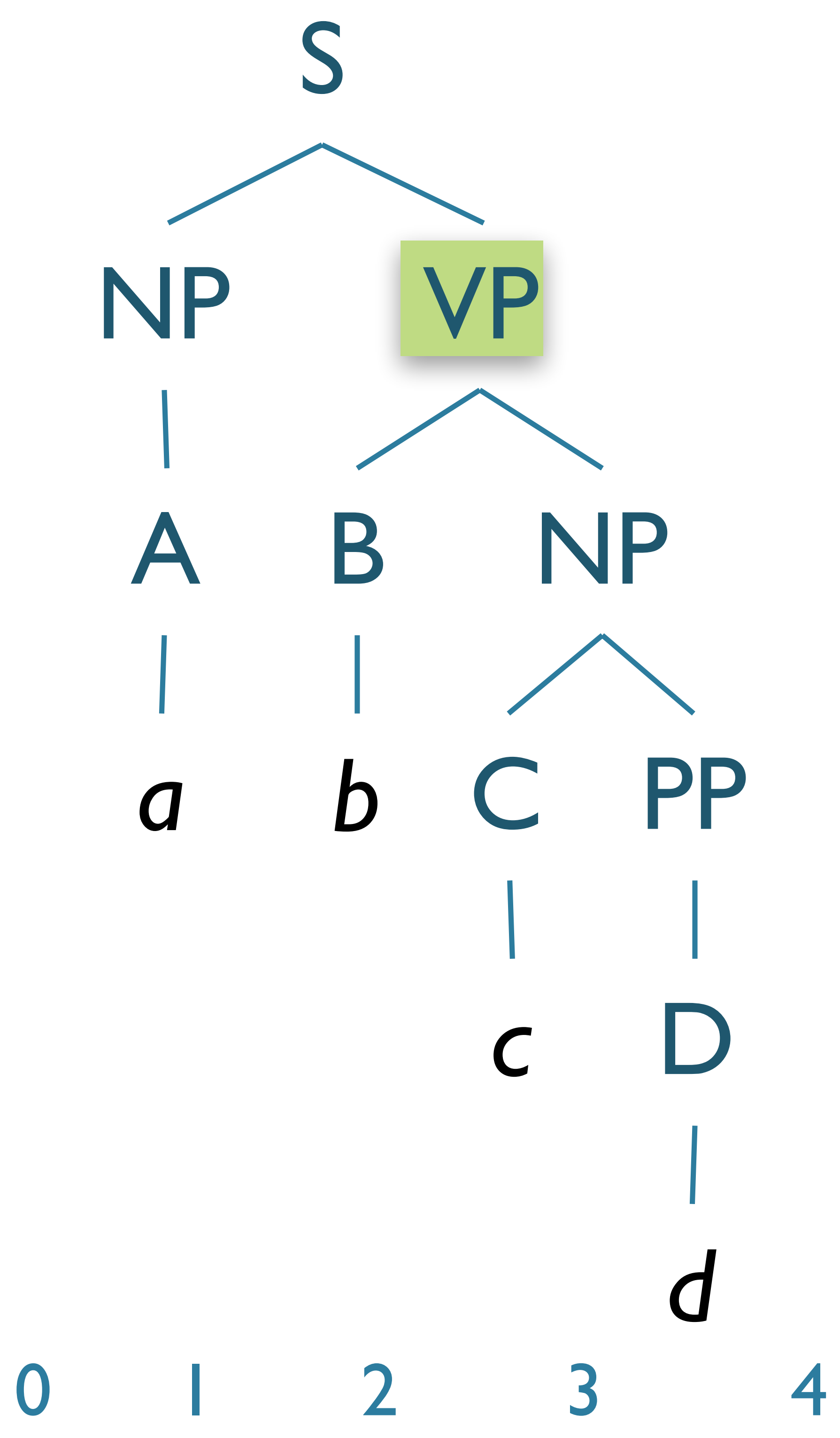
Evaluation: Example

Reference



S(0,4)
NP(0,1)
VP(1,4)

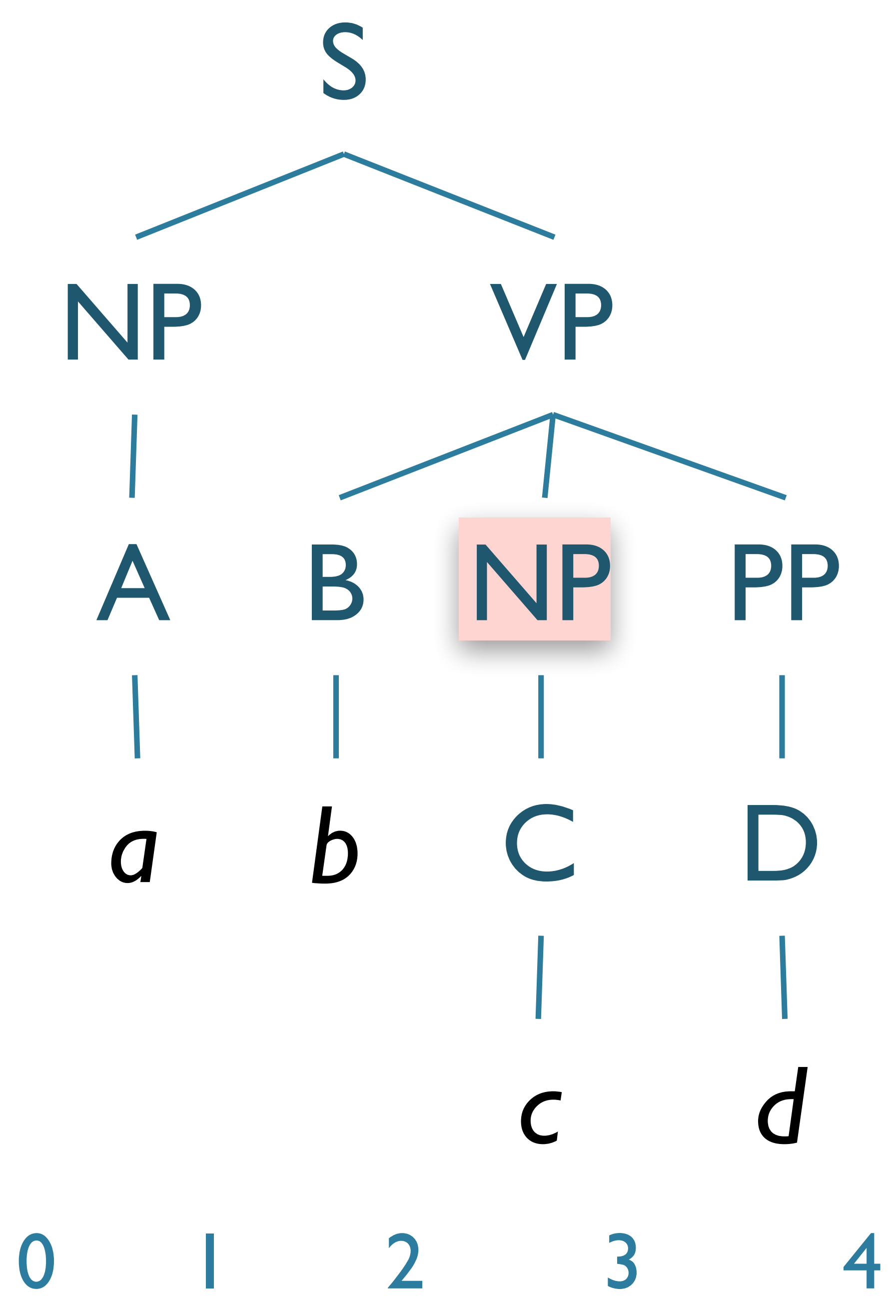
Hypothesis



S(0,4)
NP(0,1)
VP(1,4)

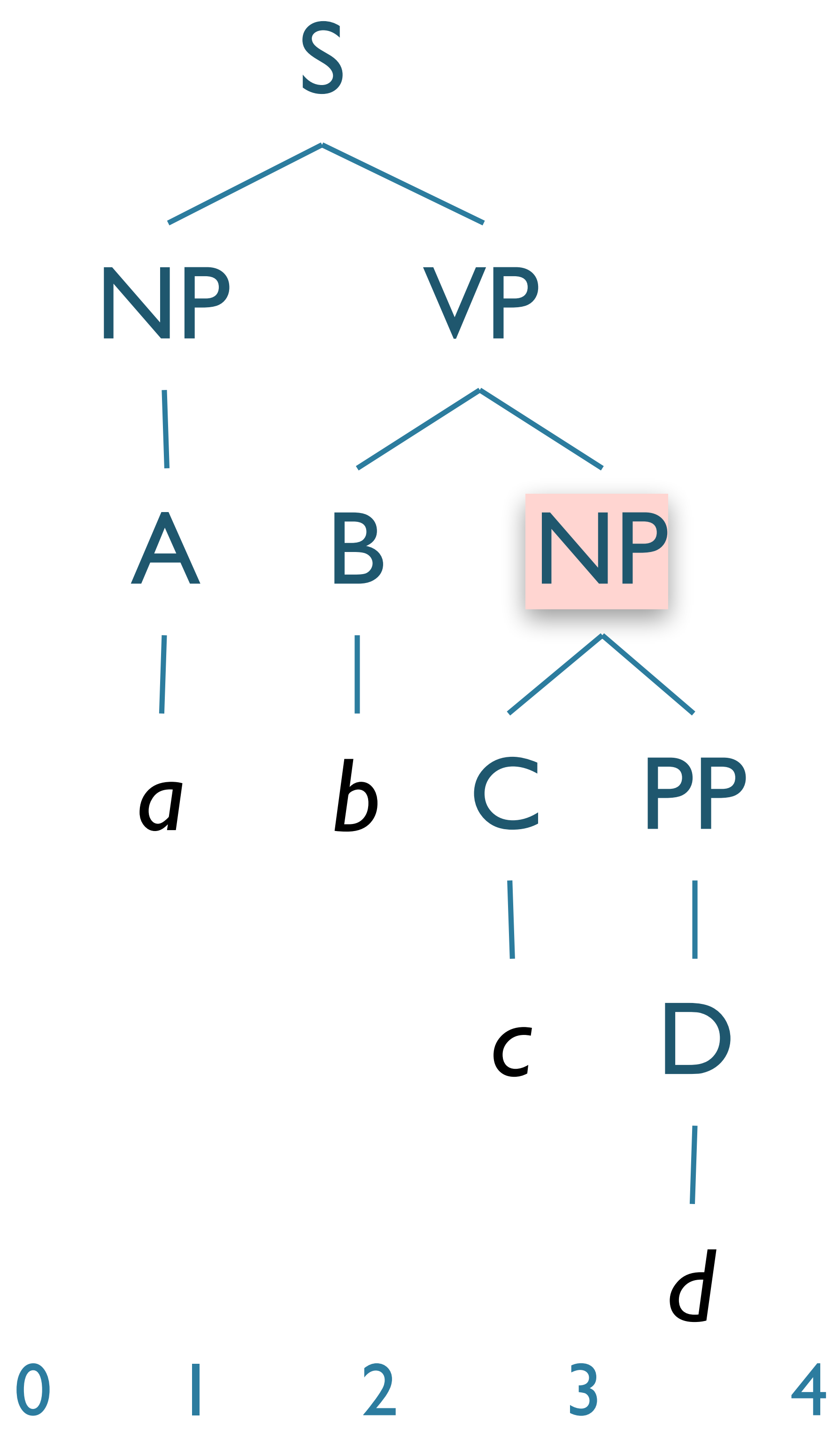
Evaluation: Example

Reference



S(0,4)
NP(0,1)
VP(1,4)
NP(2,3)

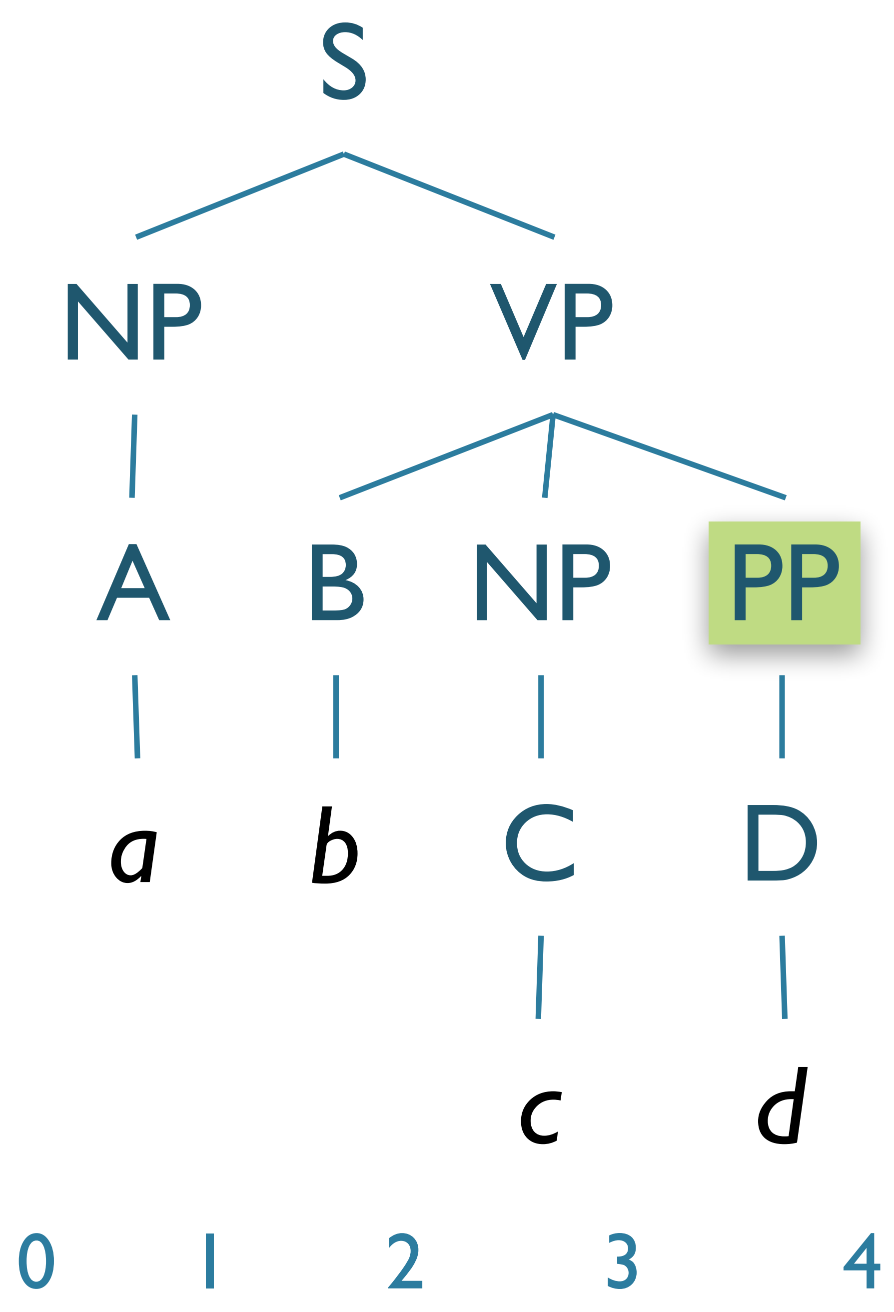
Hypothesis



S(0,4)
NP(0,1)
VP(1,4)
NP(2,4)

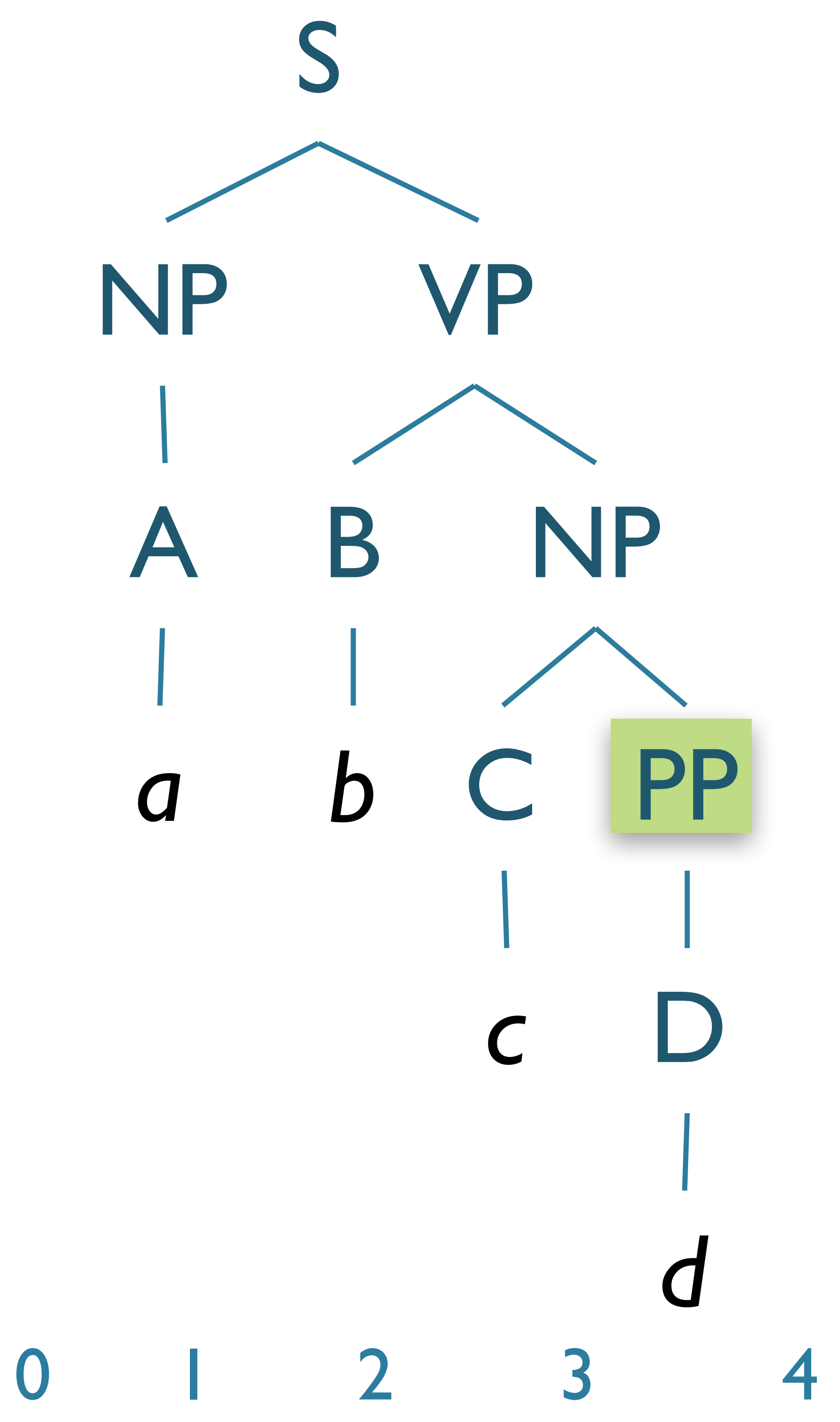
Evaluation: Example

Reference



S(0,4)
NP(0,1)
VP(1,4)
NP(2,3)
PP(3,4)

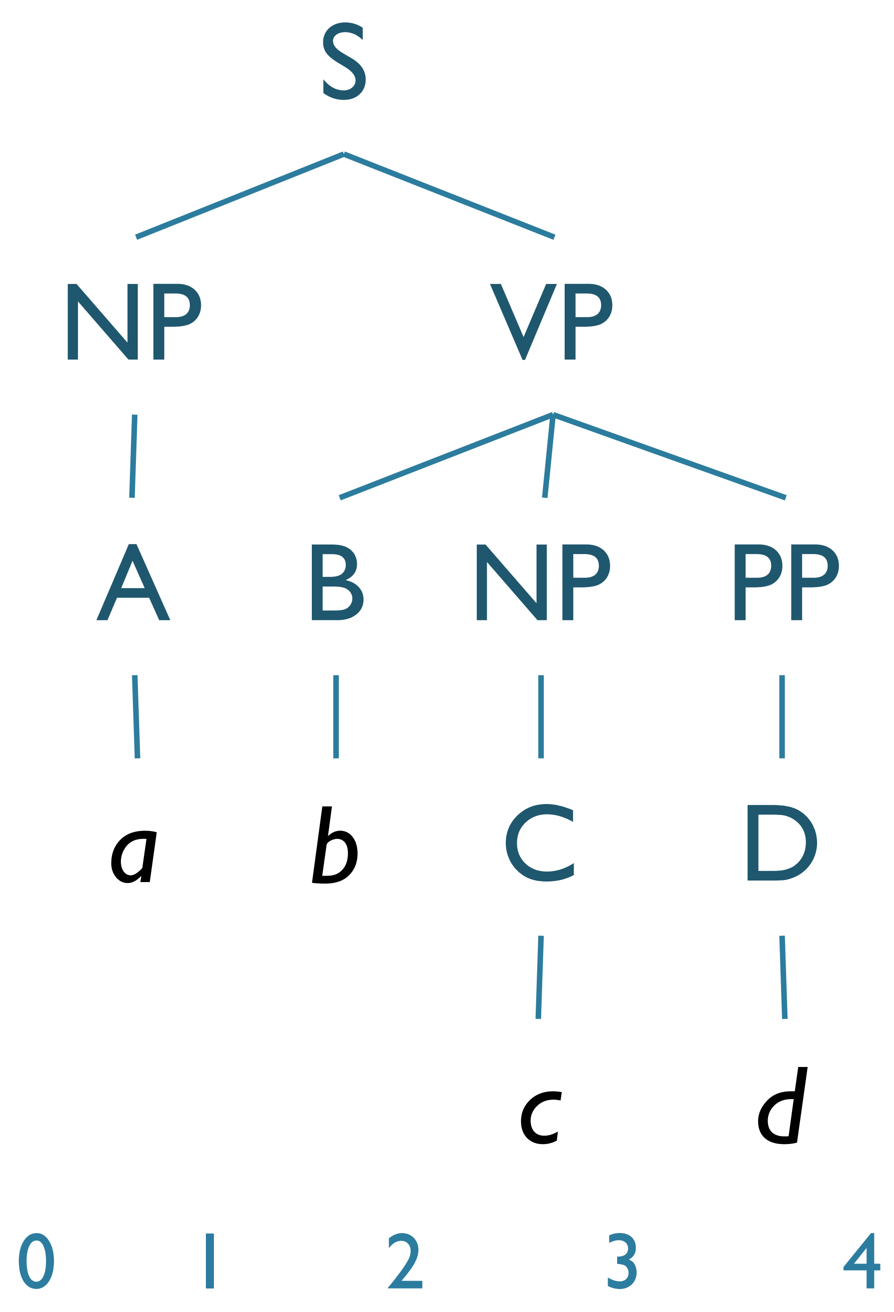
Hypothesis



S(0,4)
NP(0,1)
VP(1,4)
NP(2,4)
PP(3,4)

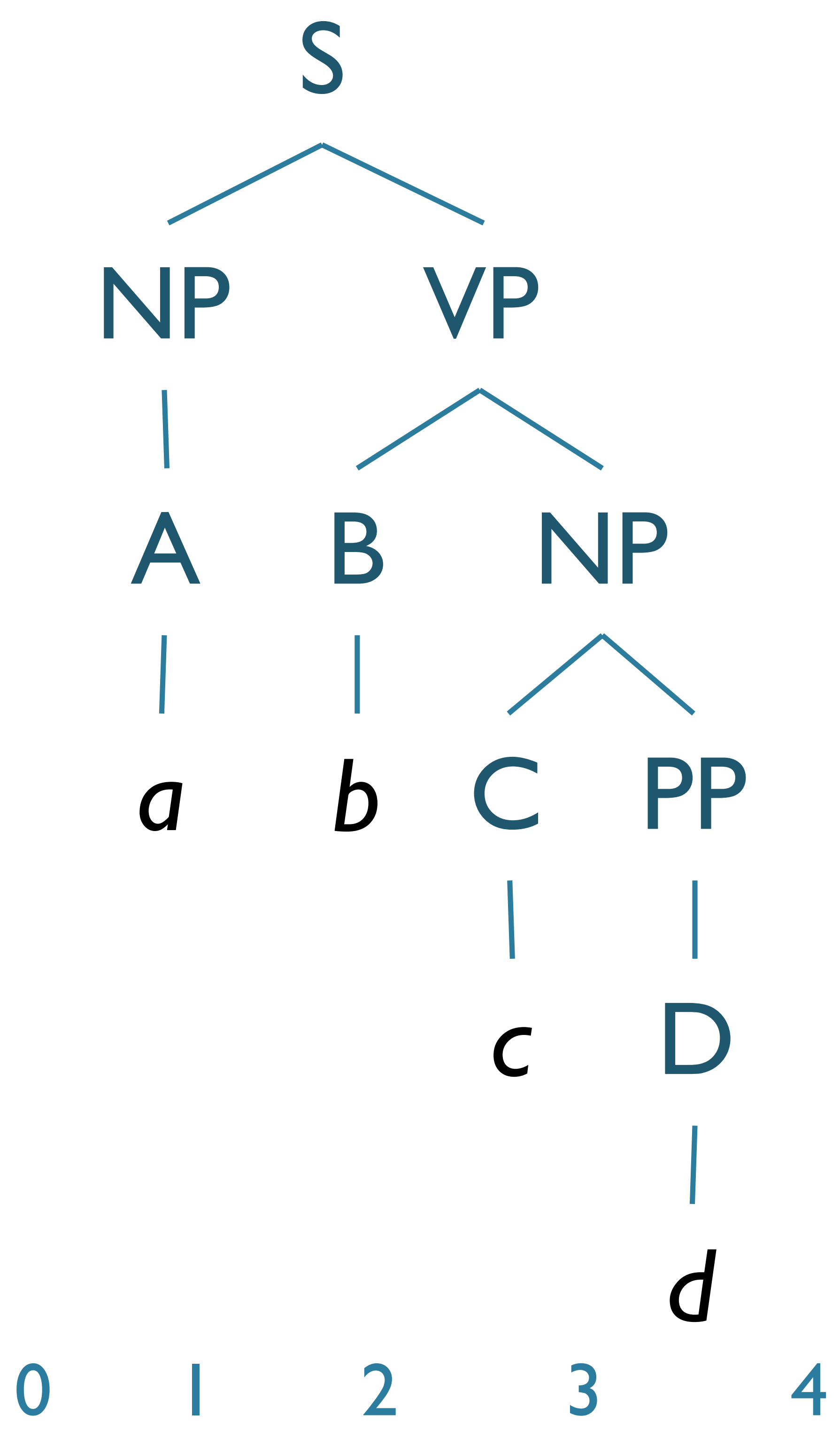
Evaluation: Example

Reference



S(0,4)
NP(0,1)
VP(1,4)
NP(2,3)
PP(3,4)

Hypothesis

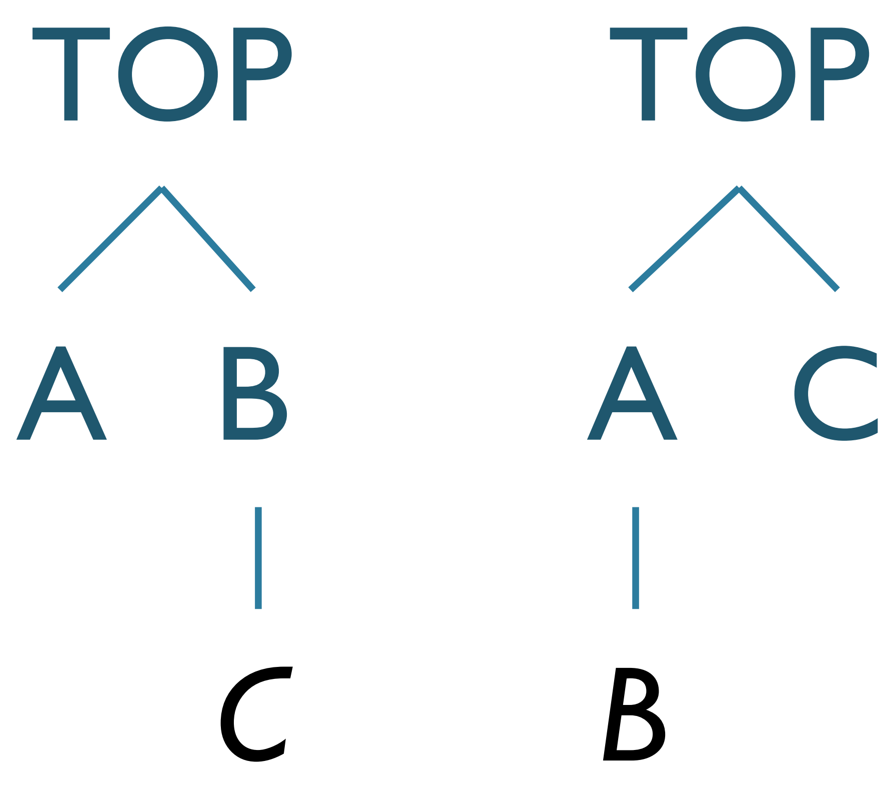


S(0,4)
NP(0,1)
VP(1,4)
NP(2,4)
PP(3,4)

LP: 4/5
LR: 4/5
F_1: 4/5

Parser Evaluation

- Crossing Brackets:
  - # of constituents where produced parse has bracketings that overlap for the siblings:
  - ((A B) C) — { (0,2), (2,3) }
    and hyp. has
    (A (B C)) — { (0,1), (1, 3) }




```
/* crossing is counted based on the brackets */
/* in test rather than gold file (by Mike)   */
for(j=0;j<bn2;j++){
  for(i=0;i<bn1;i++){
    if(bracket1[i].result != 5 &&
       bracket2[j].result != 5 &&
       ((bracket1[i].start < bracket2[j].start &&
         bracket1[i].end   > bracket2[j].start &&
         bracket1[i].end   < bracket2[j].end) ||
        (bracket1[i].start > bracket2[j].start &&
         bracket1[i].start < bracket2[j].end &&
         bracket1[i].end   > bracket2[j].end))){
```

from evalb.c

State-of-the-Art Parsing

- Parsers trained/tested on Wall Street Journal PTB
  - LR: 90%+;
  - LP: 90%+;
  - Crossing brackets: 1%

- Standard implementation of Parseval:
  - **`evalb`**

Evaluation Issues

- Only evaluating constituency
- There are other grammar formalisms:
  - LFG (Constraint-based)
  - Dependency Structure
- **Extrinsic** evaluation
  - How well does getting the correct parse match the semantics, etc?

Earley Parsing

Earley vs. CKY

- CKY doesn't capture full original structure
  - Can back-convert binarization, terminal conversion
  - Unit non-terminals require change in CKY

Earley vs. CKY

- CKY doesn't capture full original structure
  - Can back-convert binarization, terminal conversion
  - Unit non-terminals require change in CKY
- Earley algorithm
  - Supports parsing efficiently with arbitrary grammars
  - Top-down search
  - Dynamic programming
    - Tabulated partial solutions
  - Some bottom-up constraints

Earley Algorithm

- Another dynamic programming solution
  - Partial parses stored in “chart”
  - Compactly encodes ambiguity
  - $O(N^3)$
- Chart entries contain:
  - Subtree for a single grammar rule
  - Progress in completing subtree
  - Position of subtree w.r.t. input

Earley Algorithm

- First, left-to-right pass fills out a chart with *N+1* states
  - Chart entries — sit between words in the input string
  - Keep track of states of the parse at those positions
  - For each word position, chart contains set of states representing all partial parse trees generate so far
    - e.g. `chart[0]` contains all partial parse trees generated at the beginning of sentence

Chart Entries

- Three types of constituents:
  - Predicted constituents
  - In-progress constituents
  - Completed constituents

Parse Progress

- Represented by Dotted Rules
  - Position of • indicates type of constituent
- $_0$ Book $_1$ that $_2$ flight $_3$
  - *S* → • *VP* [0,0] (predicted)
  - *NP* → *Det* • *Nom* [1,2] (in progress)
  - *VP* → *V NP* • [0,3] (completed)
- [x,y] tells us what portion of the input is spanned so far by rule
- Each state s_i: <*dotted rule*>, [<*back pointer*>, <*current position*>]

$_0$ Book $_1$ that $_2$ flight $_3$

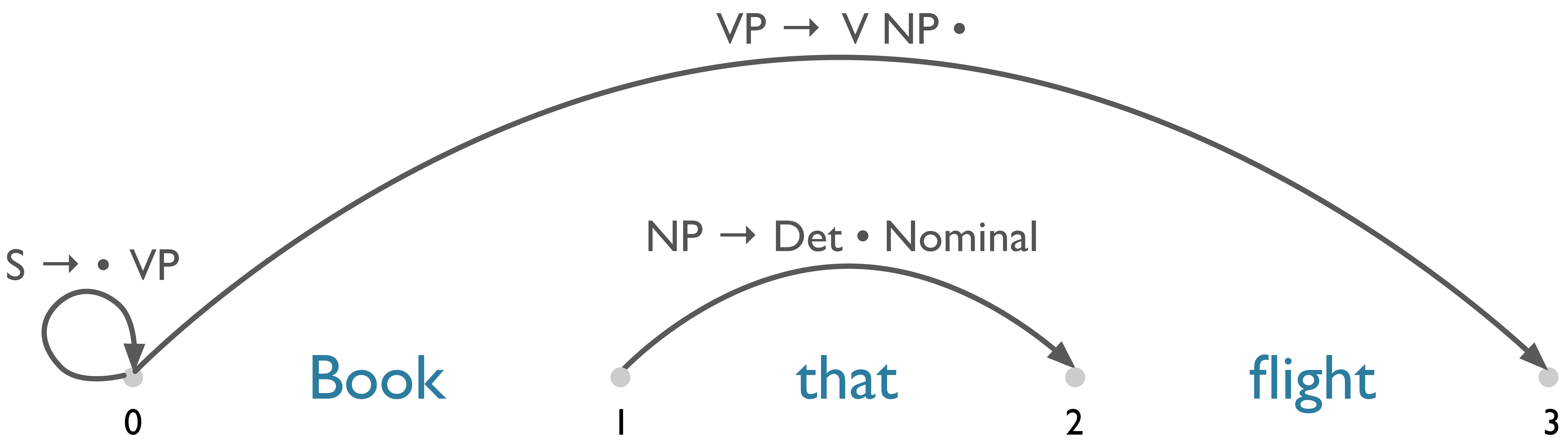
- $S \rightarrow \cdot\ VP$, [0,0]
  - First 0 means S constituent begins at the start of input
  - Second 0 means the dot is here too
  - So, this is a top-down prediction

$_0$ Book $_1$ that $_2$ flight $_3$

- $S \rightarrow \cdot\ VP$, [0,0]
  - First 0 means S constituent begins at the start of input
  - Second 0 means the dot is here too
  - So, this is a top-down prediction
- $NP \rightarrow Det \cdot Nom$, [1,2]
  - the NP begins at position 1
  - the dot is at position 2
  - so, Det has been successfully parsed
  - Nom predicted next

$_0$ Book $_1$ that $_2$ flight $_3$ (continued)

- $V \rightarrow V\ NP \bullet$ [0,3]
  - Successful VP parse of entire input



Successful Parse

- Final answer found by looking at last entry in chart
- If entry resembles $S \rightarrow \alpha \bullet [0,N]$ then input parsed successfully
- Chart will also contain record of all possible parses of input string, given the grammar

Parsing Procedure for the Earley Algorithm

- Move through each set of states in order, applying one of three operations:
  - **predictor**: add predictions to the chart
  - **scanner**: read input and add corresponding state to chart
  - **completer**: move dot to right when new constituent found
- Results (new states) added to current or next set of states in chart
- No backtracking and no states removed: keep complete history of parse

Earley Algorithm

```
function EARLEY-PARSE(words, grammar) returns chart
  ENQUEUE((γ ⟶ • S, [0,0]), chart[0])
  for i ⟵ from 0 to LENGTH(words) do
    for each state in chart[i] do
      if INCOMPLETE?(state) and
          NEXT-CAT(state) is not a part of speech then
        PREDICTOR(state)
      elseif INCOMPLETE?(state) and
          NEXT-CAT(state) is a part of speech then
        SCANNER(state)
      else
        COMPLETER(state)
      end
    end
  return(chart)
```

Earley Algorithm

procedure PREDICTOR(($A \rightarrow \alpha \bullet B\ \beta$, *[i,j]*))
  for each ($B \rightarrow \gamma$) **in** GRAMMAR-RULES-FOR(B,*grammar*) **do**
    ENQUEUE(($B \rightarrow \bullet\ \gamma$, *[j,j]*), *chart[j]*)
  end

procedure SCANNER(($A \rightarrow \alpha \bullet B\ \beta$,*[i,j]*))
  if B $\subset$ PARTS-OF-SPEECH(*word[j]*) **then**
    ENQUEUE((B $\rightarrow$ *word[j]* $\bullet$, *[j,j+1]*), *chart[j+1]*)

procedure COMPLETER(($B \rightarrow \gamma \bullet$, *[j,k]*))
  for each ($A \rightarrow \alpha \bullet B\ \beta$, *[i,j]*) **in** ***chart[j]*** **do**
    ENQUEUE(($A \rightarrow \alpha\ B \bullet\ \beta$, *[i,k]*), *chart[k]*)
  end

3 Main Subroutines of Earley

- Predictor
  - Adds predictions into the chart
- Scanner
  - Reads the input words and enters states representing those words into the chart
- Completer
  - Moves the dot to the right when new constituents are found

Predictor

- Intuition:
  - Create new state for top-down prediction of new phrase
- Applied when non part-of-speech non-terminals are to the right of a dot:
  - $S \rightarrow \cdot\ VP$ [0,0]
- Adds new states to *current* chart
  - One new state for each expansion of the non-terminal in the grammar
    $VP \rightarrow \cdot$ V [0,0]
    $VP \rightarrow \cdot\ V\ NP$ [0,0]

Chart[0]

S0	$\gamma \rightarrow \cdot S$	[0,0]	Dummy start state
S1	$S \rightarrow \cdot NP\ VP$	[0.0]	Predictor
S2	$S \rightarrow \cdot Aux\ NP\ VP$	[0,0]	Predictor
S3	$S \rightarrow \cdot VP$	[0,0]	Predictor
S4	$NP \rightarrow \cdot Pronoun$	[0,0]	Predictor
S5	$NP \rightarrow \cdot Proper\text{-}Noun$	[0,0]	Predictor
S6	$NP \rightarrow \cdot Det\ Nominal$	[0,0]	Predictor
S7	$VP \rightarrow \cdot Verb$	[0,0]	Predictor
S8	$VP \rightarrow \cdot Verb\ NP$	[0,0]	Predictor
S9	$VP \rightarrow \cdot Verb\ NP\ PP$	[0,0]	Predictor
S10	$VP \rightarrow \cdot Verb\ PP$	[0,0]	Predictor
S11	$VP \rightarrow \cdot VP\ PP$	[0,0]	Predictor

Chart[1]

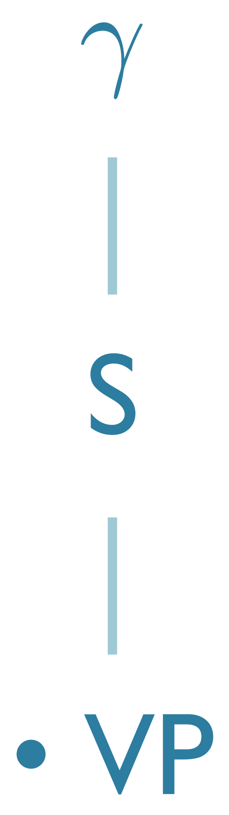
S12	*Verb* → *book* •	[0,1]	Scanner
S13	*VP* → *Verb* •	[0,1]	Completer
S14	*VP* → *Verb* • *NP*	[0,1]	Completer
S15	*VP* → *Verb* • *NP PP*	[0,1]	Completer
S16	*VP* → *Verb* • *PP*	[0,1]	Completer
S17	*S* → *VP* •	[0,1]	Completer
S18	*VP* → *VP* • *PP*	[0,1]	Completer
S19	*NP* → • *Pronoun*	[1,1]	Predictor
S20	*NP* → • *Proper-Noun*	[1,1]	Predictor
S21	*NP* → • *Det Nominal*	[1,1]	Predictor
S22	*PP* → • *Prep NP*	[1,1]	Predictor

Book that flight

S0: $\gamma \rightarrow \bullet\ S$ [0,0]

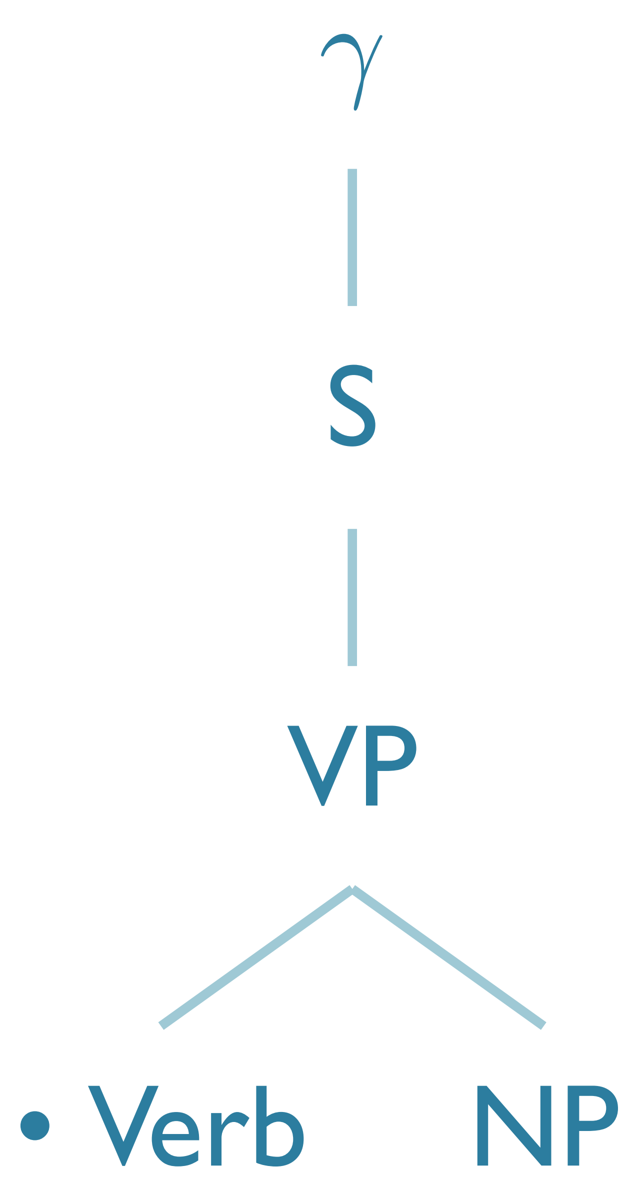
Book that flight

S0: $\gamma \rightarrow \bullet\ S$ [0,0]
S3: $S \rightarrow \bullet\ VP$ [0,0]



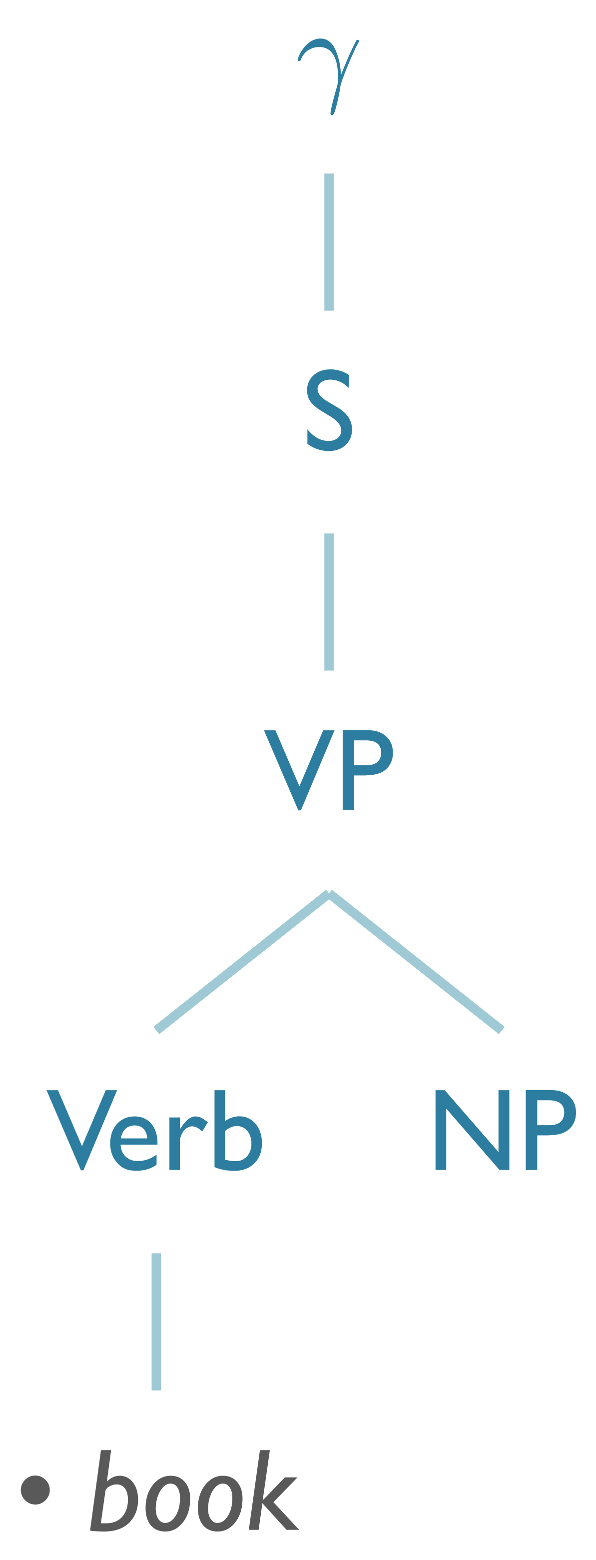
Book that flight

S0: $\gamma \rightarrow \bullet\ S$ [0,0]
S3: $S \rightarrow \bullet\ VP$ [0,0]
S8: $VP \rightarrow \bullet\ Verb\ NP$ [0,0]



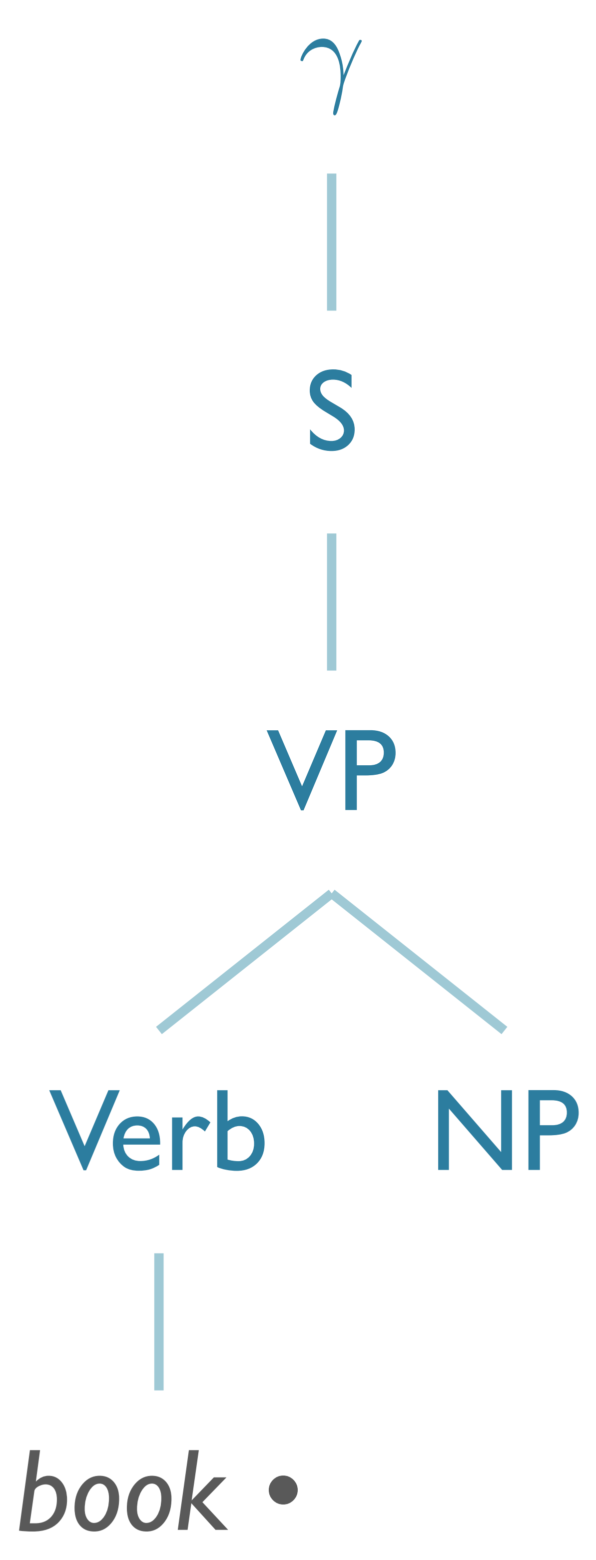
Book that flight

S0: $\gamma \rightarrow \bullet\ S$ [0,0]
S3: $S \rightarrow \bullet\ VP$ [0,0]
S8: $VP \rightarrow \bullet\ Verb\ NP$ [0,0]
S12: $Verb \rightarrow \bullet\ book$ [0,0]



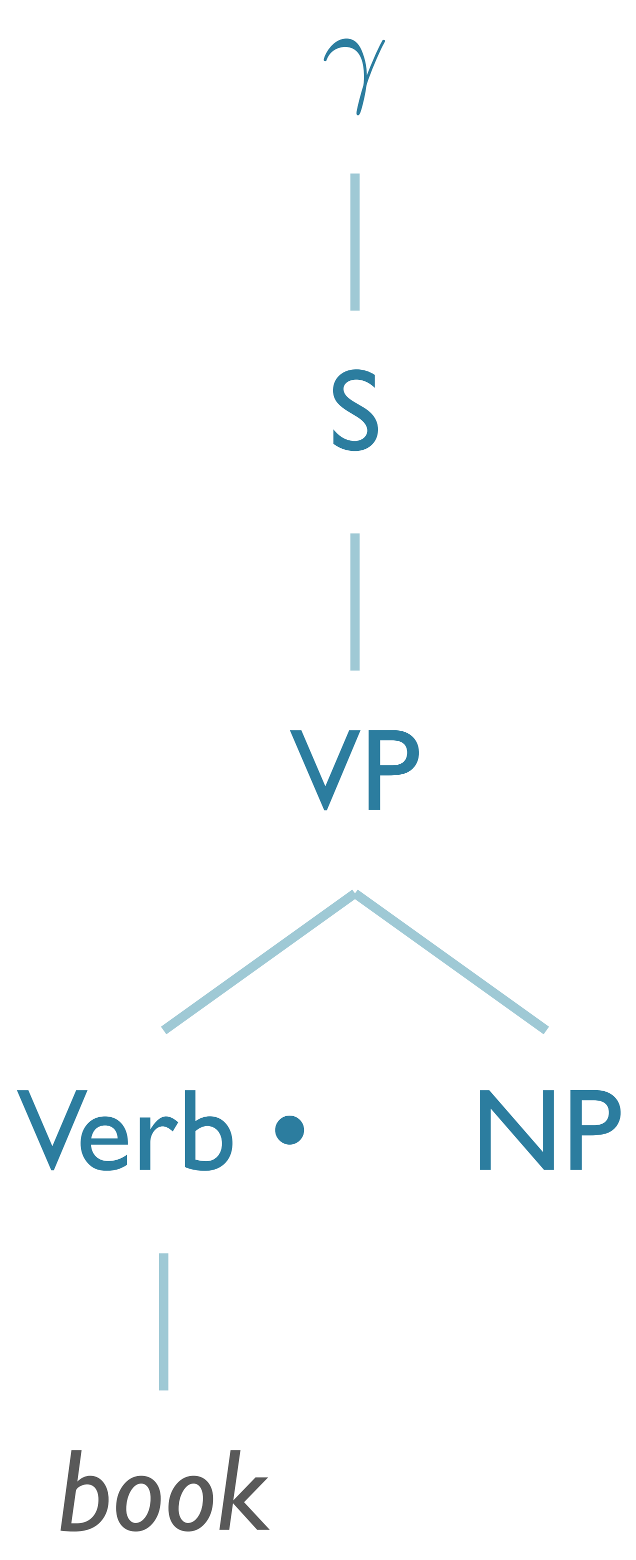
Book that flight

S0: $\gamma \rightarrow \bullet\ S$ [0,0]
S3: $S \rightarrow \bullet\ VP$ [0,0]
S8: $VP \rightarrow \bullet\ Verb\ NP$ [0,0]
S12: $Verb \rightarrow book \bullet$ [0,1]



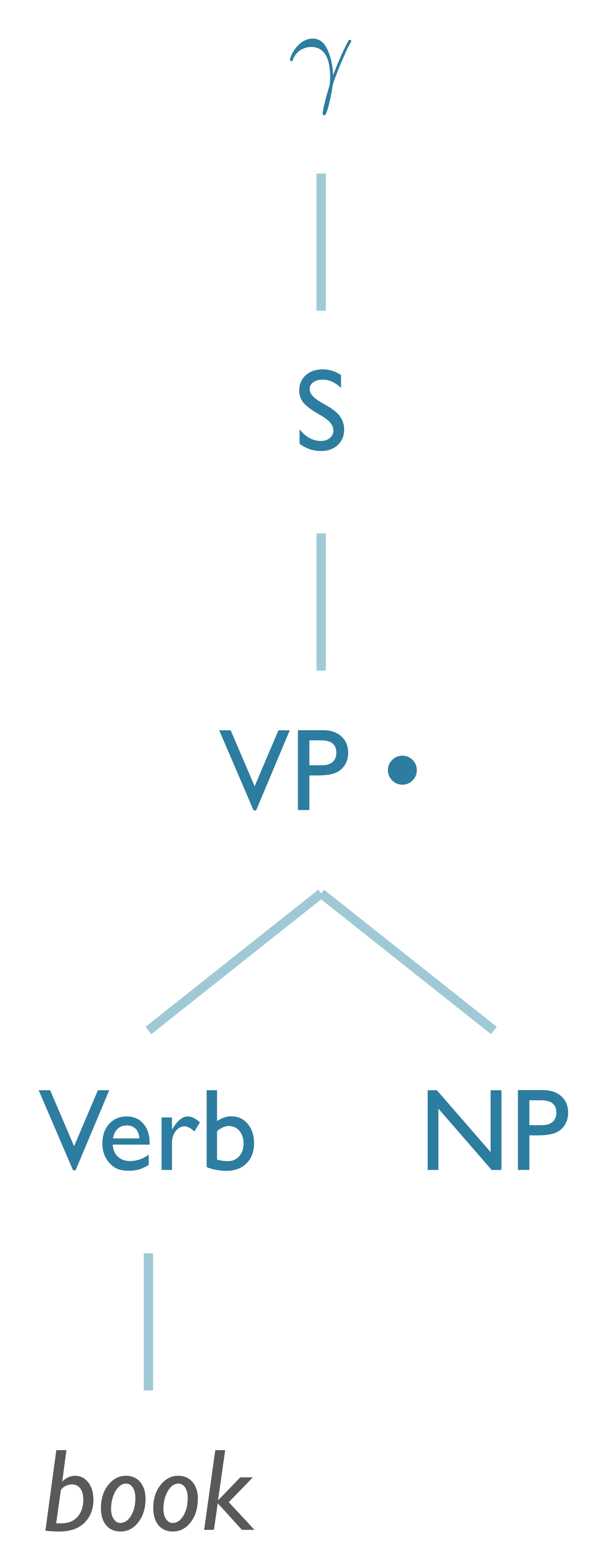
Book that flight

S0: $\gamma \rightarrow \bullet\ S$ [0,0]
S3: $S \rightarrow \bullet\ VP$ [0,0]
S8: $VP \rightarrow Verb \bullet NP$ [0,1]



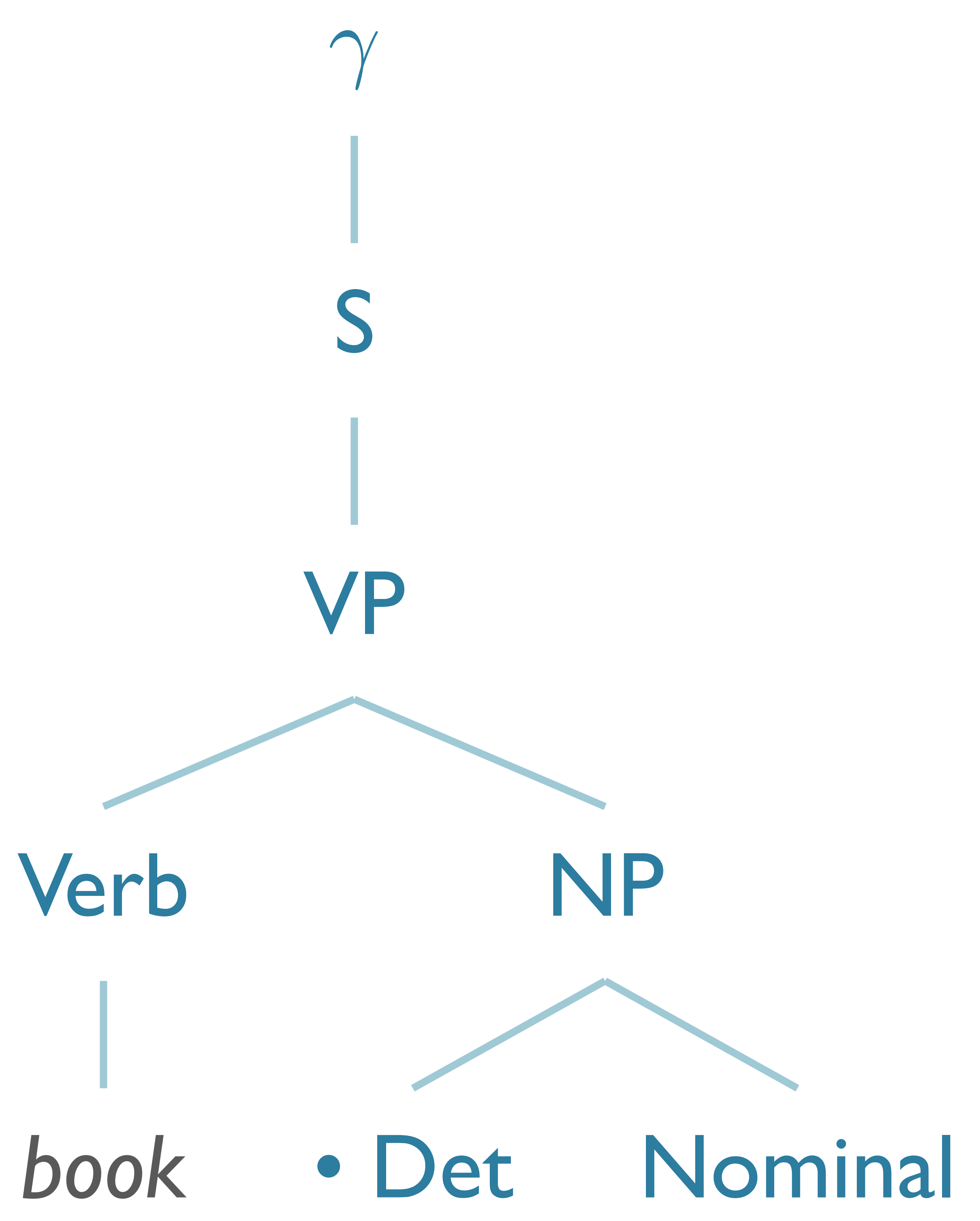
Book that flight

S0: $\gamma \rightarrow \bullet\, S$ [0,0]
S3: $S \rightarrow VP \bullet$ [0,1]
S8: $VP \rightarrow Verb \bullet NP$ [0,1]



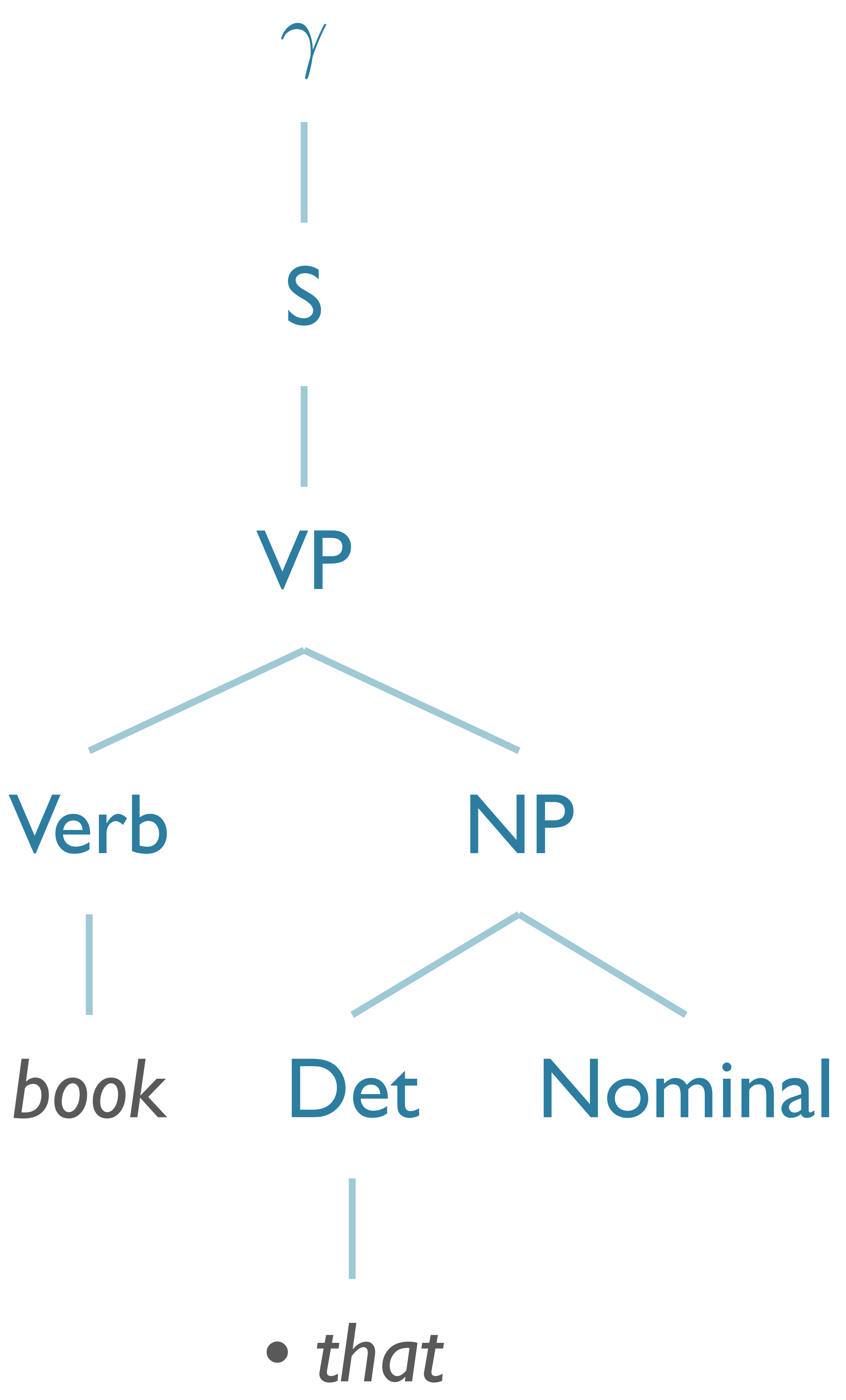
Book that flight

S0: $\gamma \rightarrow \bullet\ S$ [0,0]
S3: $S \rightarrow VP \bullet$ [0,1]
S8: $VP \rightarrow Verb \bullet NP$ [0,1]
S21: $NP \rightarrow \bullet\ Det\ Nominal$ [1,1]



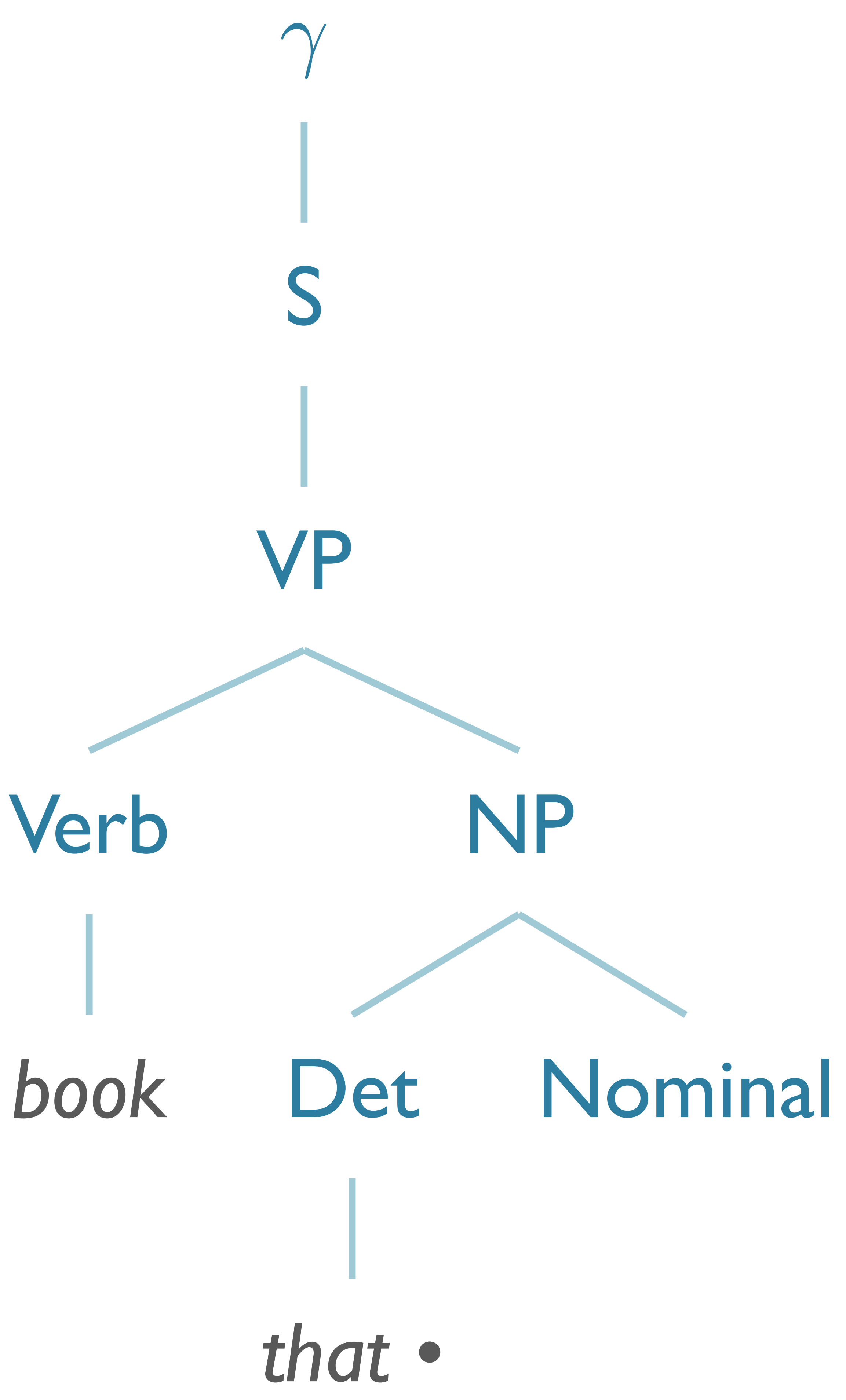
Book that flight

S0: $\gamma \rightarrow \bullet$ *S* [0,0]
S3: *S* $\rightarrow$ *VP* $\bullet$ [0,1]
S8: *VP* $\rightarrow$ *Verb* $\bullet$ *NP* [0,1]
S21: *NP* $\rightarrow$ $\bullet$ *Det Nominal* [1,1]
S23: *Det* $\rightarrow$ $\bullet$ *"that"* [1,1]



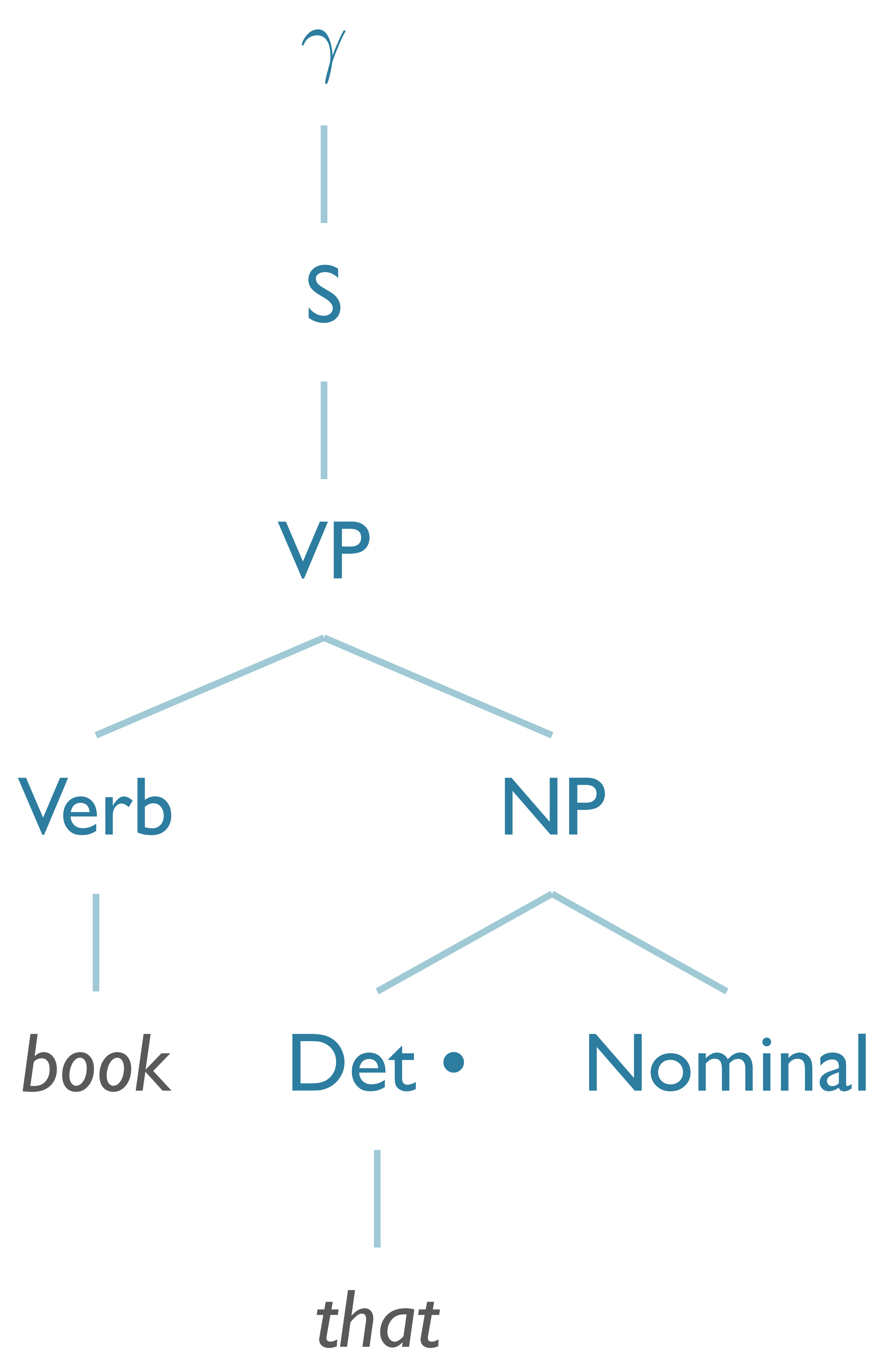
Book that flight

S0: $\gamma \rightarrow \bullet\ S$ [0,0]
S3: $S \rightarrow VP\ \bullet$ [0,1]
S8: $VP \rightarrow Verb \bullet NP$ [0,1]
S21: $NP \rightarrow \bullet\ Det\ Nominal$ [1,1]
S23: $Det \rightarrow$ *"that"* $\bullet$ [1,2]



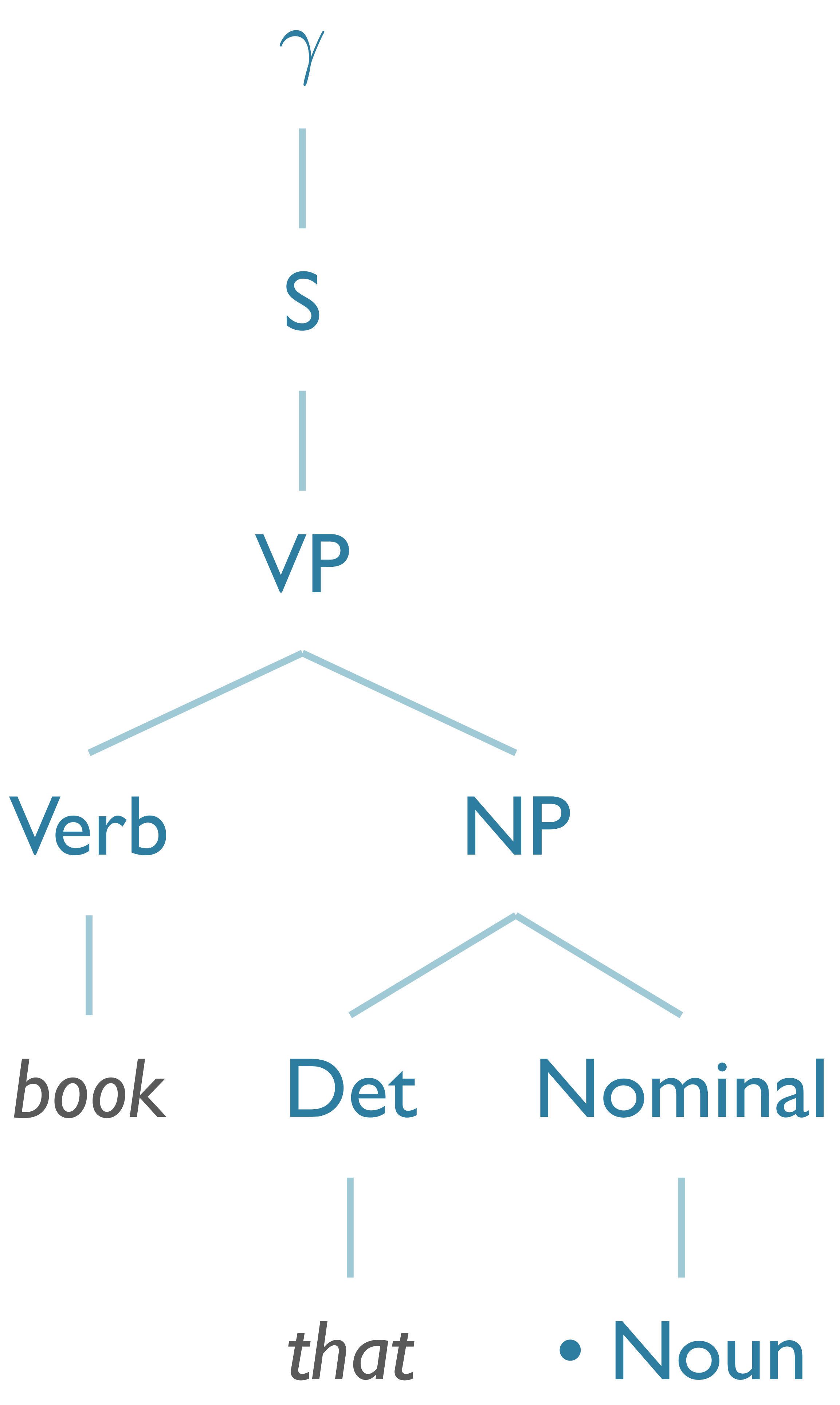
Book that flight

S0: $\gamma \rightarrow \bullet\ S$ [0,0]
S3: $S \rightarrow VP \bullet$ [0,1]
S8: $VP \rightarrow Verb \bullet NP$ [0,1]
S21: $NP \rightarrow Det \bullet Nominal$ [1,2]



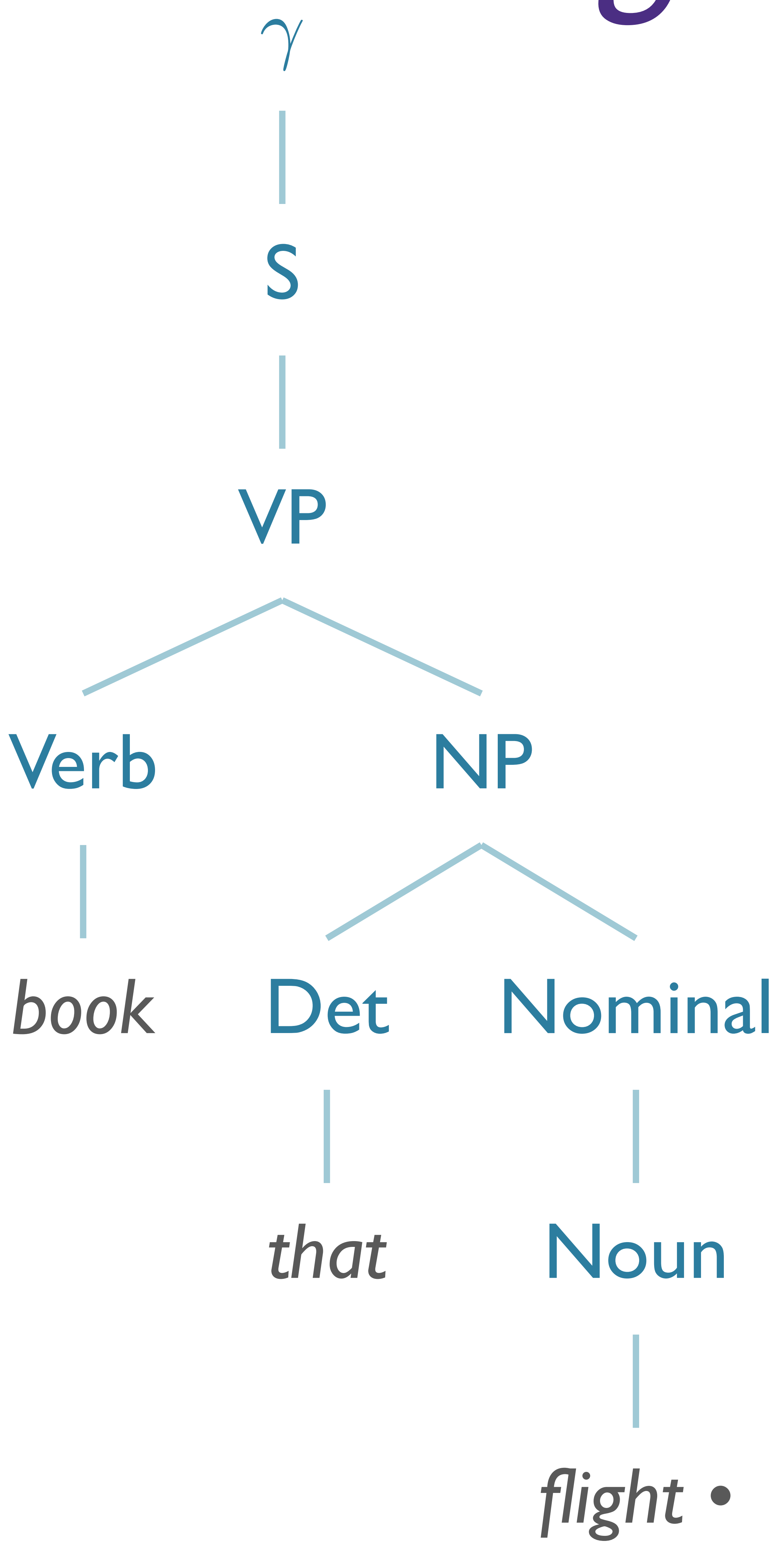
Book that flight

S0: $\gamma \rightarrow \bullet\ S\ [0,0]$
S3: $S \rightarrow VP \bullet [0,1]$
S8: $VP \rightarrow Verb \bullet NP\ [0,1]$
S21: $NP \rightarrow Det \bullet Nominal\ [1,2]$
S25: $Nominal \rightarrow \bullet\ Noun\ [2,2]$



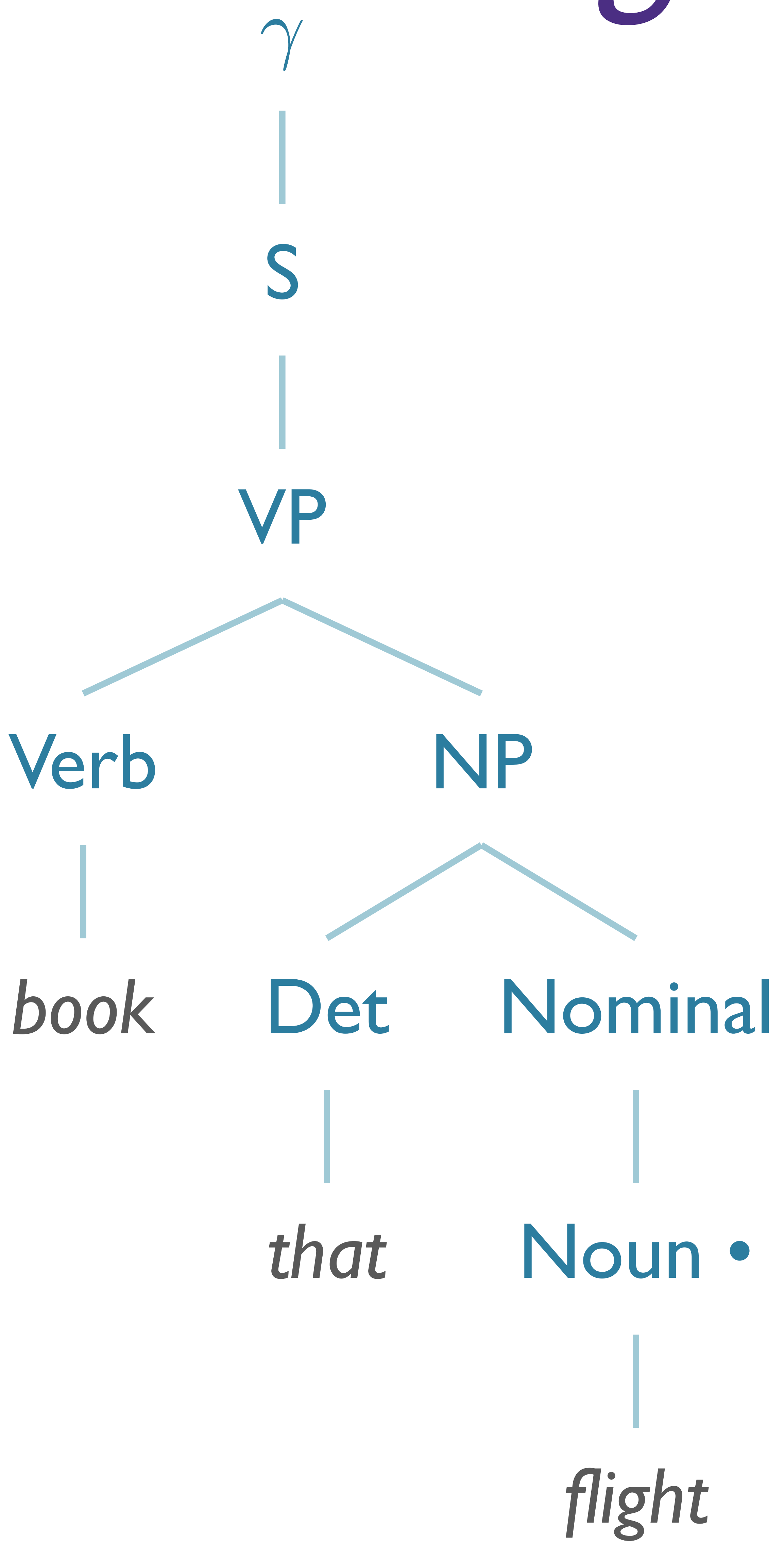
Book that flight

S0: $\gamma \rightarrow \bullet\ S$ [0,0]
S3: $S \rightarrow VP \bullet$ [0,1]
S8: $VP \rightarrow Verb \bullet NP$ [0,1]
S21: $NP \rightarrow Det \bullet Nominal$ [1,2]
S25: $Nominal \rightarrow \bullet\ Noun$ [2,2]
S28: $Noun \rightarrow$ "*flight*" $\bullet$ [2,3]



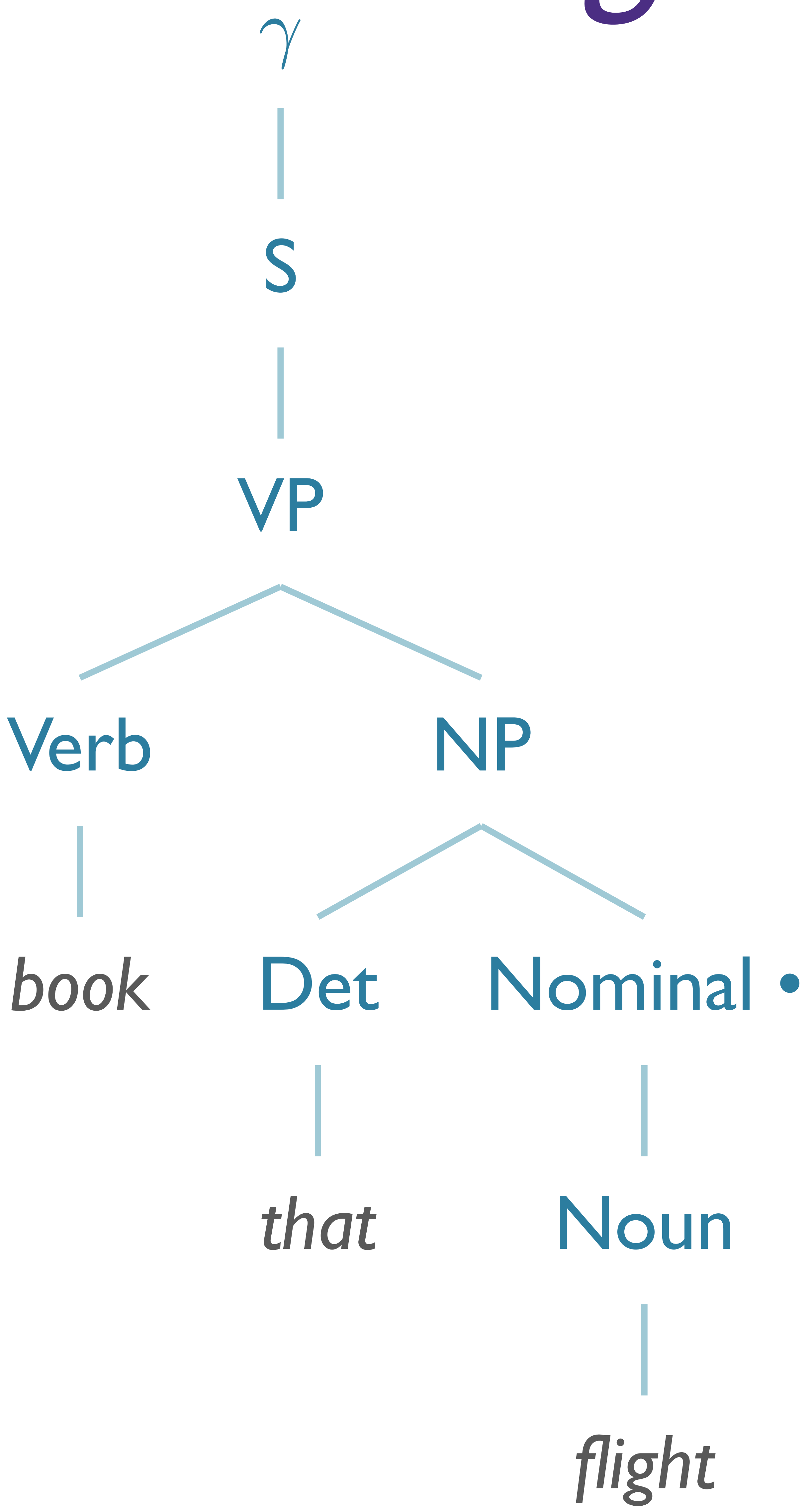
Book that flight

S0: $\gamma \rightarrow \bullet\ S$ [0,0]
S3: $S \rightarrow\ VP \bullet$ [0,1]
S8: $VP \rightarrow\ Verb \bullet NP$ [0,1]
S21: $NP \rightarrow\ Det \bullet Nominal$ [1,2]
S25: $Nominal \rightarrow\ Noun \bullet$ [2,3]



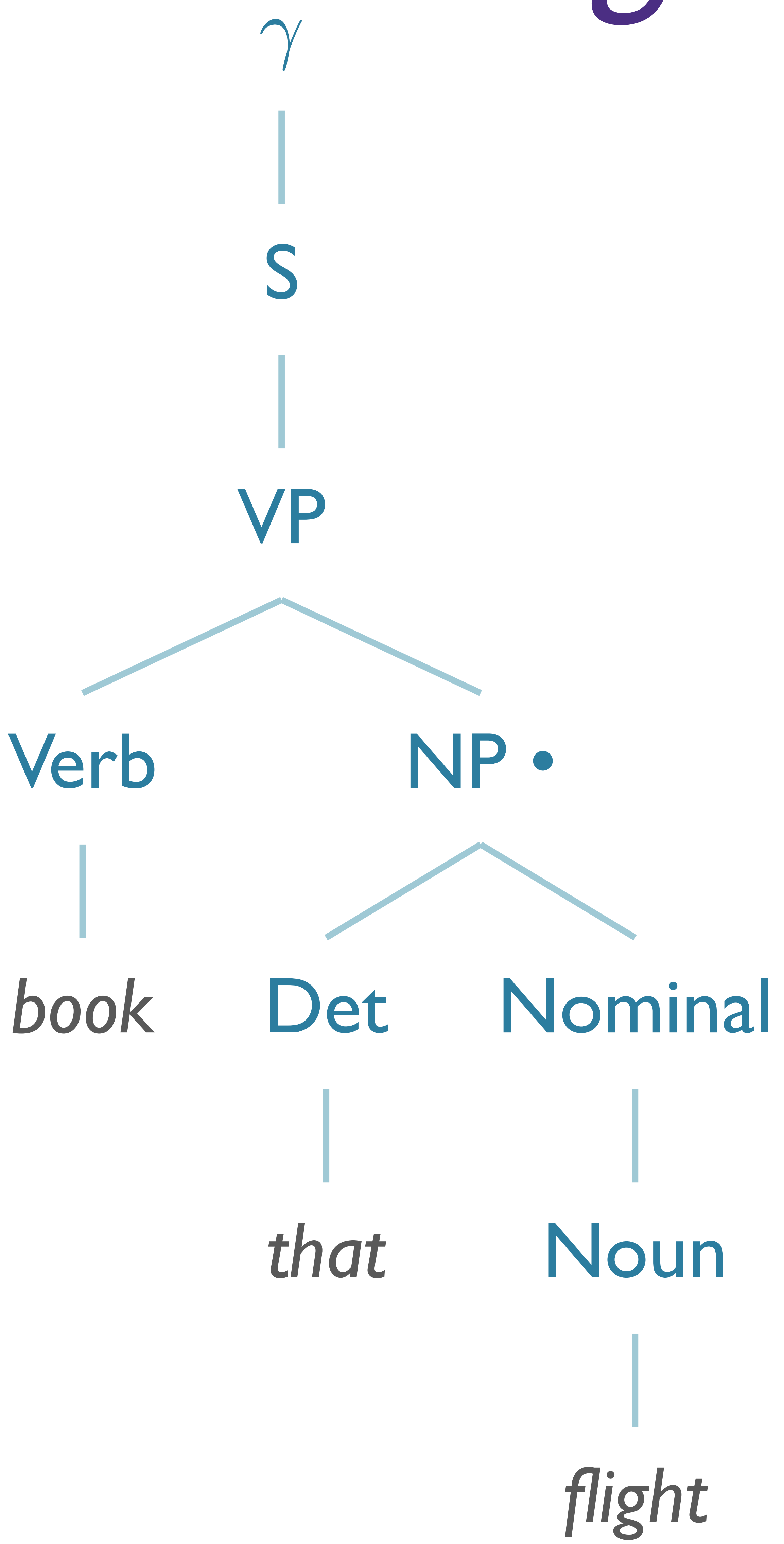
Book that flight

S0: $\gamma \rightarrow \bullet\ S$ [0,0]
S3: $S \rightarrow VP \bullet$ [0,1]
S8: $VP \rightarrow Verb \bullet NP$ [0,1]
S21: $NP \rightarrow Det\ Nominal \bullet$ [1,3]



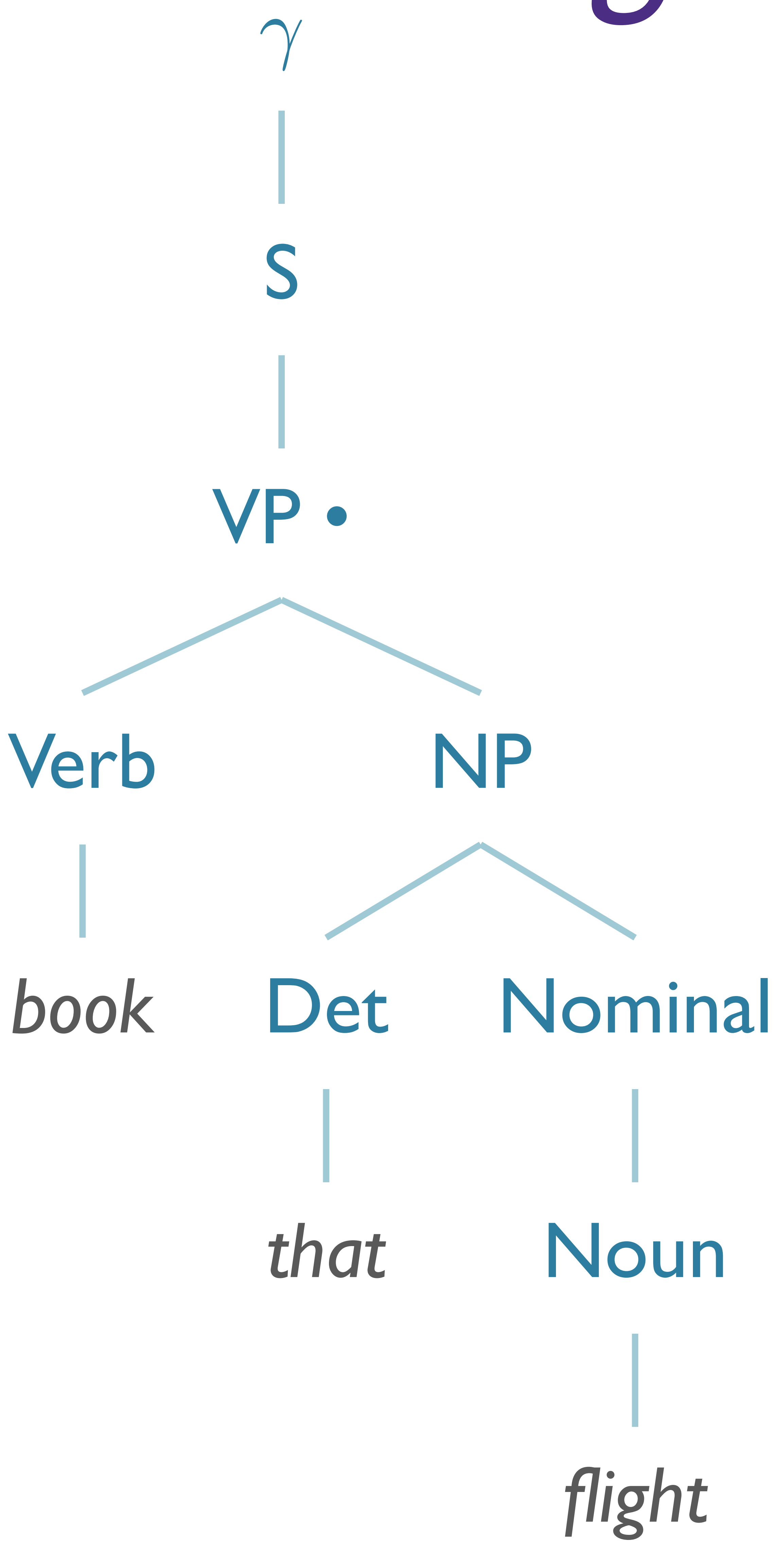
Book that flight

S0: $\gamma \rightarrow \bullet\ S$ [0,0]
S3: $S \rightarrow VP \bullet$ [0,1]
S8: $VP \rightarrow Verb\ NP \bullet$ [0,3]



Book that flight

S0: $\gamma \rightarrow \bullet\ S$ [0,0]
S3: $S \rightarrow VP \bullet$ [0,3]

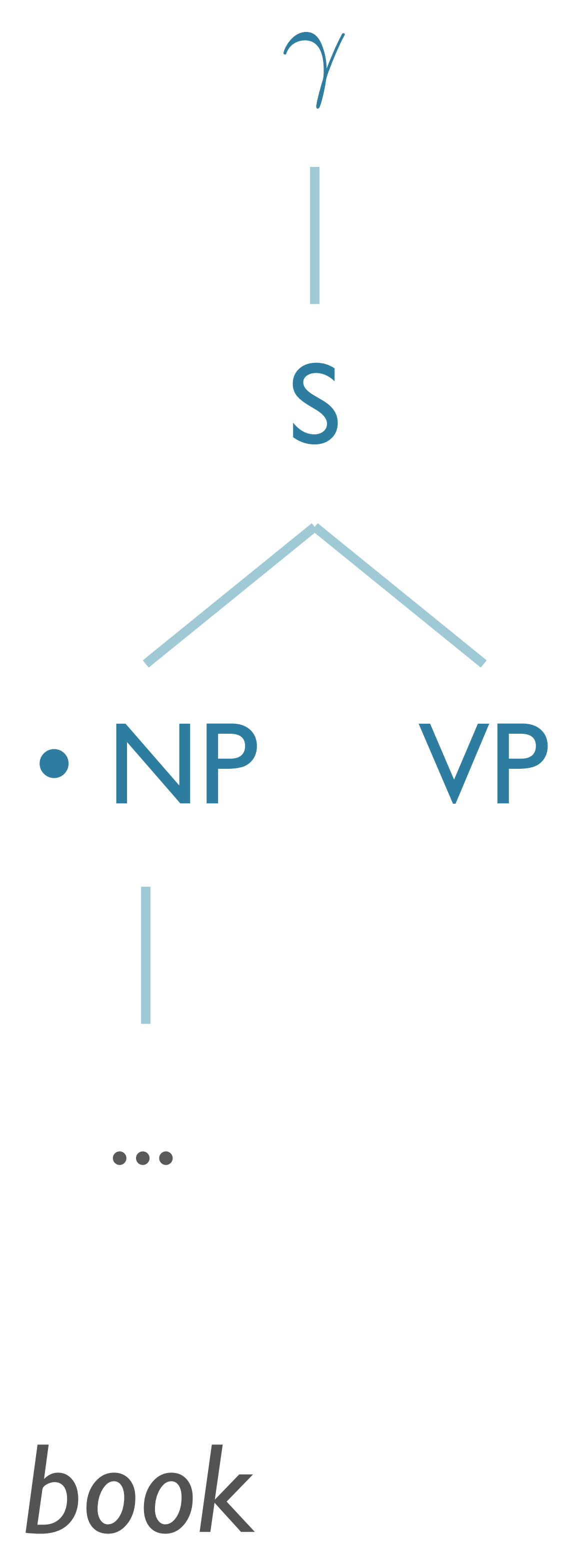


What About Dead Ends?

Book that flight

S0: $\gamma \rightarrow \bullet\ S$ [0,0]
S1: $S \rightarrow \bullet\ NP\ VP$ [0,0]

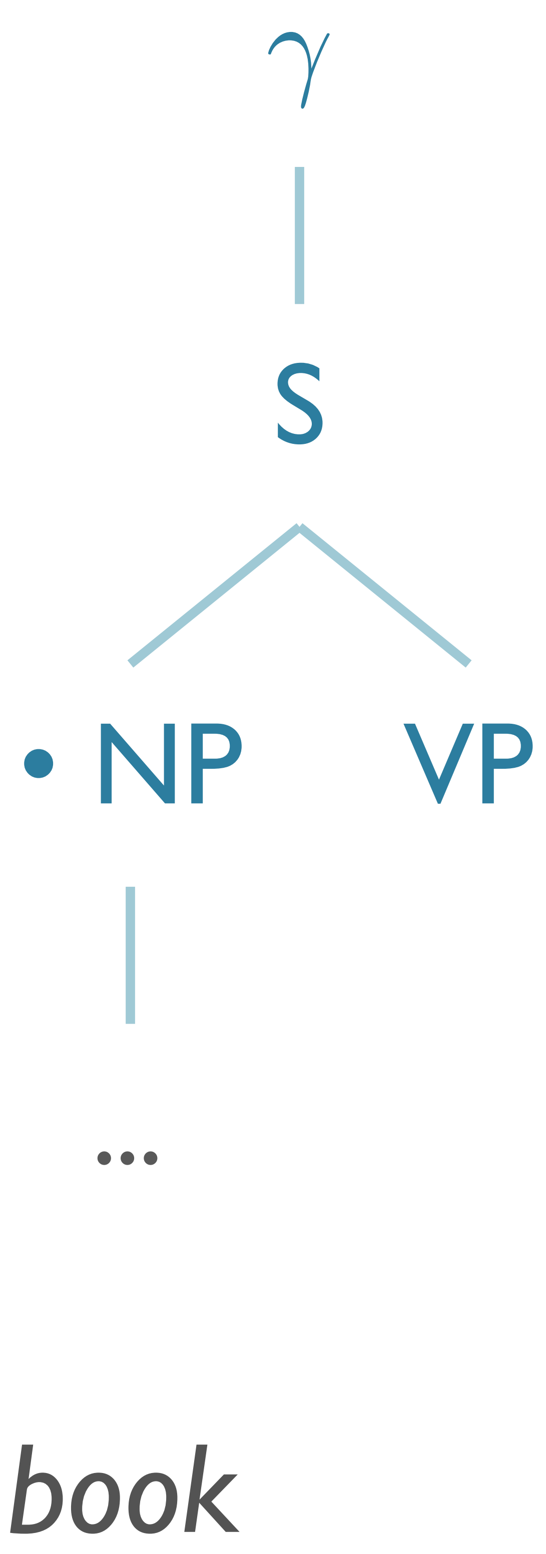
$NP \rightarrow \bullet\ Pronoun$
$NP \rightarrow \bullet\ Proper\text{-}Noun$
$NP \rightarrow \bullet\ Det\ Nominal$



Book that flight

S0: $\gamma \rightarrow \bullet\ S$ [0,0]
S1: $S \rightarrow \bullet\ NP\ VP$ [0,0]

~~*NP* → • *Pronoun*~~
~~*NP* → • *Proper-Noun*~~
~~*NP* → • *Det Nominal*~~



What About Recursion?

What about recursion?

What about recursion?

- We now have a top-down parser in hand. Does it enter infinite loops on rules like S -> S ‘and’ S?

What about recursion?

- We now have a top-down parser in hand. Does it enter infinite loops on rules like S -> S 'and' S?
- No!

procedure ENQUEUE(*state*, *chart-entry*)
  if *state* is not already in *chart-entry* **then**
    PUSH(*state*, *chart-entry*)
  end

What about recursion?

- We now have a top-down parser in hand. Does it enter infinite loops on rules like S -> S 'and' S?
- No!

procedure ENQUEUE(*state*, *chart-entry*)
  if *state* is not already in *chart-entry* **then**
    PUSH(*state*, *chart-entry*)
  end

Exercise: parse 'table and chair' using the very simple grammar
Nom -> Nom 'and' Nom | 'table' | 'chair'

HW #3

CKY Parsing: Goals

- Complete implementation of CKY parser
- Implement dynamic programming approach
- Incorporate/follow backpointers to recover parse

Implementation

- Build full parser
- You may use existing data structures for rules, trees
  - e.g. NLTK has nice `tree` data structure
  - CKY algorithm must be your own
- Dynamic programming table filling crucial!
- Will use smaller grammar (similar to HW #1)
- Back to ATIS for HW #4

Implementation

- For CKY Implementation:
  - NLTK's **`CFG.productions()`** method:
    - optional `rhs=` argument *only looks at first token of RHS*
    - Be-ware: NOT the entire RHS

Notes

- Teams:

  You may work in teams of two on this assignment

- Test grammar

  Pre-converted to CNF

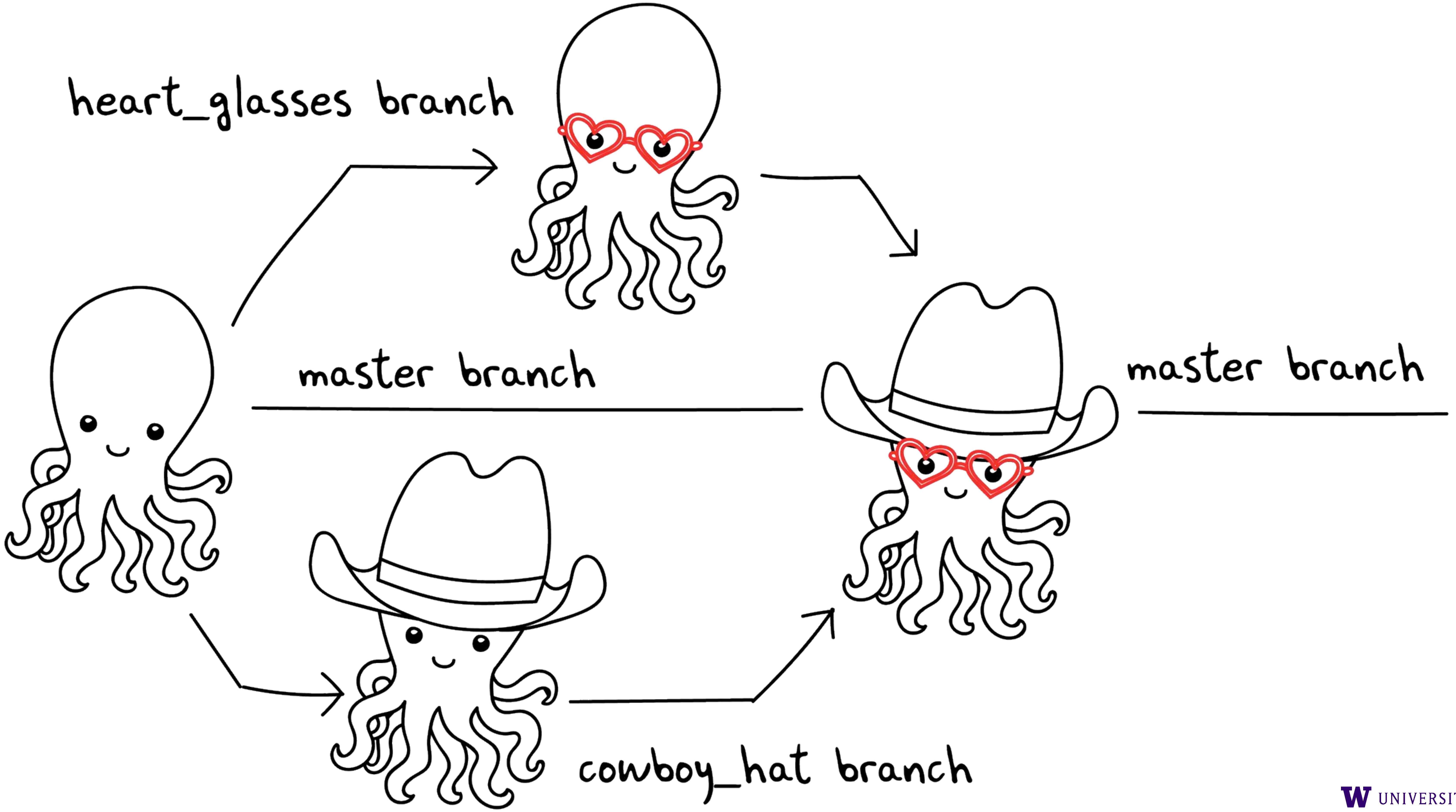
  Start symbol: $\mathbf{TOP}$

  Parse should span input and be rooted at: $\mathbf{TOP}$

Some Collaboration Basics

Git Branches

- Good for semi-isolating your development code from the shared, reviewed code



Recommended Git Flow

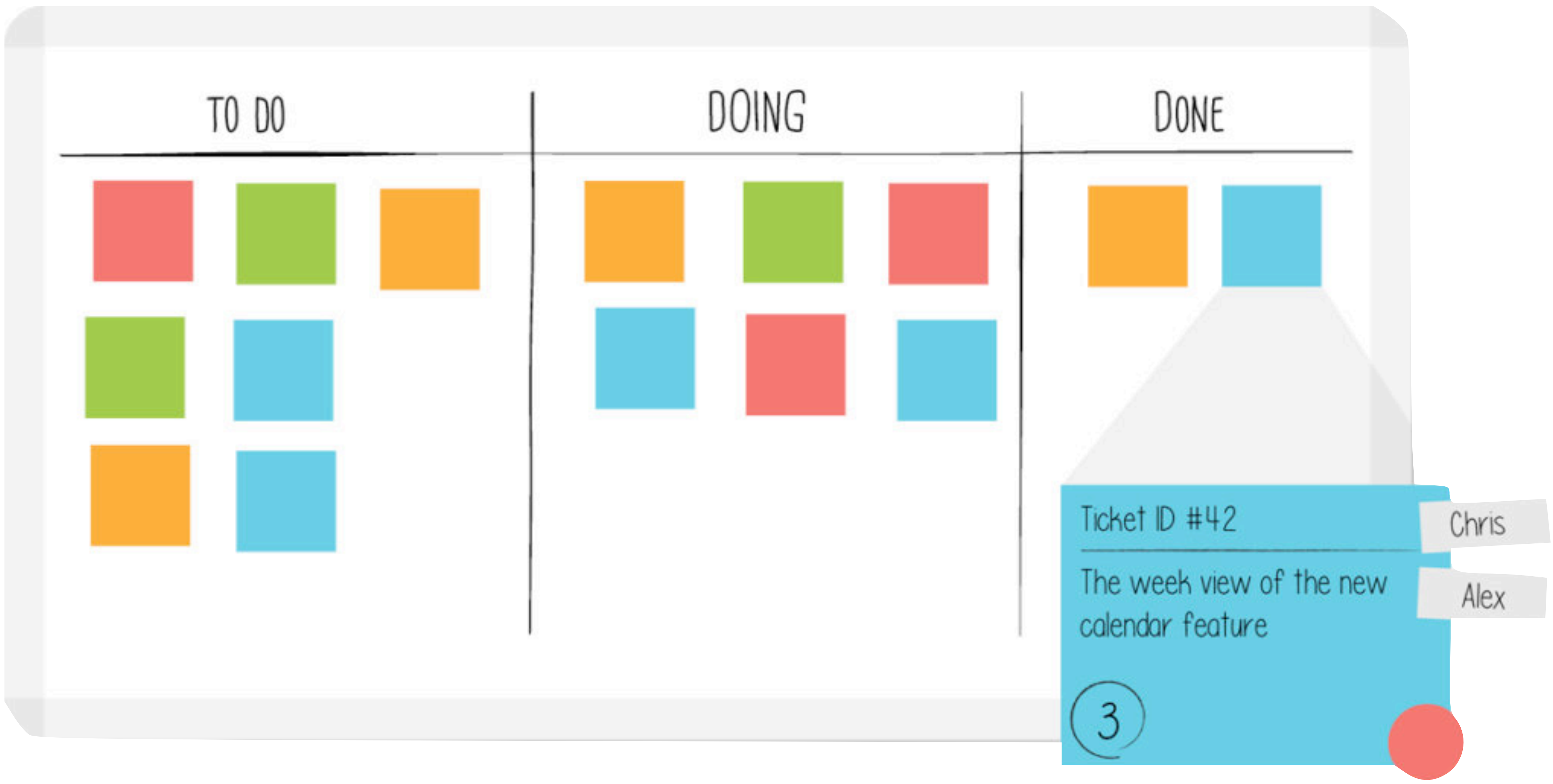
- Initialize a git repository, with a `main` branch
  - (Create initial commit, if necessary)
- Create a new branch, maybe "`adding_rule_objects`"
- Make regular commits on your branch (like saving)
- Switch to `main` branch, and "pull"
- Merge your branch to main
- …rinse & repeat
- If using GitHub (or GitLab, etc): **MUST BE PRIVATE REPO!**

Communication: Check-ins

- For check-ins, three main points:
  - What have you been working on?
  - What do you plan to work on next?
  - Is there anything “blocking” you?
- In industry, these brief check-ins among small teams are often done daily

Project Planning: Kanban Boards

- Before you start working:
  - Write out tasks on sticky notes.
  - Place in three columns:
    - To-Do
    - Doing
    - Done
  - As you work, you can move them from column to column
  - Add tasks as new issues come up



- trello.com – has free online implementation of Kanban Boards