

Regular Expressions and Context Free Grammars

COMP7607 — Lecture 5

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Many materials from Columbia CS4705 with special thanks!

Regular Expressions

A formal language for specifying text strings

How can we search for any of these?

woodchuck
woodchucks
Woodchuck
Woodchucks



Regular Expressions: Disjunctions

Letters inside square brackets []

Pattern	Matches
[wW]oodchuck	Woodchuck, woodchuck
[1234567890]	Any digit

Ranges [A-Z]

Pattern	Matches	
[A-Z]	An upper case letter	<u>D</u> renched Blossoms
[a-z]	A lower case letter	<u>m</u> y beans were impatient
[0-9]	A single digit	Chapter <u>1</u> : Down the Rabbit Hole

Regular Expressions: Negation in Disjunction

Negations [^Ss]

Caret means negation only when first in []

Pattern	Matches	
[^A-Z]	Not an upper case letter	O <u>y</u> fn pripetchik
[^Ss]	Neither 'S' nor 's'	<u>I</u> have no exquisite reason”
[^e^]	Neither e nor ^	Look <u>h</u> ere
a^b	The pattern a caret b	Look up <u>a^b</u> now

Regular Expressions: More Disjunction

Woodchucks is another name for groundhog!

The pipe | for disjunction

Pattern	Matches
groundhog woodchuck	
yours mine	yours mine
a b c	= [abc]
[gG]roundhog [Ww]oodchuck	

Regular Expressions: ? * + .

Pattern	Matches	
colou?r	Optional previous char	<u>color</u> <u>colour</u>
oo*h!	0 or more of previous char	<u>oh!</u> <u>ooh!</u> <u>oooh!</u> <u>ooooh!</u>
o+h!	1 or more of previous char	<u>oh!</u> <u>ooh!</u> <u>oooh!</u> <u>ooooh!</u>
baa+		<u>baa</u> <u>baaa</u> <u>baaaa</u> <u>baaaaa</u>
beg.n		<u>begin</u> <u>begun</u> <u>begun</u> <u>beg3n</u>

Regular Expressions: Anchors ^ \$

Pattern	Matches
<code>^[A-Z]</code>	<u>P</u> alo Alto
<code>^[^A-Za-z]</code>	<u>1</u> <u>“Hello”</u>
<code>\.\$</code>	The end <u>.</u>
<code>.\$</code>	The end <u>? The end!</u>

Example

Find me all instances of the word “the” in a text.

the

Misses capitalized examples

[tT]he

Incorrectly returns other or theology

[^a-zA-Z][tT]he[^a-zA-Z]

Find me the email address on a webpage.

Example

Junxian He
Group
Publications
Junxian He
Junxian He
何俊贤
Assistant Professor at HKUST

Hong Kong
junxianh@cse.ust.hk
Twitter
Github
Google Scholar

I am a tenure-track assistant professor in The Hong Kong University of Science and Technology, Department of Computer Science and Engineering. I obtained my PhD from Carnegie Mellon University, Language Technologies Institute in 2022, where I was co-advised by Graham Neubig and Taylor Berg-Kirkpatrick. Before that, I received the bachelor degree in Electronic Engineering from Shanghai Jiao Tong University in 2017. I also spent some time at Facebook AI Research (2019) and Salesforce Research (2020).

Prospective Students:
I am always actively looking for strong and self-motivated students to join us! Current PhD applications are for 2025 Fall, I encourage you to reach out early to ensure consideration. I also have several research assistant positions opening starting anytime. Please drop me an email if you are interested.

Research
I am generally interested in machine learning and natural language processing. Currently, I am passionate about long-horizon reasoning and planning of large language models.

Teaching
[2024 Spring] Machine Learning [COMP 5212]
[2024 Fall] Machine Learning [COMP 5212]

Service
Area Chair: ICLR, EMNLP, ACL, ARR
Reviewer: ICLR, NeurIPS, ICML, ACL, EMNLP, NAACL, ARR, TMLR

Awards
Baidu PhD Fellowship, class of 2020 (10 recipients worldwide)
National Scholarship in China (2014/2015/2016)
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Aa " " ☰ ☲ ☳ ☴ ☵ ☶ ☷ [a-z]+@[a-z\.\.]+ Find Find Prev

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BioPublicationsTalksstudentsServiceResumeGroup (Join Us!)
Bio
Tao Yu is an Assistant Professor of Computer Science at The University of Hong Kong and a director of the XLANG Lab (as part of the HKU NLP Group). He spent one year in the UW NLP Group working with Noah Smith, Luke Zettlemoyer, and Mari Ostendorf. He completed his Ph.D. in Computer Science from Yale University, advised by Dragomir Radev and master's at Columbia University advised by Owen Rambow and Kathleen McKeown.

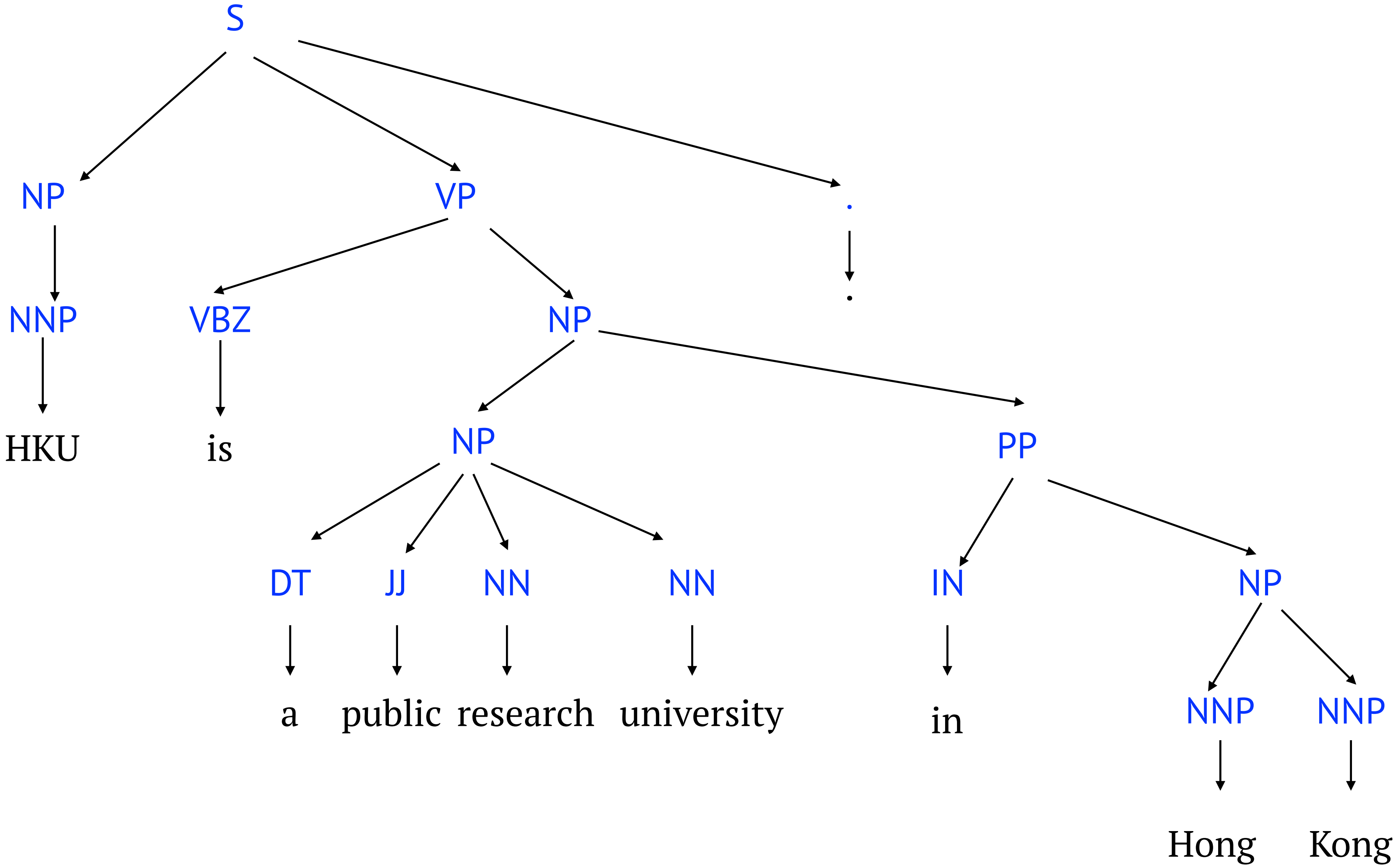
a " " ☰ ☲ ☳ ☴ ☵ ☶ ☷ [a-z\.\.]+[](|@|AT|\\[AT\\])[a-z\.\.]+ Find Find Prev

Example

Match strings with equal number of a and b.

e.g., aaabbb, aabb, aaaabbbb...

Linguistic Structures



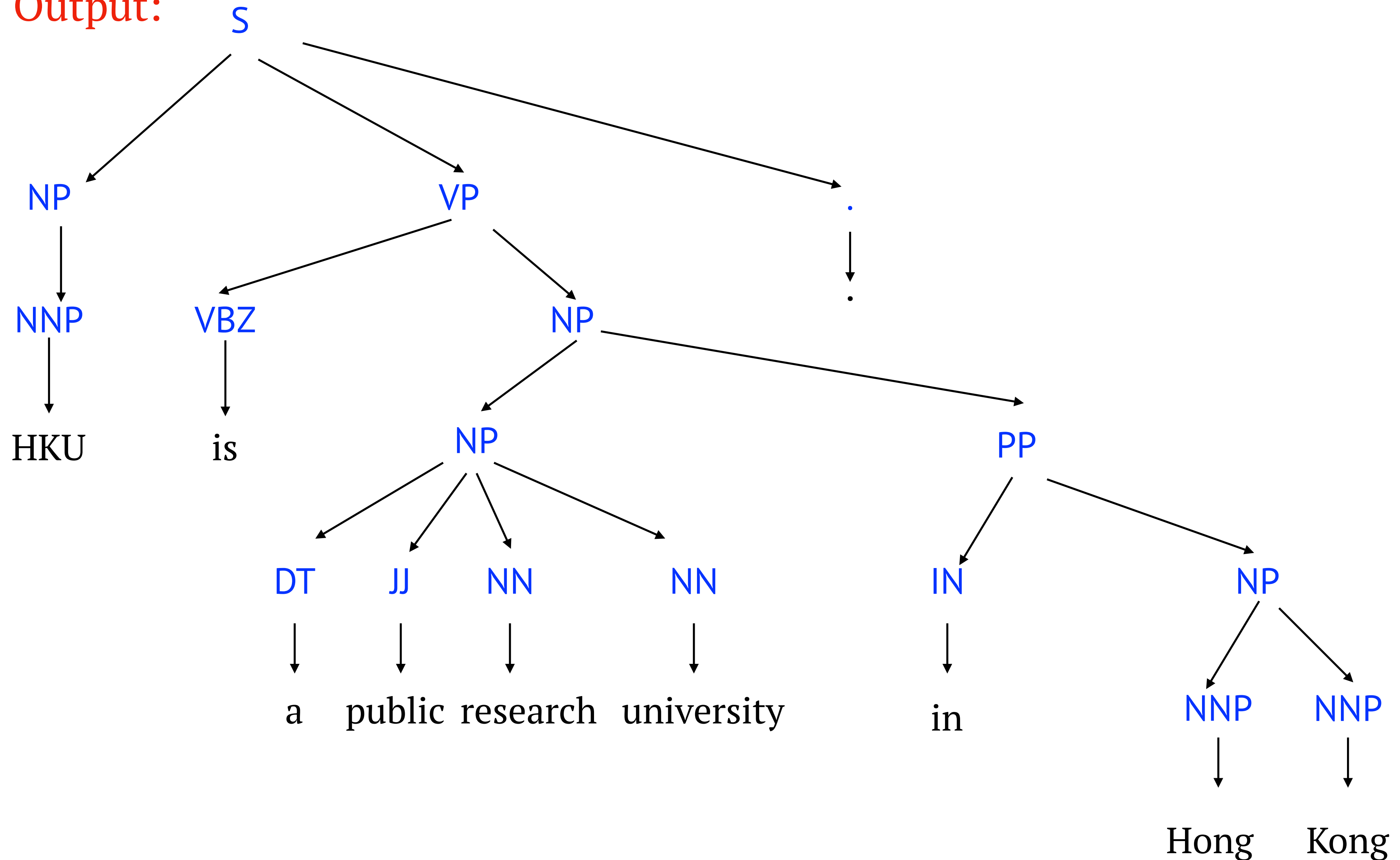
phrase-Structure tree,
constituency tree

Parsing (Phrase-structure Parsing)

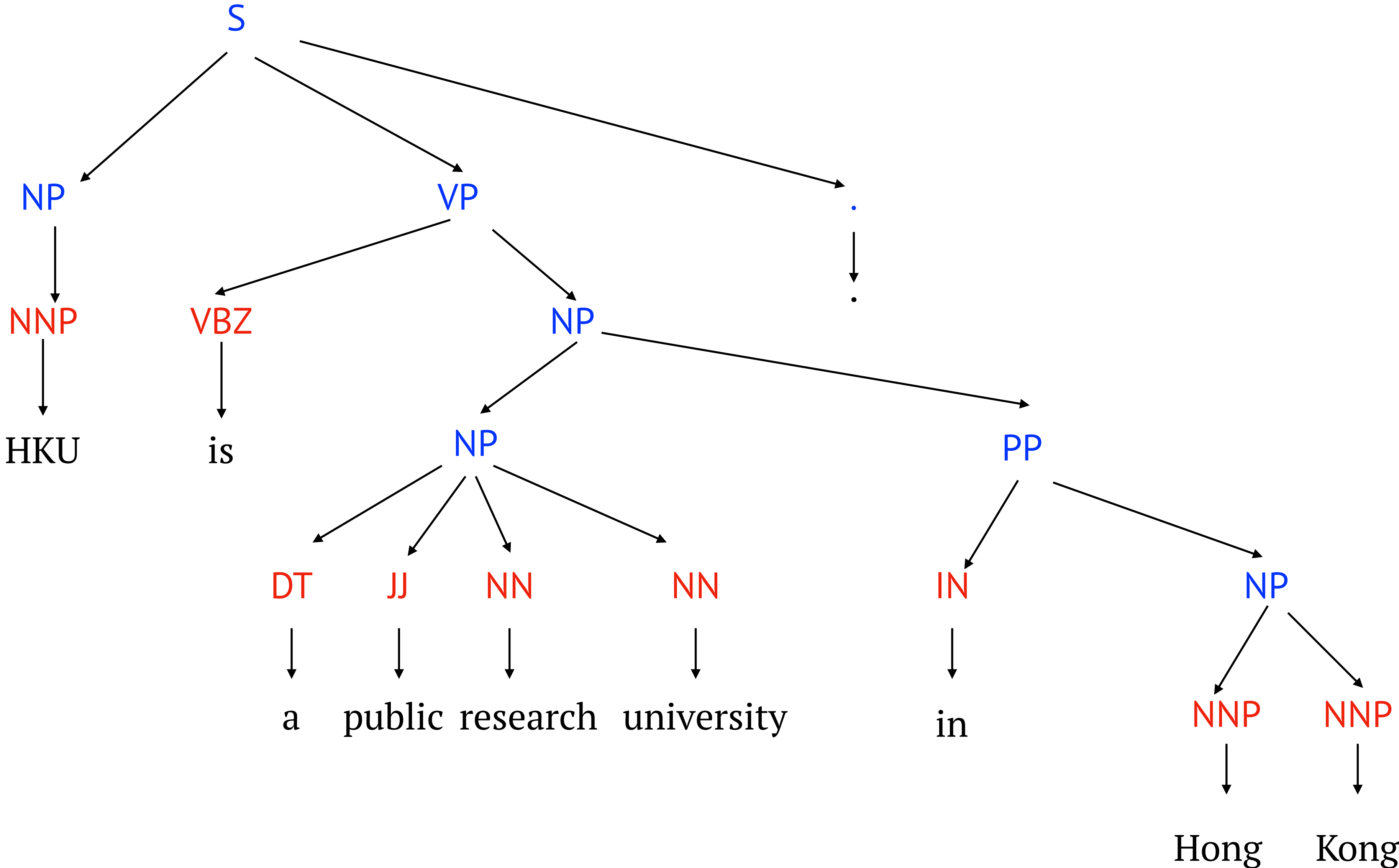
Input:

HKU is a public
research university
in Hong Kong.

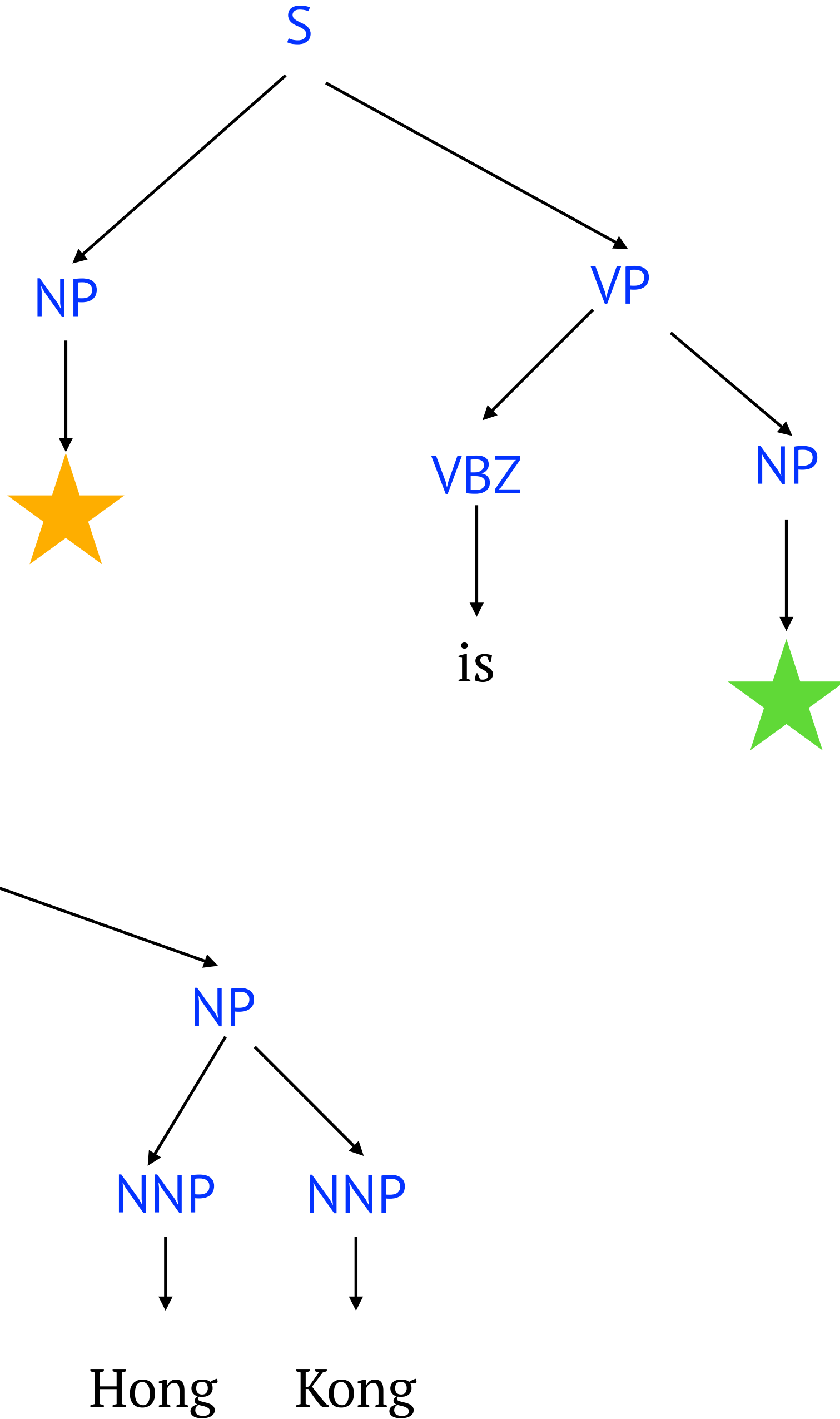
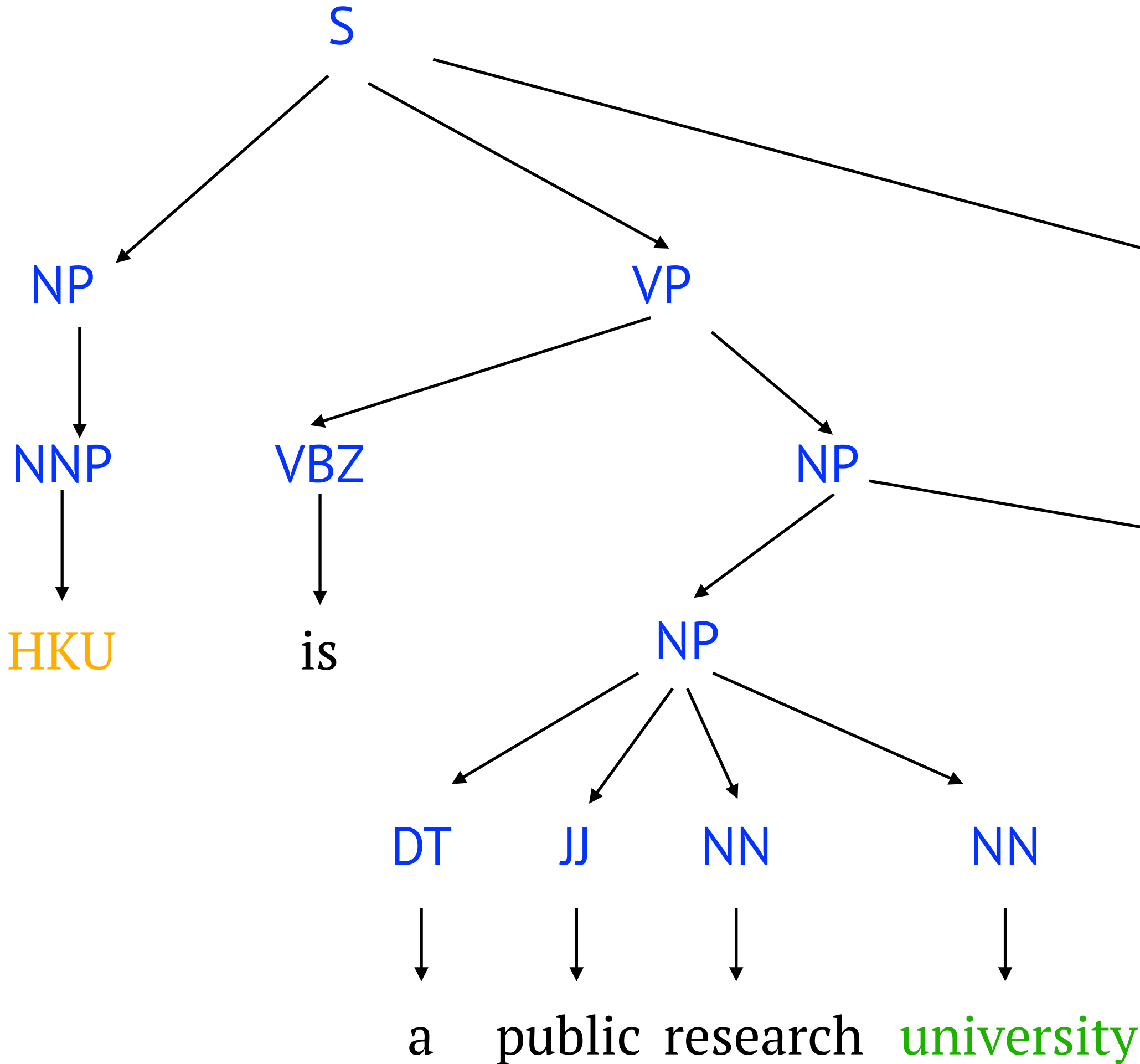
Output:



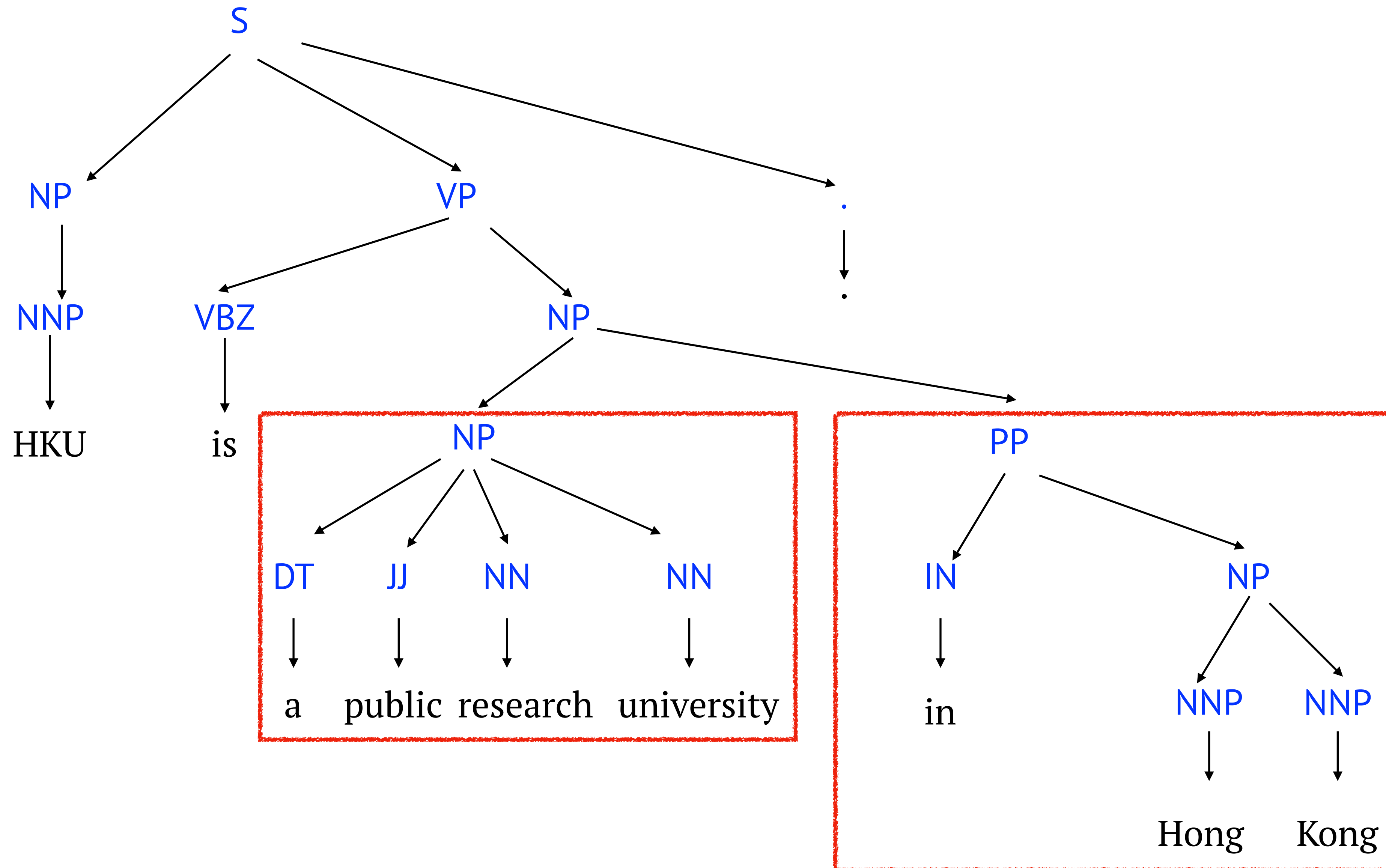
Parse Trees



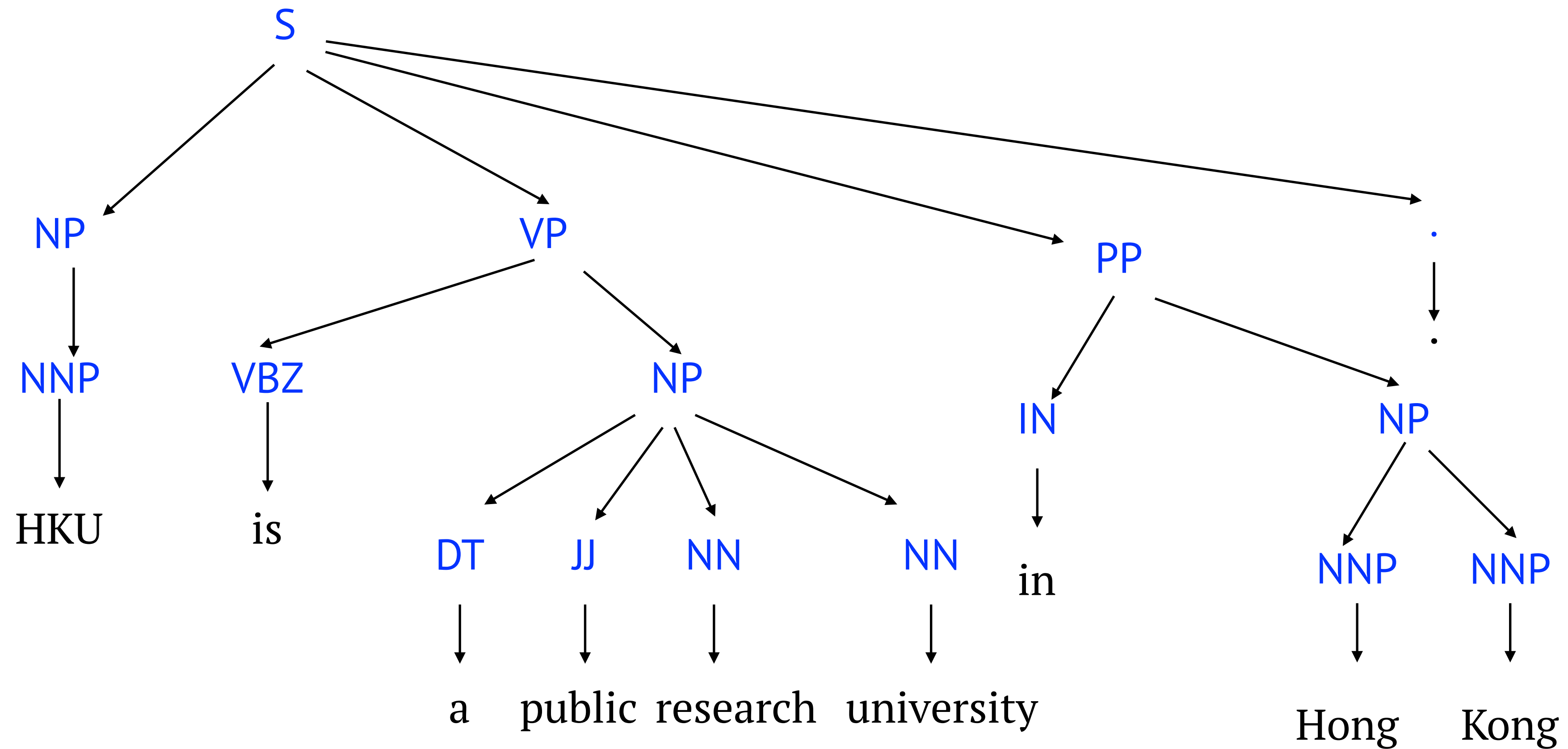
Parse Trees



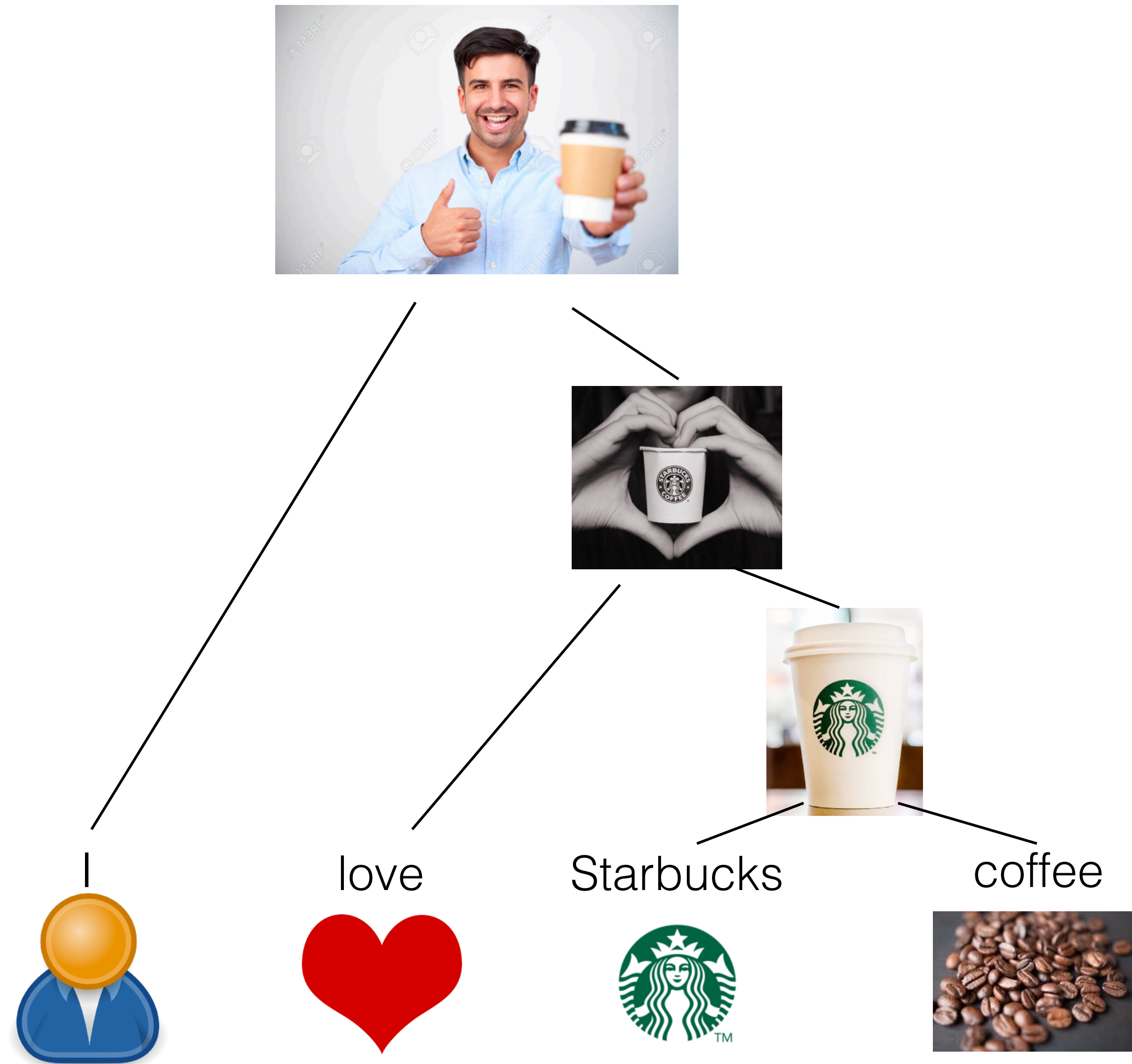
Parse Trees



Parse Trees



Compositional Meaning



Context-Free Grammars

A context free grammar $G = (N, \Sigma, R, S)$ where:

N is a set of non-terminal symbols

Σ is a set of terminal symbols

R is a set of rules of the form $X \rightarrow Y_1 Y_2 \dots Y_n$

for $n \geq 0$ $X \in N$ $Y_i \in (N \cup \Sigma)$

$S \in N$ is a distinguished start symbol

A Context-Free Grammar for English

$N = \{S, NP, VP, PP, DT, Vi, Vt, NN, IN\}$

$S = S$

$\Sigma = \{\text{sleeps, saw, man, woman, telescope, the, with, in}\}$

$R =$

$S \longrightarrow NP VP$

$Vi \longrightarrow \text{sleeps}$

$Vt \longrightarrow \text{saw}$

$VP \longrightarrow Vi$

$VP \longrightarrow Vt NP$

$NN \longrightarrow \text{man}$

$VP \longrightarrow VP PP$

$NN \longrightarrow \text{woman}$

$NN \longrightarrow \text{telescope}$

$NP \longrightarrow DT NN$

$DT \longrightarrow \text{the}$

$NP \longrightarrow NP PP$

$IN \longrightarrow \text{with}$

$PP \longrightarrow IN NP$

$IN \longrightarrow \text{in}$

Left-Most Derivations

$R =$

S \longrightarrow NP VP

VP \longrightarrow Vi

VP \longrightarrow Vt NP

VP \longrightarrow VP PP

NP \longrightarrow DT NN

NP \longrightarrow NP PP

PP \longrightarrow IN NP

Vi \longrightarrow sleeps

Vt \longrightarrow saw

NN \longrightarrow man

NN \longrightarrow woman

NN \longrightarrow telescope

DT \longrightarrow the

IN \longrightarrow with

IN \longrightarrow in

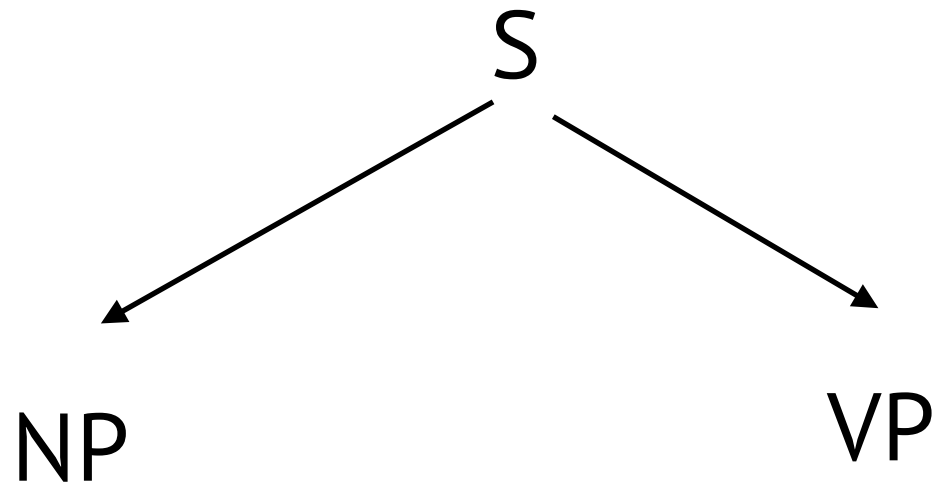
S

(S)

Left-Most Derivations

$R =$

$S \longrightarrow NP VP$	$Vi \longrightarrow$ sleeps
$VP \longrightarrow Vi$	$Vt \longrightarrow$ saw
$VP \longrightarrow Vt NP$	$NN \longrightarrow$ man
$VP \longrightarrow VP PP$	$NN \longrightarrow$ woman
$NP \longrightarrow DT NN$	$NN \longrightarrow$ telescope
$NP \longrightarrow NP PP$	$DT \longrightarrow$ the
$PP \longrightarrow IN NP$	$IN \longrightarrow$ with
	$IN \longrightarrow$ in

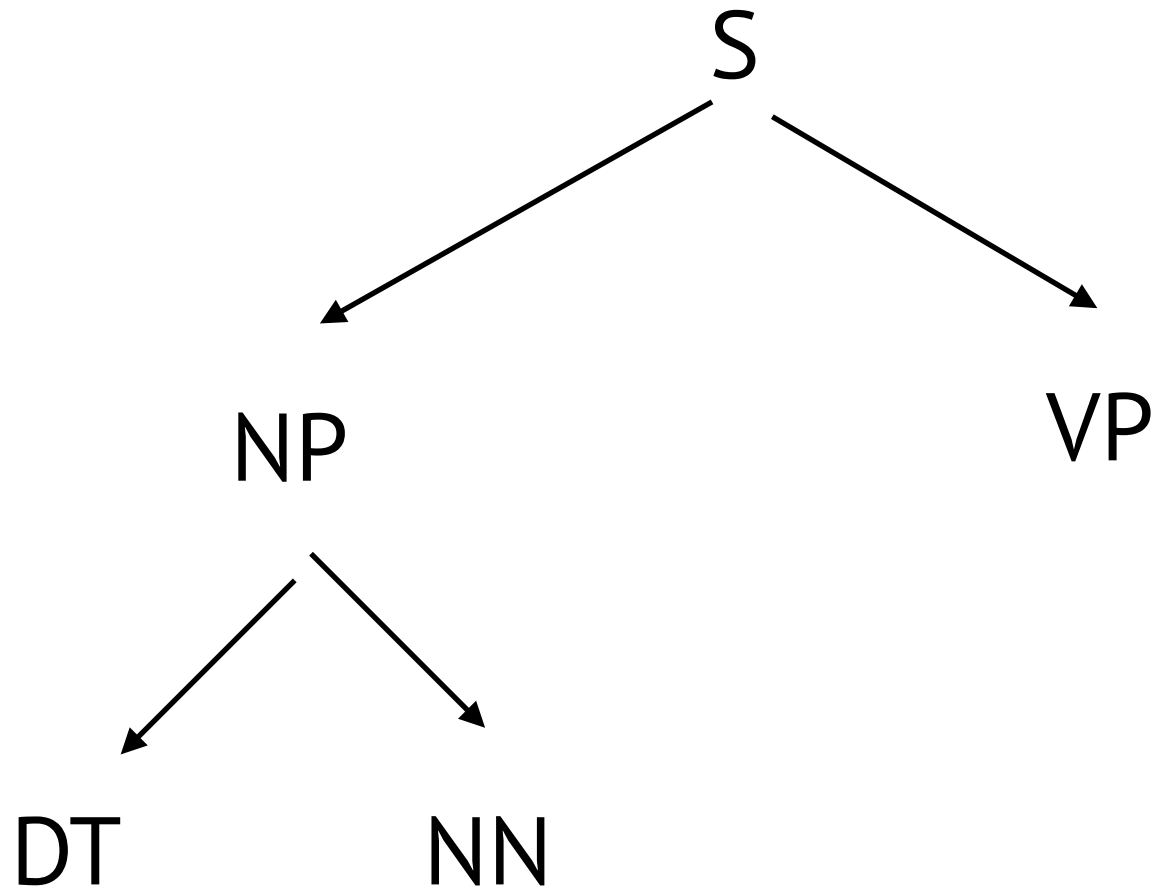


(NP VP)

Left-Most Derivations

$R =$

S	→	NP	VP	Vi	→	sleeps
				Vt	→	saw
VP	→	Vi		NN	→	man
VP	→	Vt	NP	NN	→	woman
VP	→	VP	PP	NN	→	telescope
NP	→	DT	NN	DT	→	the
NP	→	NP	PP	IN	→	with
PP	→	IN	NP	IN	→	in

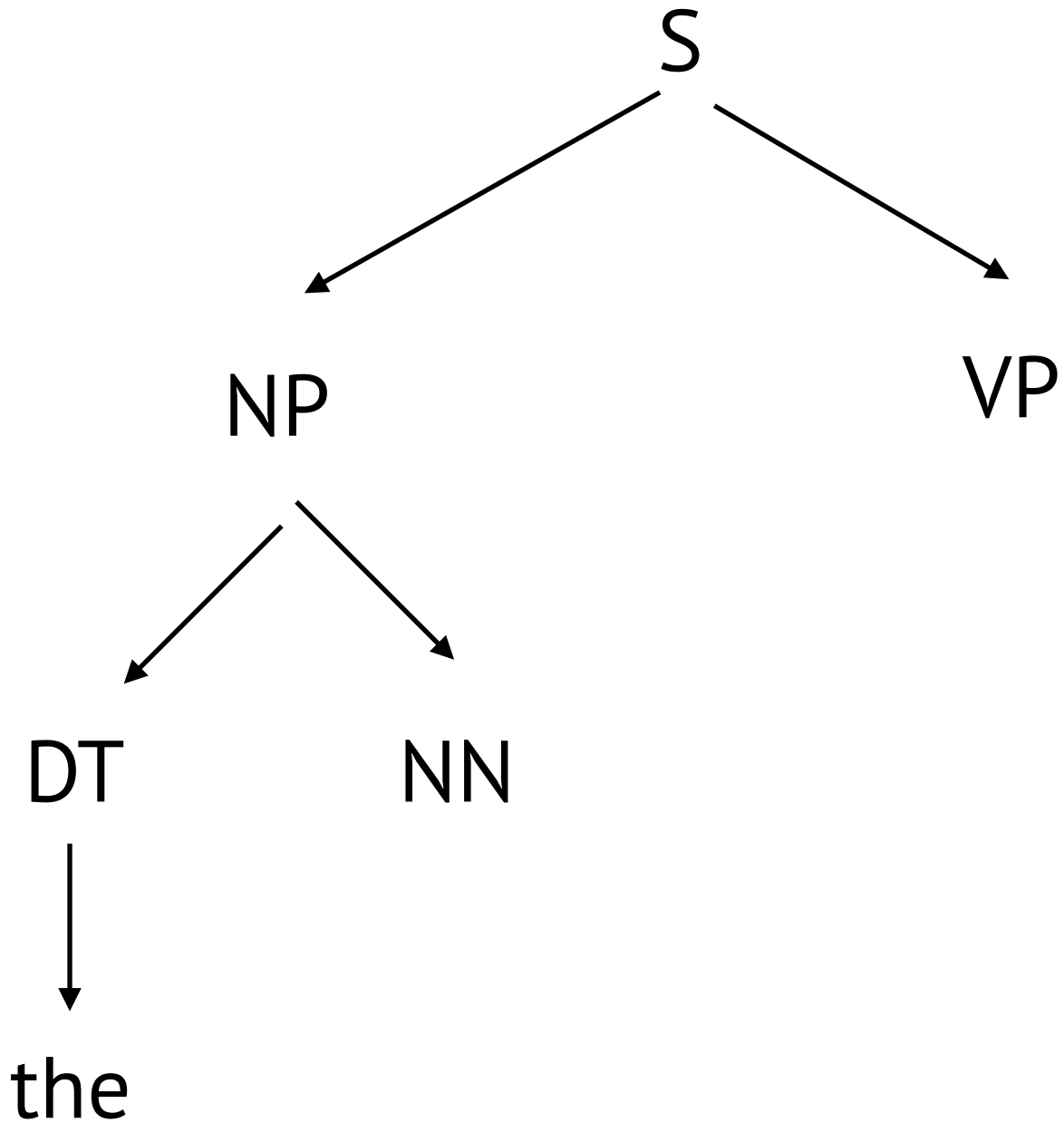


(DT NN VP)

Left-Most Derivations

$R =$

S	→	NP	VP	Vi	→	sleeps
				Vt	→	saw
VP	→	Vi		NN	→	man
VP	→	Vt	NP	NN	→	woman
VP	→	VP	PP	NN	→	telescope
NP	→	DT	NN	DT	→	the
NP	→	NP	PP	IN	→	with
PP	→	IN	NP	IN	→	in

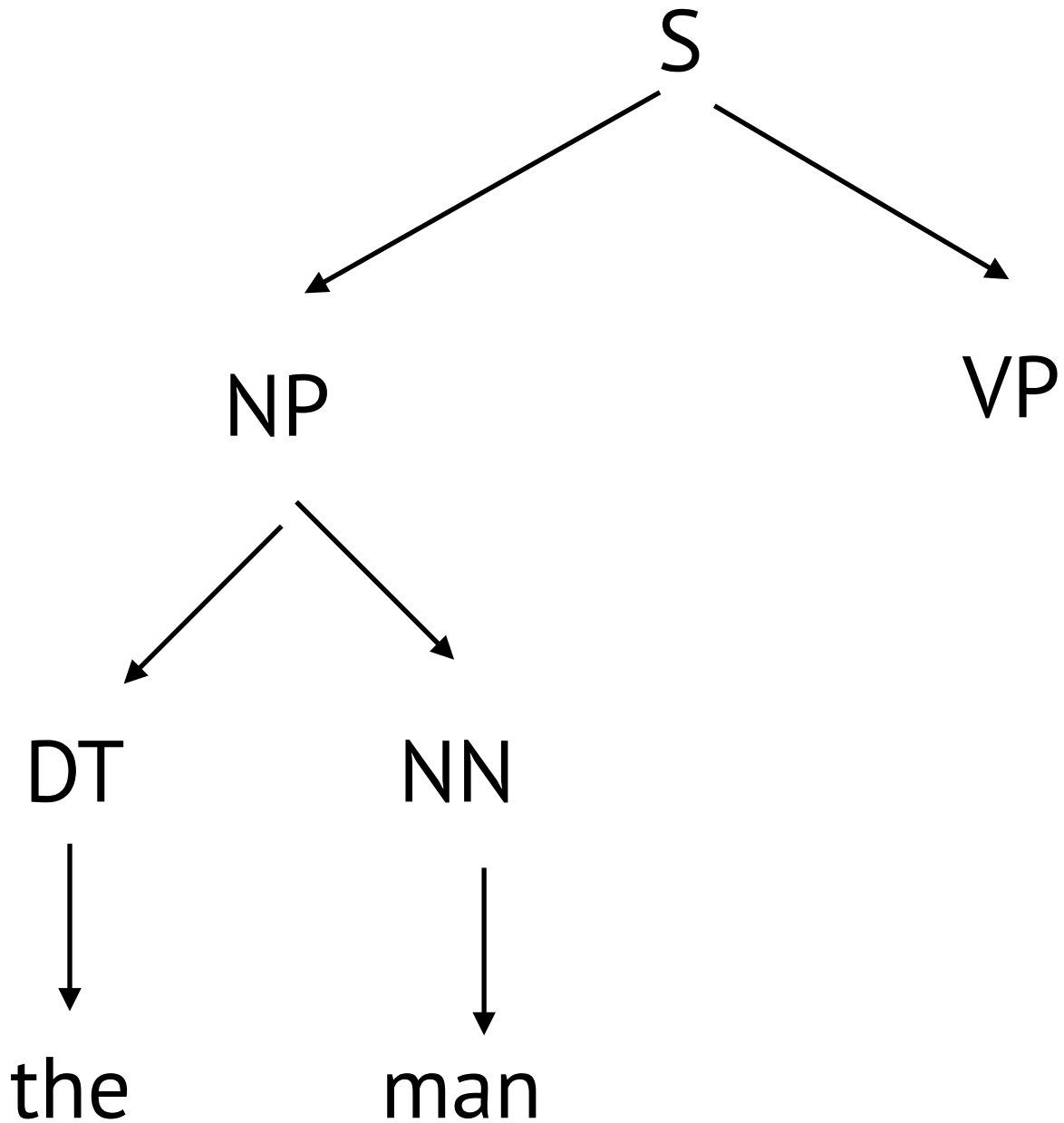


(the NN VP)

Left-Most Derivations

$R =$

S	→	NP VP	Vi	→	sleeps
VP	→	Vi	Vt	→	saw
VP	→	Vt NP	NN	→	man
VP	→	VP PP	NN	→	woman
NP	→	DT NN	NN	→	telescope
NP	→	NP PP	DT	→	the
PP	→	IN NP	IN	→	with
			IN	→	in

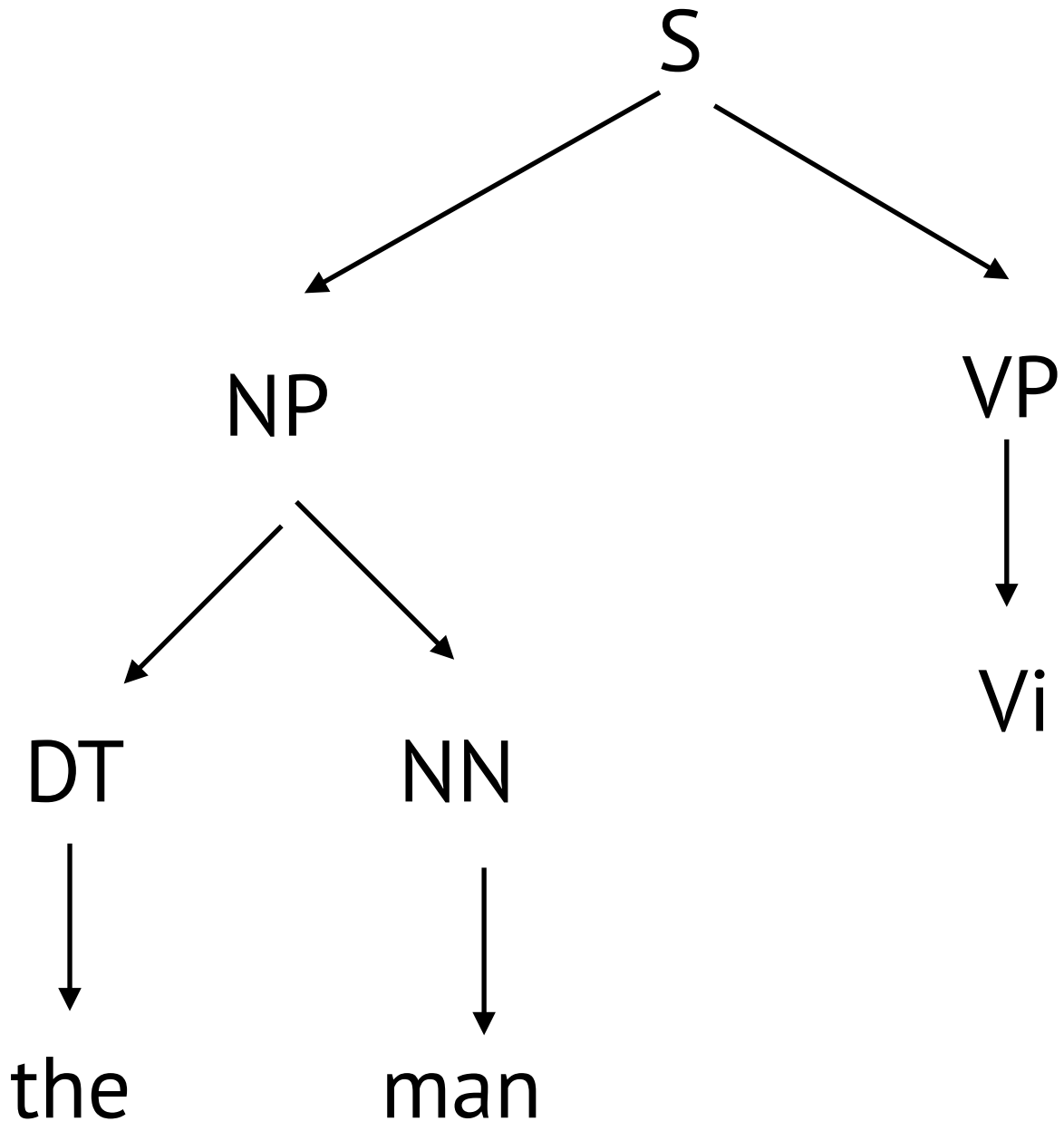


(the man VP)

Left-Most Derivations

$R =$

S	→	NP VP	Vi	→	sleeps
			Vt	→	saw
VP	→	Vi	NN	→	man
VP	→	Vt NP	NN	→	woman
VP	→	VP PP	NN	→	telescope
NP	→	DT NN	DT	→	the
NP	→	NP PP	IN	→	with
PP	→	IN NP	IN	→	in

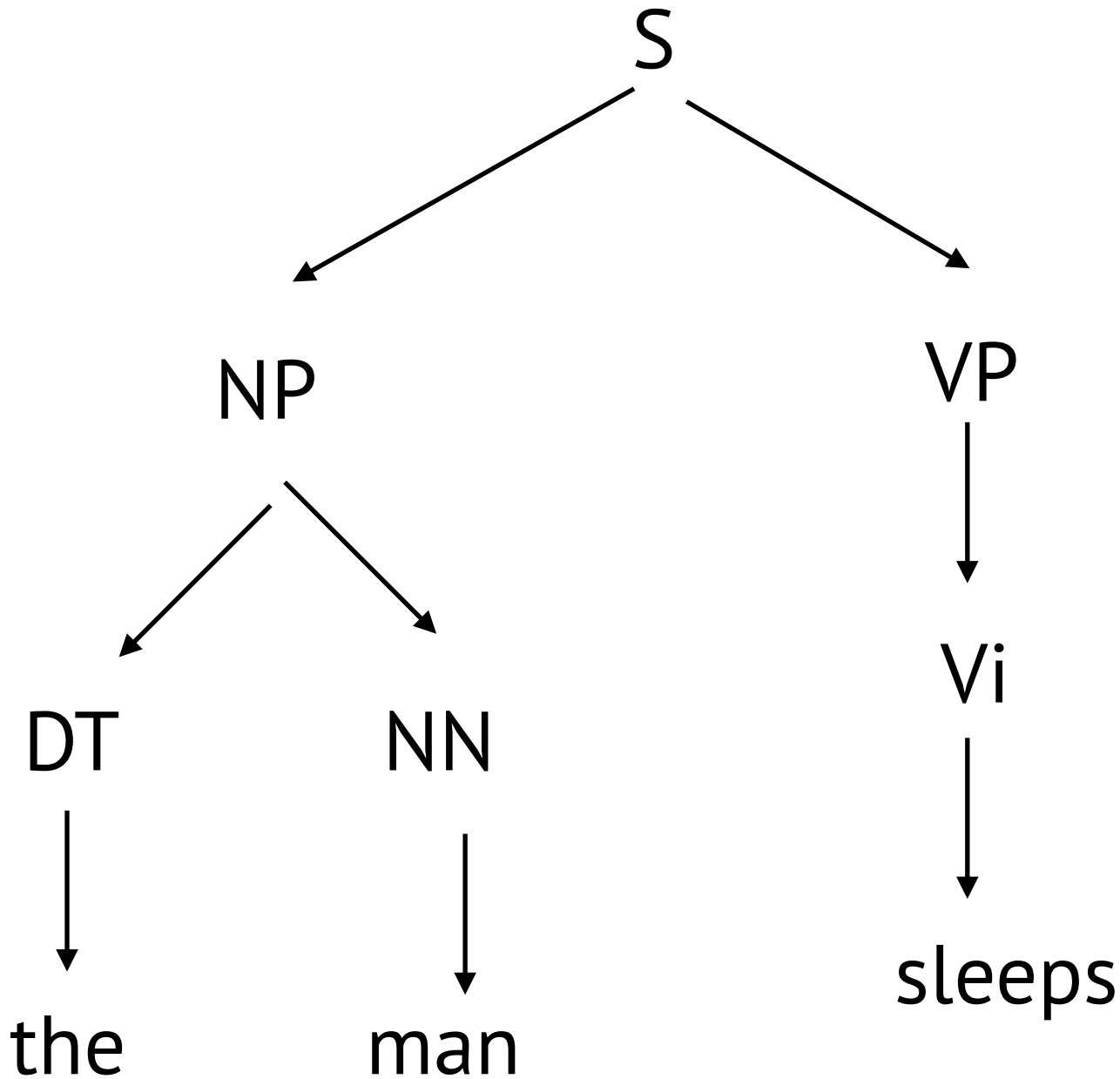


(the man Vi)

Left-Most Derivations

$R =$

S	→	NP VP	Vi	→	sleeps
			Vt	→	saw
VP	→	Vi	NN	→	man
VP	→	Vt NP	NN	→	woman
VP	→	VP PP	NN	→	telescope
NP	→	DT NN	DT	→	the
NP	→	NP PP	IN	→	with
PP	→	IN NP	IN	→	in

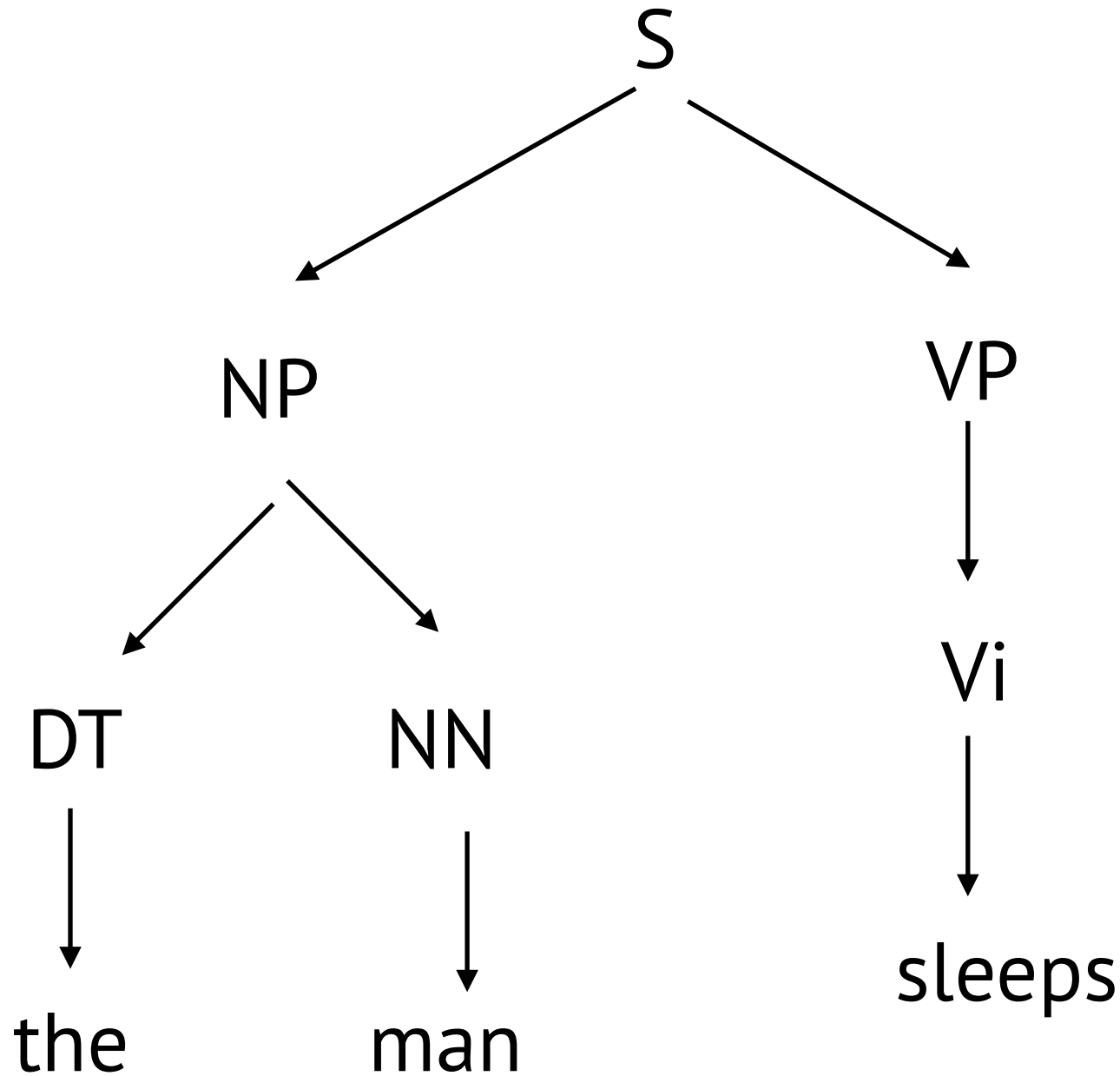


(the man sleeps)

Left-Most Derivations

$R =$

S	→	NP VP	Vi	→	sleeps
			Vt	→	saw
VP	→	Vi	NN	→	man
VP	→	Vt NP	NN	→	woman
VP	→	VP PP	NN	→	telescope
NP	→	DT NN	DT	→	the
NP	→	NP PP	IN	→	with
PP	→	IN NP	IN	→	in

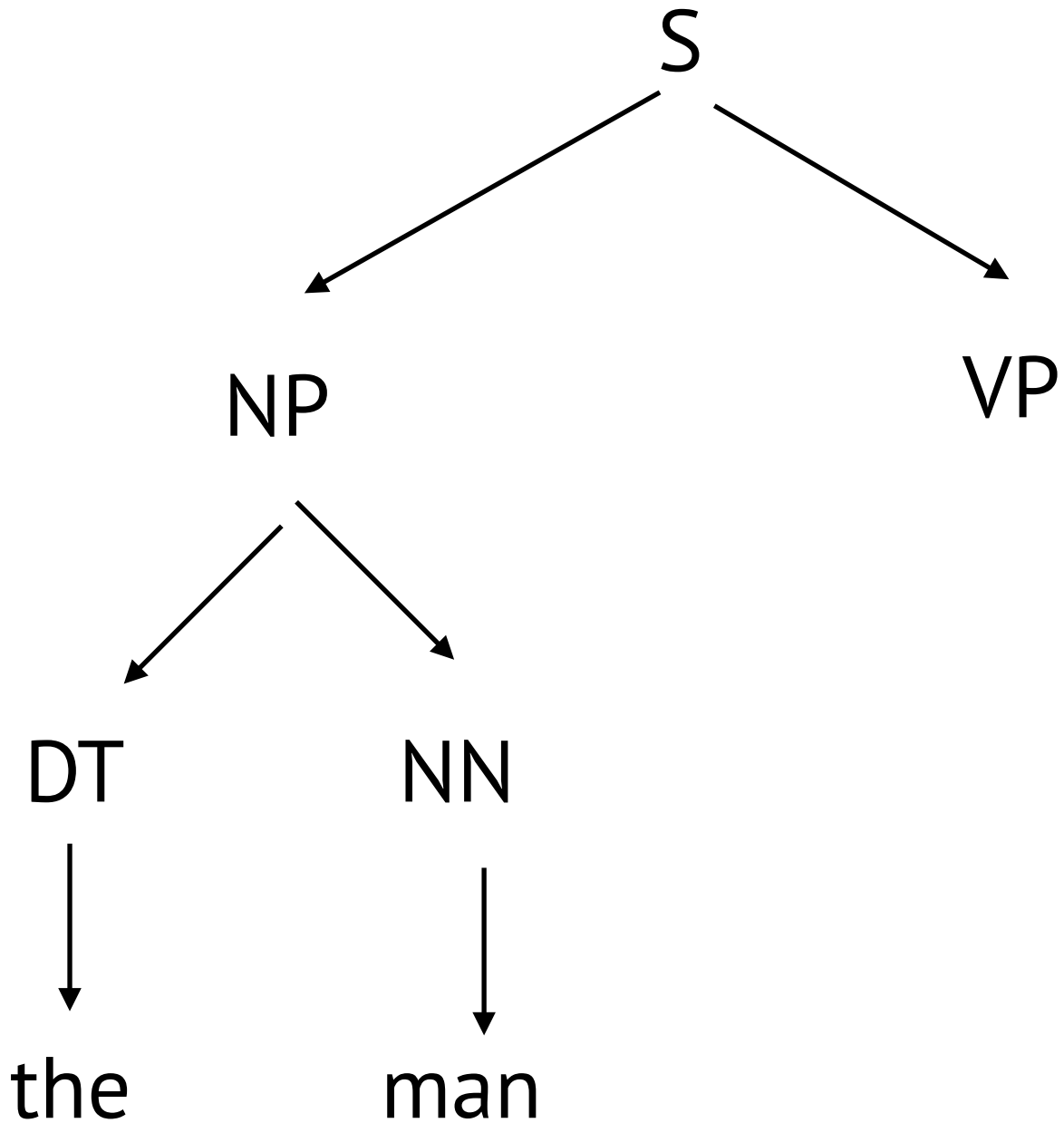


(the man sleeps)

Left-Most Derivations

$R =$

S	→	NP VP	Vi	→	sleeps
			Vt	→	saw
VP	→	Vi	NN	→	man
VP	→	Vt NP	NN	→	woman
VP	→	VP PP	NN	→	telescope
NP	→	DT NN	DT	→	the
NP	→	NP PP	IN	→	with
PP	→	IN NP	IN	→	in

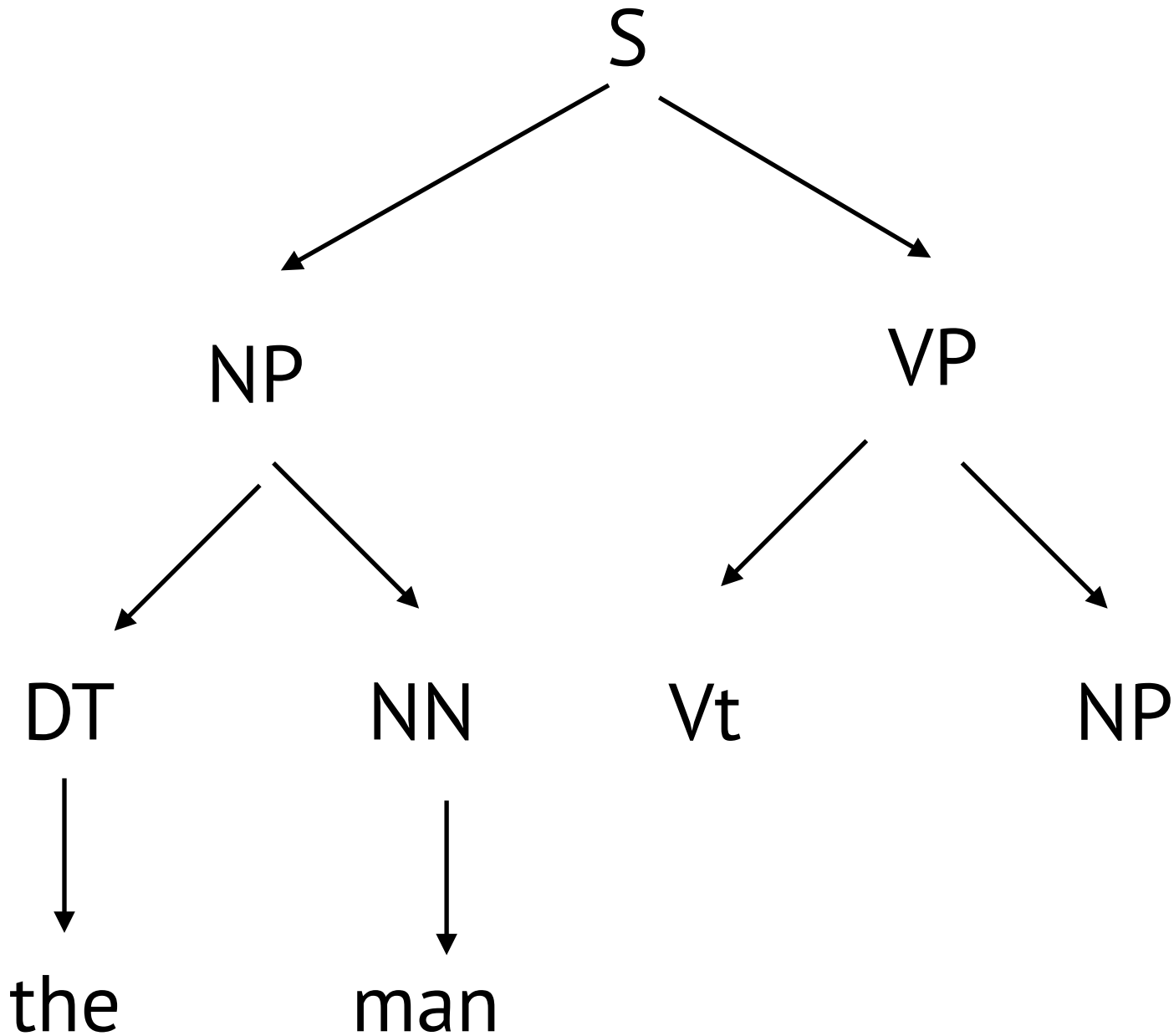


(the man VP)

Left-Most Derivations

$R =$

S	→	NP VP	Vi	→	sleeps
VP	→	Vi	Vt	→	saw
VP	→	Vt NP	NN	→	man
VP	→	VP PP	NN	→	woman
NP	→	DT NN	NN	→	telescope
NP	→	NP PP	DT	→	the
PP	→	IN NP	IN	→	with
			IN	→	in

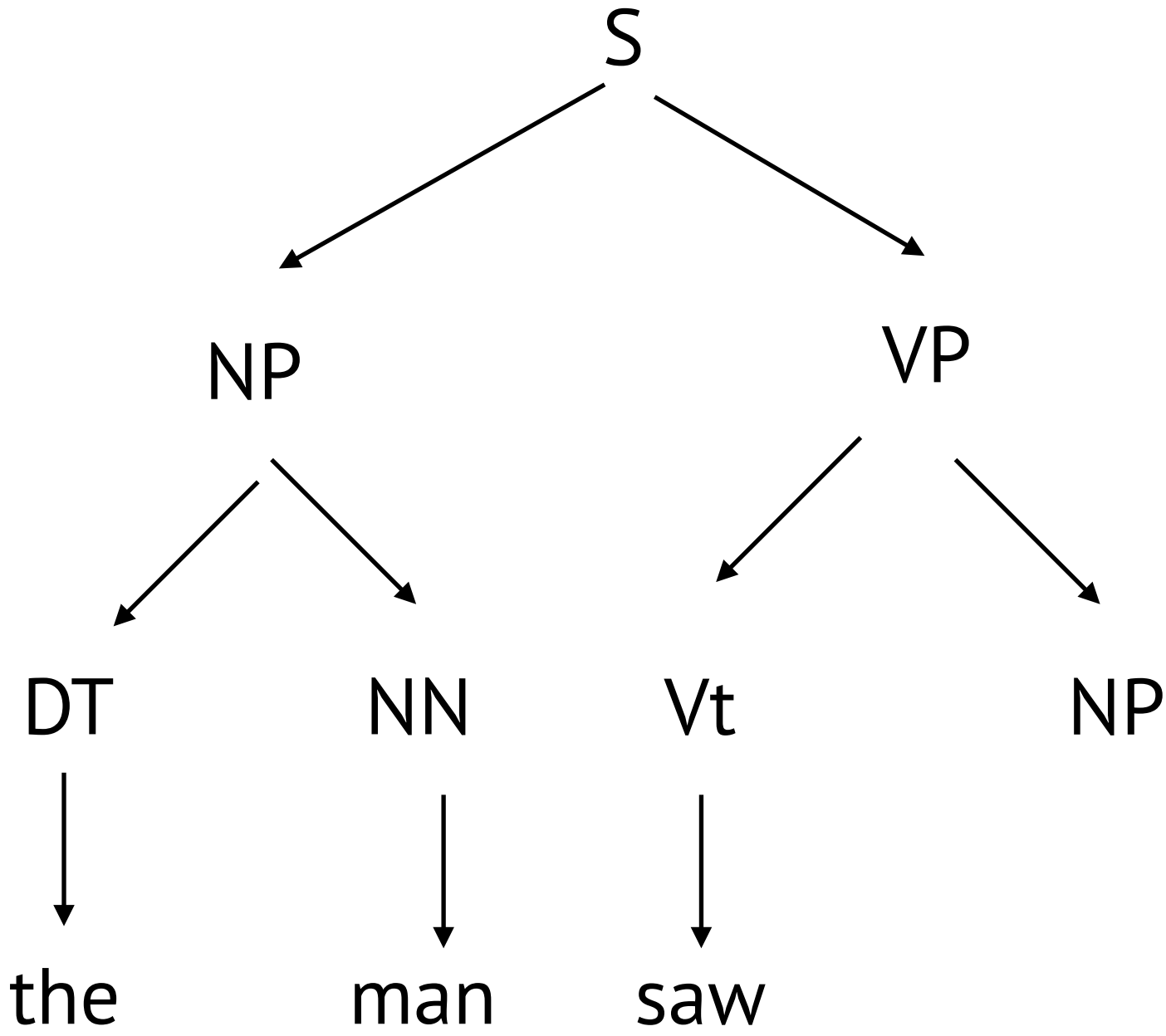


(the man Vt NP)

Left-Most Derivations

$R =$

S	→	NP VP	Vi	→	sleeps
			Vt	→	saw
VP	→	Vi	NN	→	man
VP	→	Vt NP	NN	→	woman
VP	→	VP PP	NN	→	telescope
NP	→	DT NN	DT	→	the
NP	→	NP PP	IN	→	with
PP	→	IN NP	IN	→	in

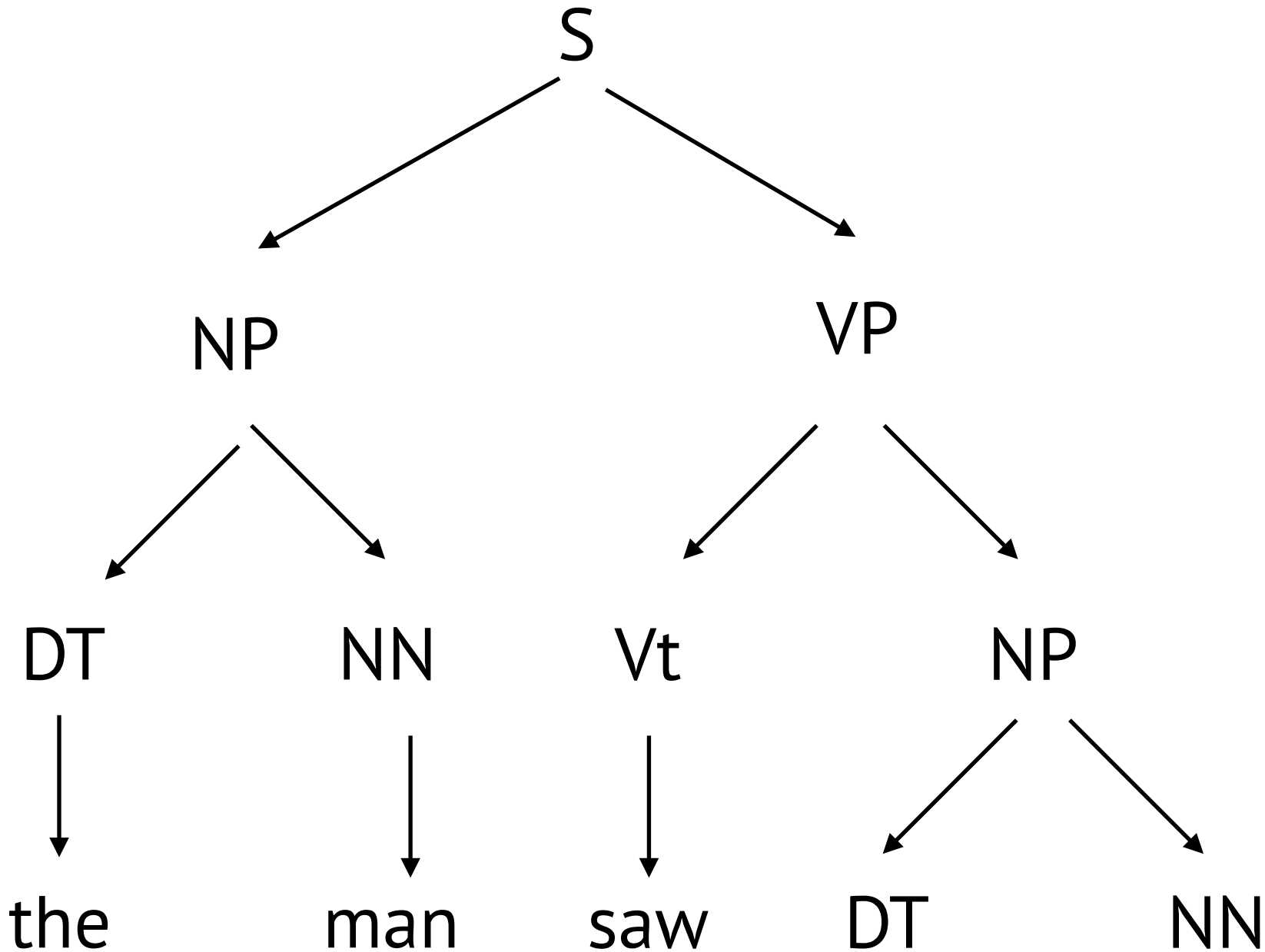


(the man saw NP)

Left-Most Derivations

$R =$

S	→	NP VP	Vi	→	sleeps
			Vt	→	saw
VP	→	Vi	NN	→	man
VP	→	Vt NP	NN	→	woman
VP	→	VP PP	NN	→	telescope
NP	→	DT NN	DT	→	the
NP	→	NP PP	IN	→	with
PP	→	IN NP	IN	→	in

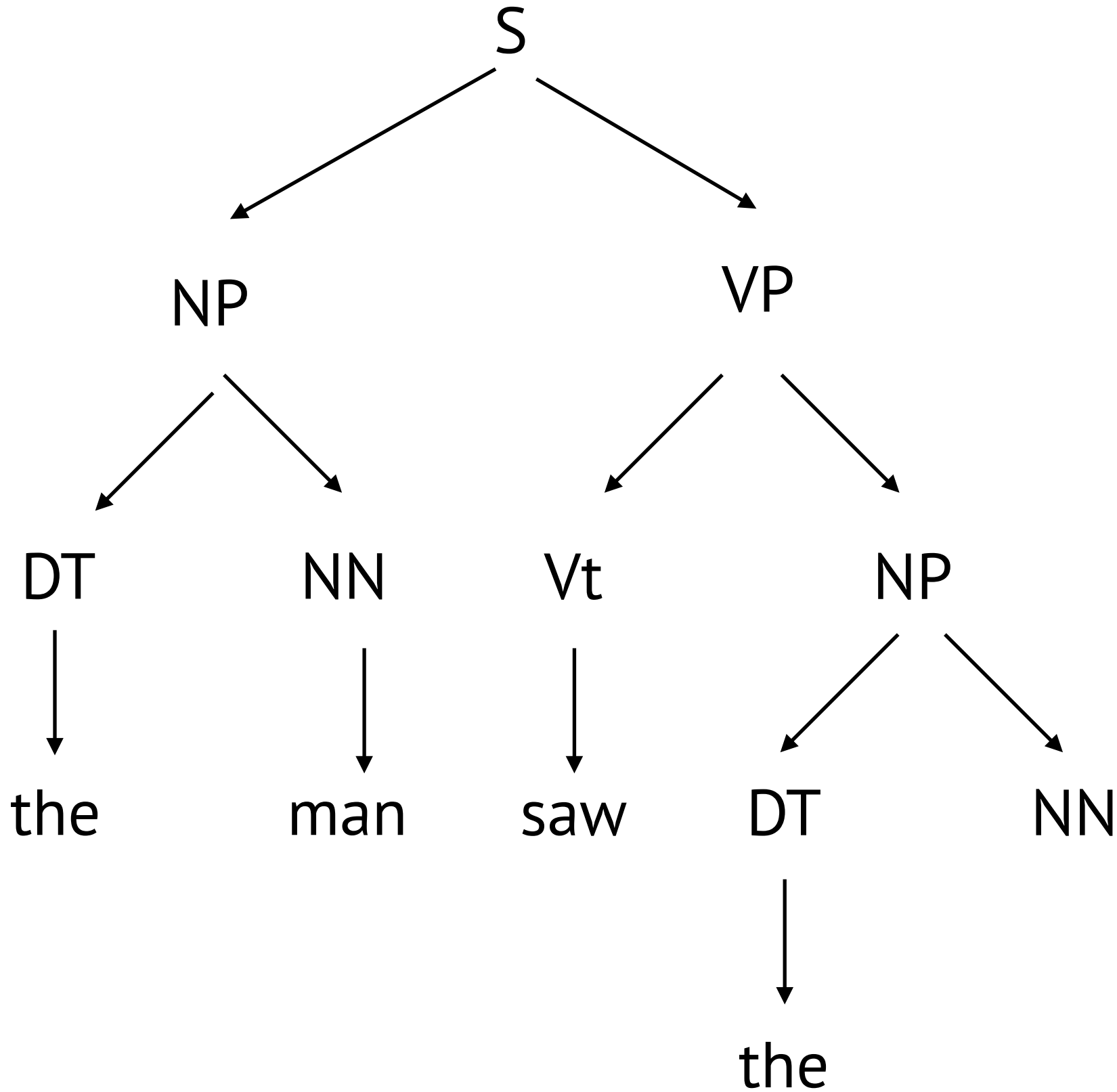


(the man saw DT NN)

Left-Most Derivations

$R =$

S	→	NP VP	Vi	→	sleeps
			Vt	→	saw
VP	→	Vi	NN	→	man
VP	→	Vt NP	NN	→	woman
VP	→	VP PP	NN	→	telescope
NP	→	DT NN	DT	→	the
NP	→	NP PP	IN	→	with
PP	→	IN NP	IN	→	in

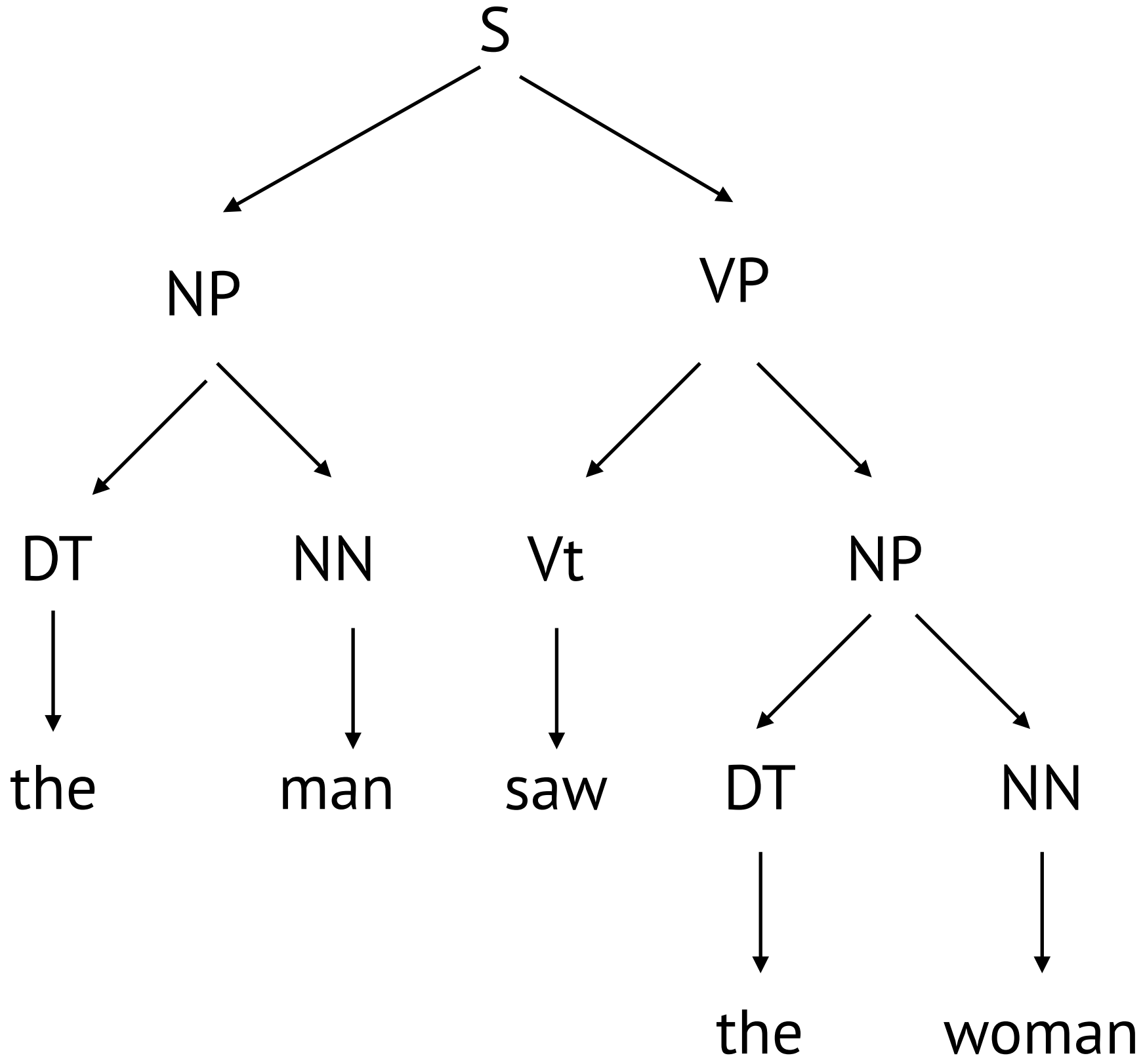


(the man saw the NN)

Left-Most Derivations

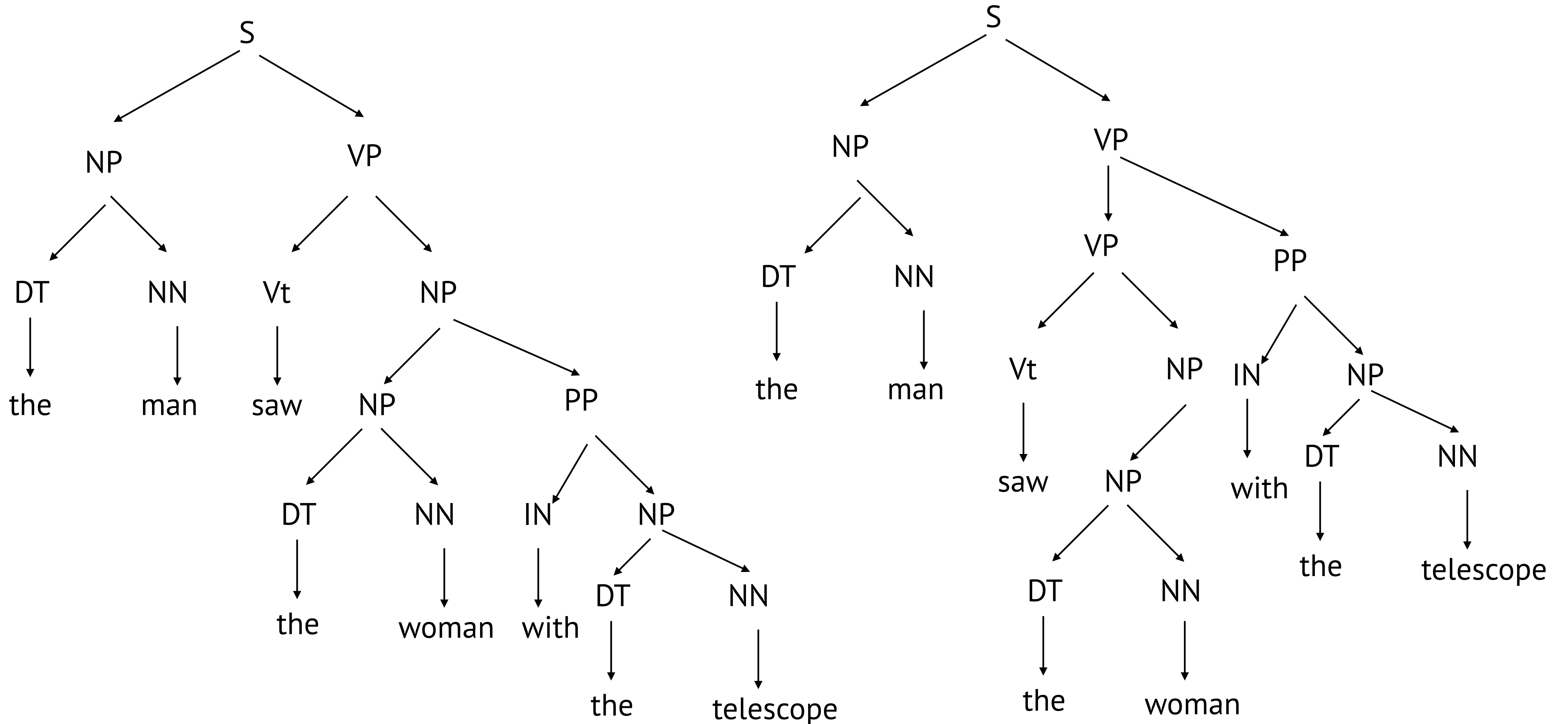
$R =$

S	→	NP VP	Vi	→	sleeps
			Vt	→	saw
VP	→	Vi	NN	→	man
VP	→	Vt NP	NN	→	woman
VP	→	VP PP	NN	→	telescope
NP	→	DT NN	DT	→	the
NP	→	NP PP	IN	→	with
PP	→	IN NP	IN	→	in



(the man saw the woman)

Different Derivations Can Lead to the Same String



“Context-Free” — What does it mean?

$N = \{S, NP, VP, PP, DT, Vi, Vt, NN, IN\}$

$S = S$

$\Sigma = \{\text{sleeps, saw, man, woman, telescope, the, with, in}\}$

$R =$

$S \longrightarrow NP VP$

$VP \longrightarrow Vi$

$VP \longrightarrow Vt NP$

$VP \longrightarrow VP PP$

$NP \longrightarrow DT NN$

$NP \longrightarrow NP PP$

$PP \longrightarrow IN NP$

$Vi \longrightarrow \text{sleeps}$

$Vt \longrightarrow \text{saw}$

$NN \longrightarrow \text{man}$

$NN \longrightarrow \text{woman}$

$NN \longrightarrow \text{telescope}$

$DT \longrightarrow \text{the}$

$IN \longrightarrow \text{with}$

$IN \longrightarrow \text{in}$

$Vt NP \longrightarrow Vt NP PP$

“Context-Free” — What does it mean?

$N = \{S, NP, VP, PP, DT, Vi, Vt, NN, IN\}$

$S = S$

$\Sigma = \{\text{sleeps, saw, man, woman, telescope, the, with, in}\}$

$R =$

$S \longrightarrow NP VP$	$Vi \longrightarrow \text{sleeps}$
$VP \longrightarrow Vi$	$Vt \longrightarrow \text{saw}$
$VP \longrightarrow Vt NP$	$NN \longrightarrow \text{man}$
$VP \longrightarrow VP PP$	$NN \longrightarrow \text{woman}$
$NP \longrightarrow DT NN$	$NN \longrightarrow \text{telescope}$
$Vt NP \longrightarrow Vt NP PP$	$DT \longrightarrow \text{the}$
$PP \longrightarrow IN NP$	$IN \longrightarrow \text{with}$
	$IN \longrightarrow \text{in}$

non-context-free

Probabilistic Context-Free Grammars

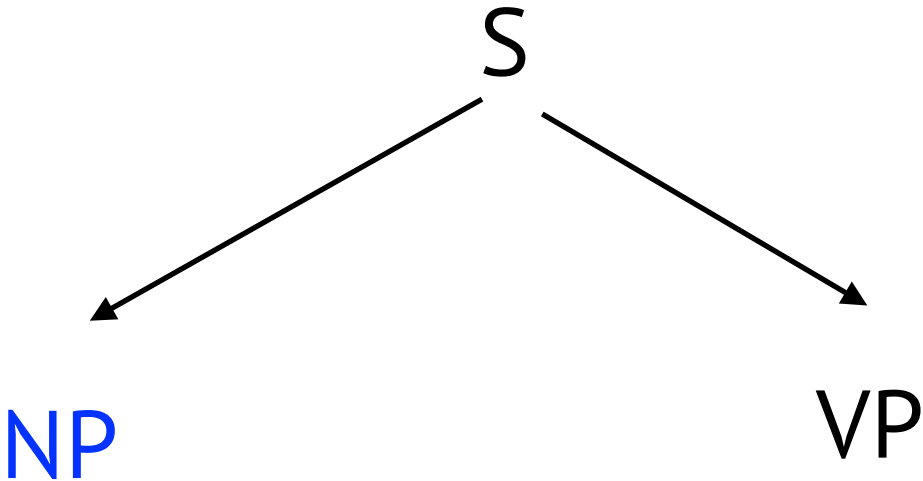
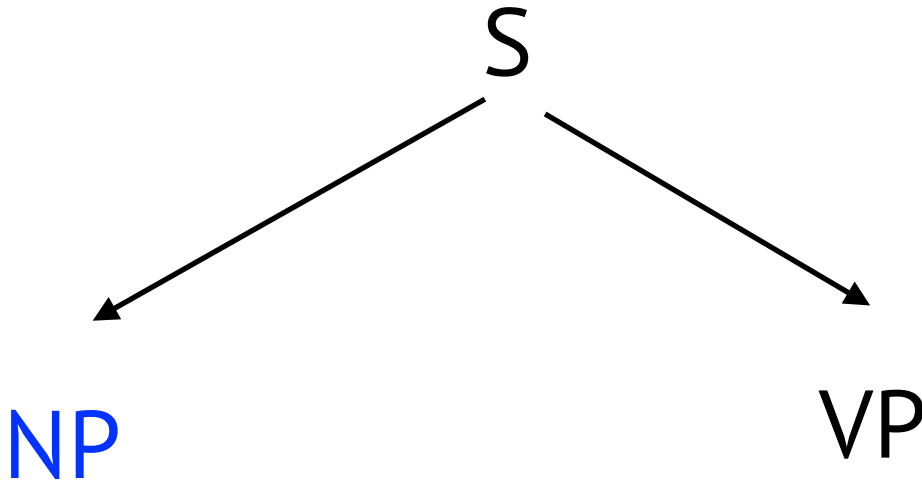
$R =$

S	→	NP VP	1.0	Vi	→	sleeps	1.0
VP	→	Vi	0.4	Vt	→	saw	1.0
VP	→	Vt NP	0.4	NN	→	man	0.7
VP	→	VP PP	0.2	NN	→	woman	0.2
NP	→	DT NN	0.3	NN	→	telescope	0.1
NP	→	NP PP	0.7	DT	→	the	1.0
PP	→	IN NP	1.0	IN	→	with	0.5
				IN	→	in	0.5

Probabilistic Context-Free Grammars

$R =$

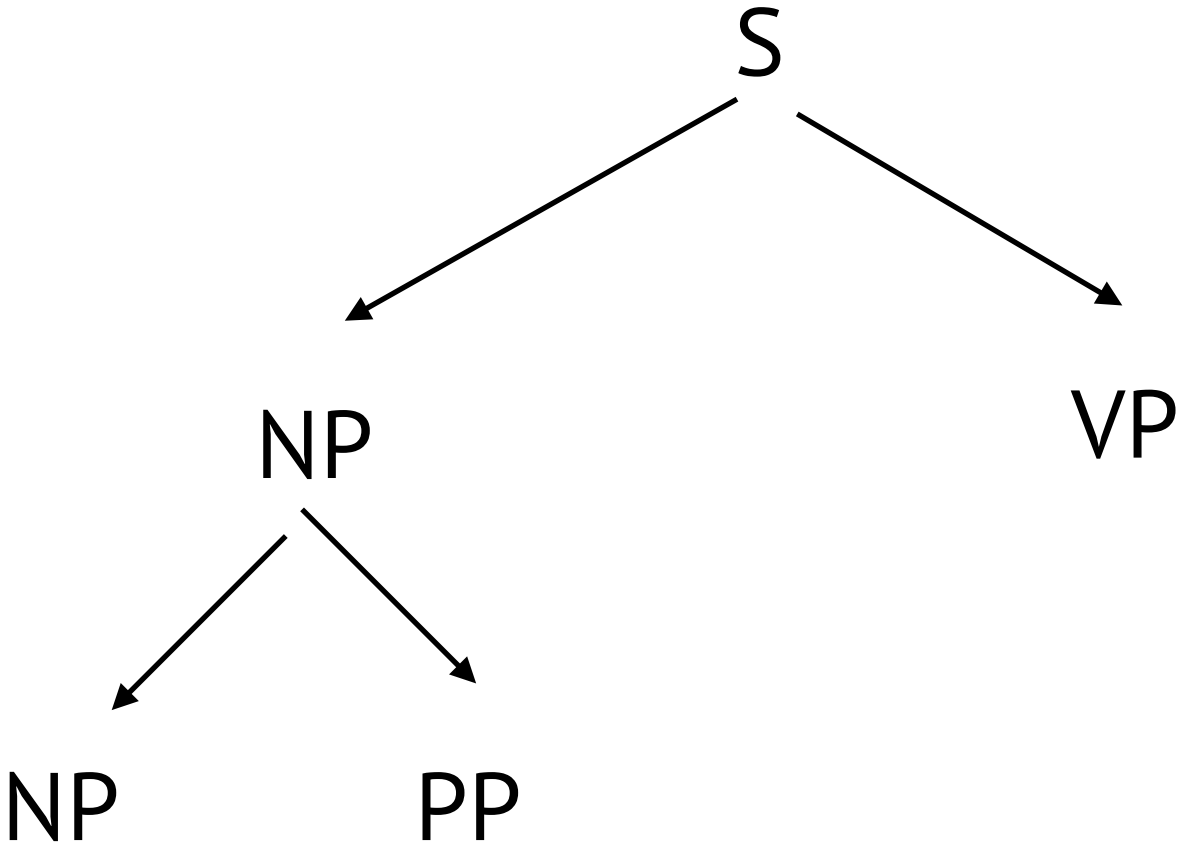
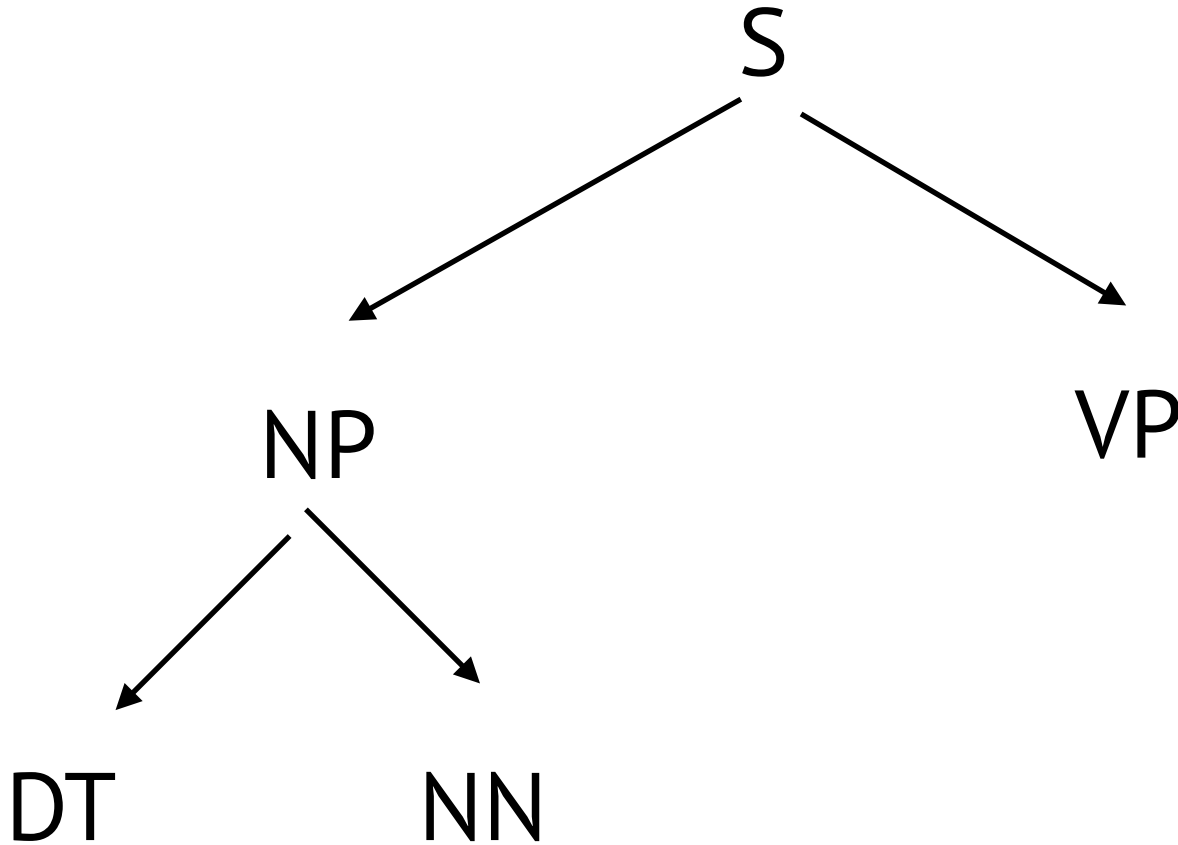
S	→	NP VP	1.0	Vi	→	sleeps	1.0
VP	→	Vi	0.4	Vt	→	saw	1.0
VP	→	Vt NP	0.4	NN	→	man	0.7
VP	→	VP PP	0.2	NN	→	woman	0.2
NP	→	DT NN	0.3	NN	→	telescope	0.1
NP	→	NP PP	0.7	DT	→	the	1.0
PP	→	IN NP	1.0	IN	→	with	0.5
				IN	→	in	0.5



Probabilistic Context-Free Grammars

$R =$

S	→	NP VP	1.0	Vi	→	sleeps	1.0
VP	→	Vi	0.4	Vt	→	saw	1.0
VP	→	Vt NP	0.4	NN	→	man	0.7
VP	→	VP PP	0.2	NN	→	woman	0.2
NP	→	DT NN	0.3	NN	→	telescope	0.1
NP	→	NP PP	0.7	DT	→	the	1.0
PP	→	IN NP	1.0	IN	→	with	0.5
				IN	→	in	0.5



Probabilistic Context-Free Grammars

$R =$

S	→	NP VP	1.0	Vi	→	sleeps	1.0
VP	→	Vi	0.4	Vt	→	saw	1.0
VP	→	Vt NP	0.4	NN	→	man	0.7
VP	→	VP PP	0.2	NN	→	woman	0.2
NP	→	DT NN	0.3	NN	→	telescope	0.1
NP	→	NP PP	0.7	DT	→	the	1.0
PP	→	IN NP	1.0	IN	→	with	0.5
				IN	→	in	0.5

Derivation Example

$R =$

S	→	NP VP	1.0	Vi	→	sleeps	1.0
				Vt	→	saw	1.0
VP	→	Vi	0.4				
VP	→	Vt NP	0.4	NN	→	man	0.7
VP	→	VP PP	0.2	NN	→	woman	0.2
				NN	→	telescope	0.1
NP	→	DT NN	0.3	DT	→	the	1.0
NP	→	NP PP	0.7				
PP	→	IN NP	1.0	IN	→	with	0.5
				IN	→	in	0.5

S

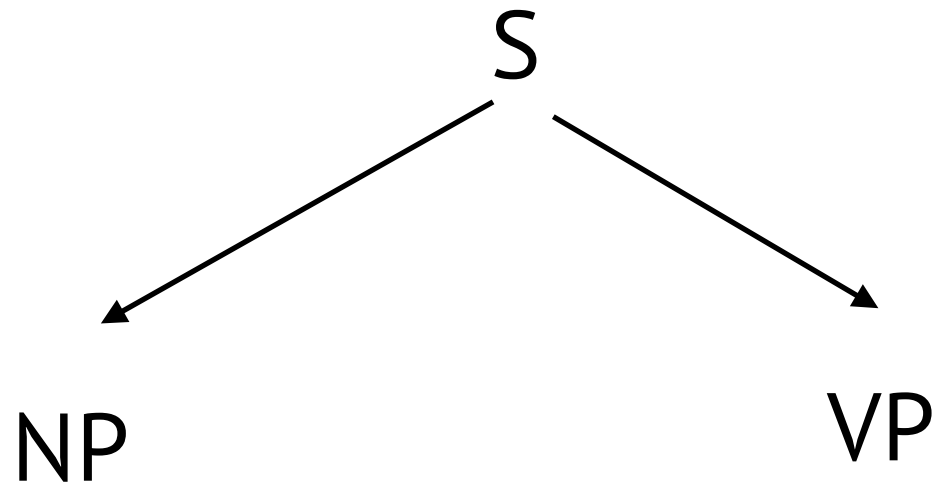
(S)

$P(x, y) =$

Derivation Example

$R =$

S	→	NP VP	1.0	Vi	→	sleeps	1.0
				Vt	→	saw	1.0
VP	→	Vi	0.4				
VP	→	Vt NP	0.4	NN	→	man	0.7
VP	→	VP PP	0.2	NN	→	woman	0.2
				NN	→	telescope	0.1
NP	→	DT NN	0.3	DT	→	the	1.0
NP	→	NP PP	0.7				
PP	→	IN NP	1.0	IN	→	with	0.5
				IN	→	in	0.5



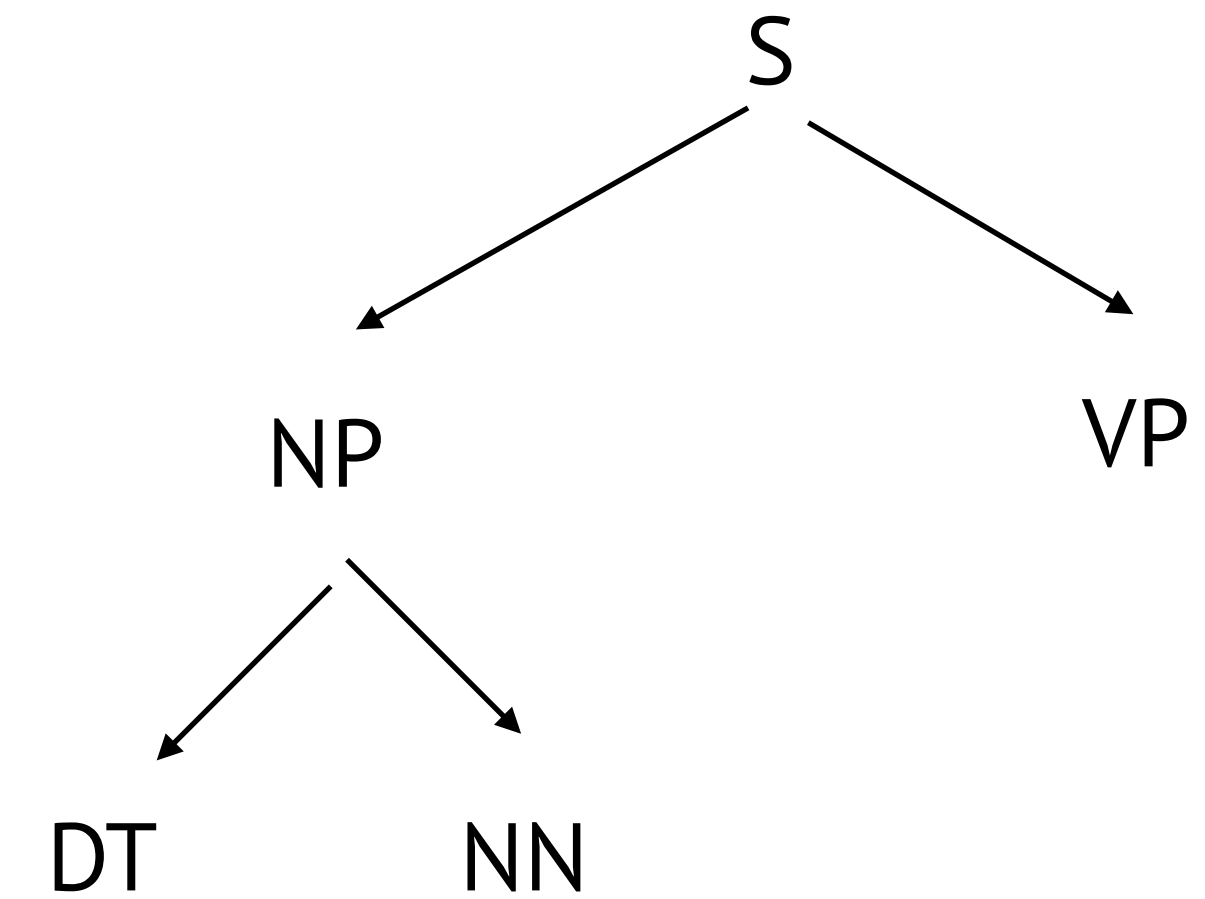
(S (NP VP))

$P(x, y) = 1 \times$

Derivation Example

$R =$

S	→	NP VP	1.0	Vi	→	sleeps	1.0
				Vt	→	saw	1.0
VP	→	Vi	0.4				
VP	→	Vt NP	0.4	NN	→	man	0.7
VP	→	VP PP	0.2	NN	→	woman	0.2
				NN	→	telescope	0.1
NP	→	DT NN	0.3	DT	→	the	1.0
NP	→	NP PP	0.7				
PP	→	IN NP	1.0	IN	→	with	0.5
				IN	→	in	0.5



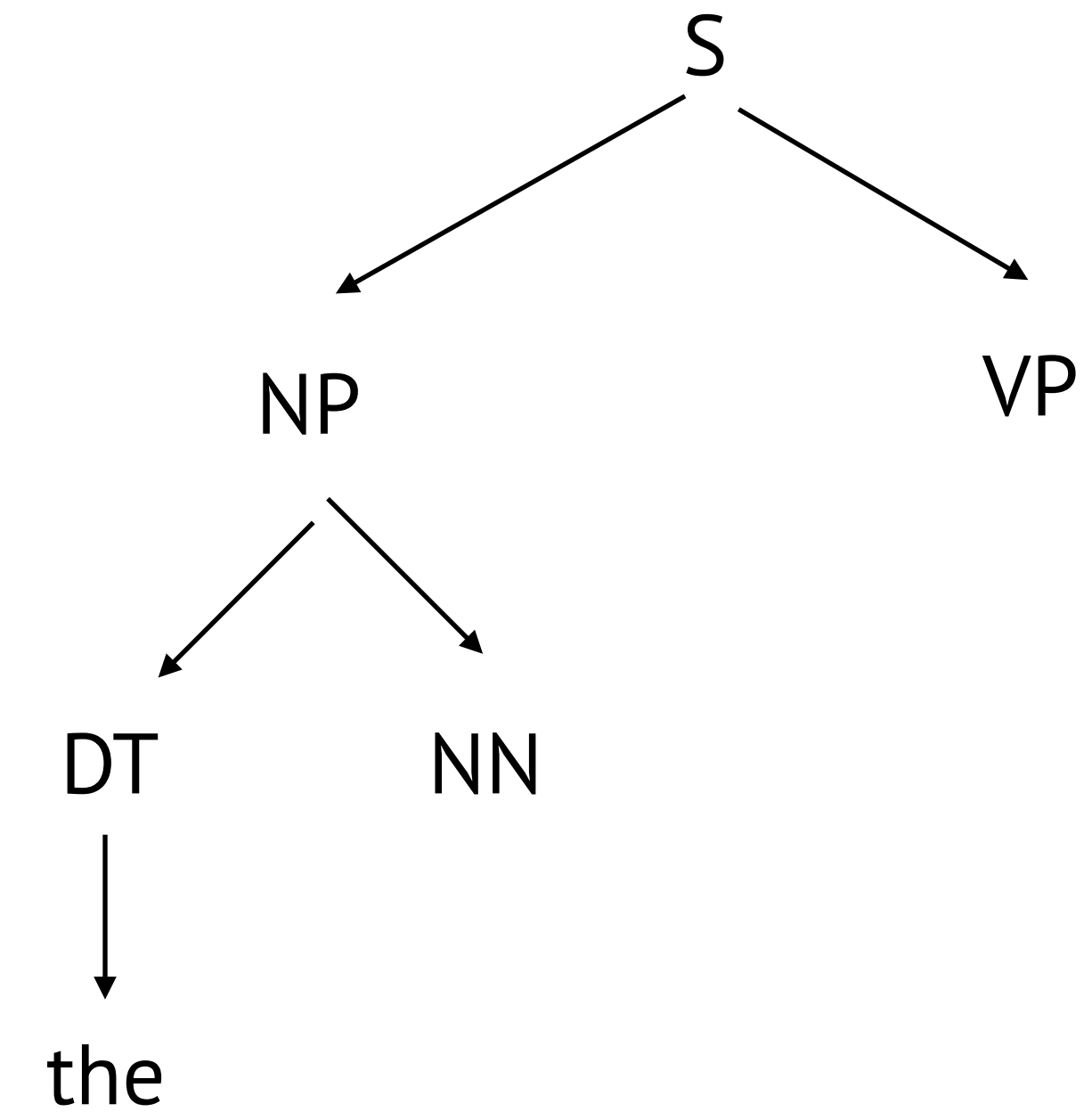
(S (NP (DT NN) VP))

$$P(\mathbf{x}, \mathbf{y}) = 1 \times 0.3 \times$$

Derivation Example

$R =$

S	→	NP VP	1.0	Vi	→	sleeps	1.0
				Vt	→	saw	1.0
VP	→	Vi	0.4				
VP	→	Vt NP	0.4	NN	→	man	0.7
VP	→	VP PP	0.2	NN	→	woman	0.2
				NN	→	telescope	0.1
NP	→	DT NN	0.3	DT	→	the	1.0
NP	→	NP PP	0.7				
PP	→	IN NP	1.0	IN	→	with	0.5
				IN	→	in	0.5



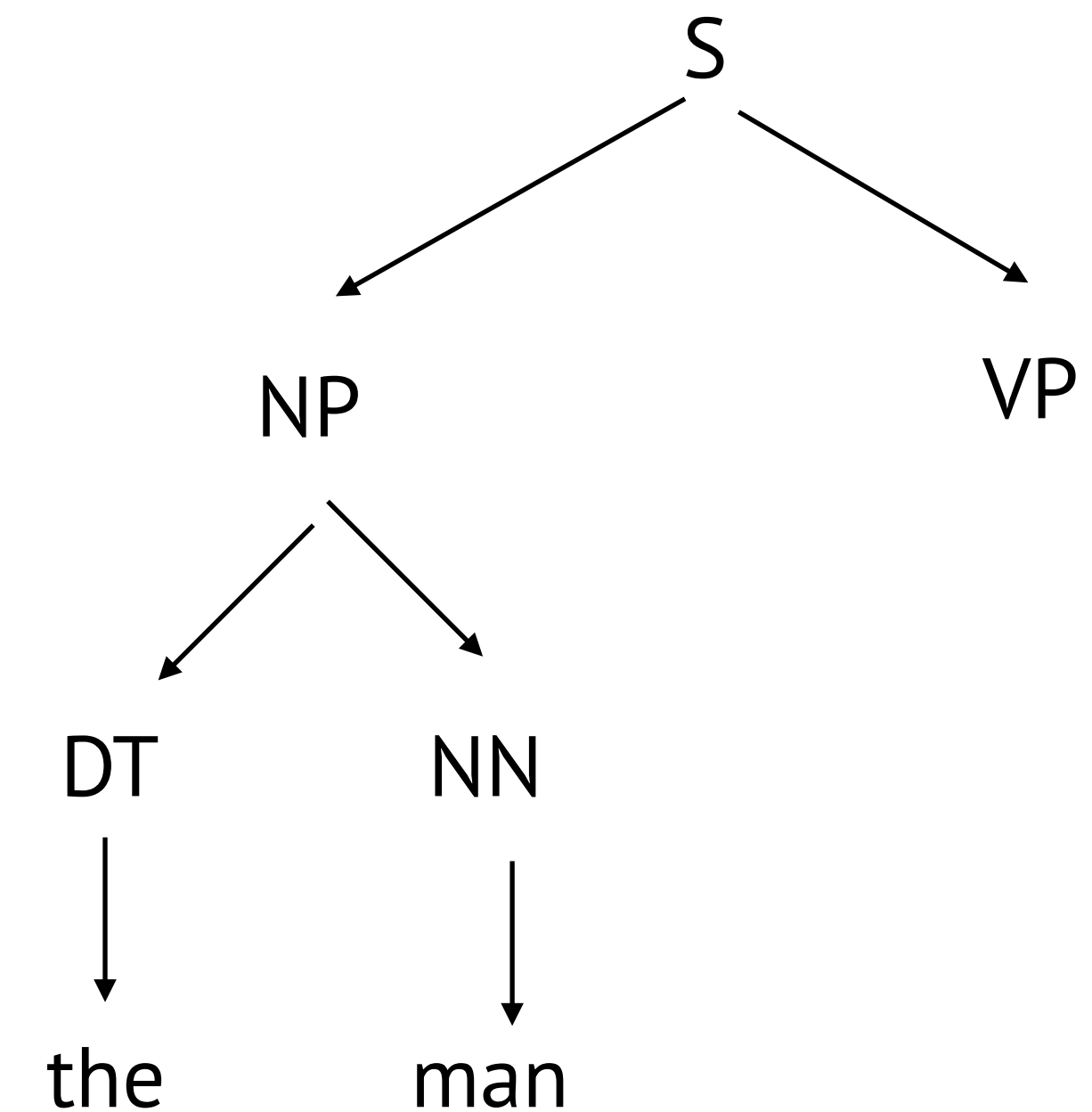
(S (NP ((DT the) NN) VP))

$$P(x, y) = 1 \times 0.3 \times 1 \times$$

Derivation Example

$R =$

S	→	NP VP	1.0	Vi	→	sleeps	1.0
				Vt	→	saw	1.0
VP	→	Vi	0.4				
VP	→	Vt NP	0.4	NN	→	man	0.7
VP	→	VP PP	0.2	NN	→	woman	0.2
				NN	→	telescope	0.1
NP	→	DT NN	0.3	DT	→	the	1.0
NP	→	NP PP	0.7	IN	→	with	0.5
PP	→	IN NP	1.0	IN	→	in	0.5



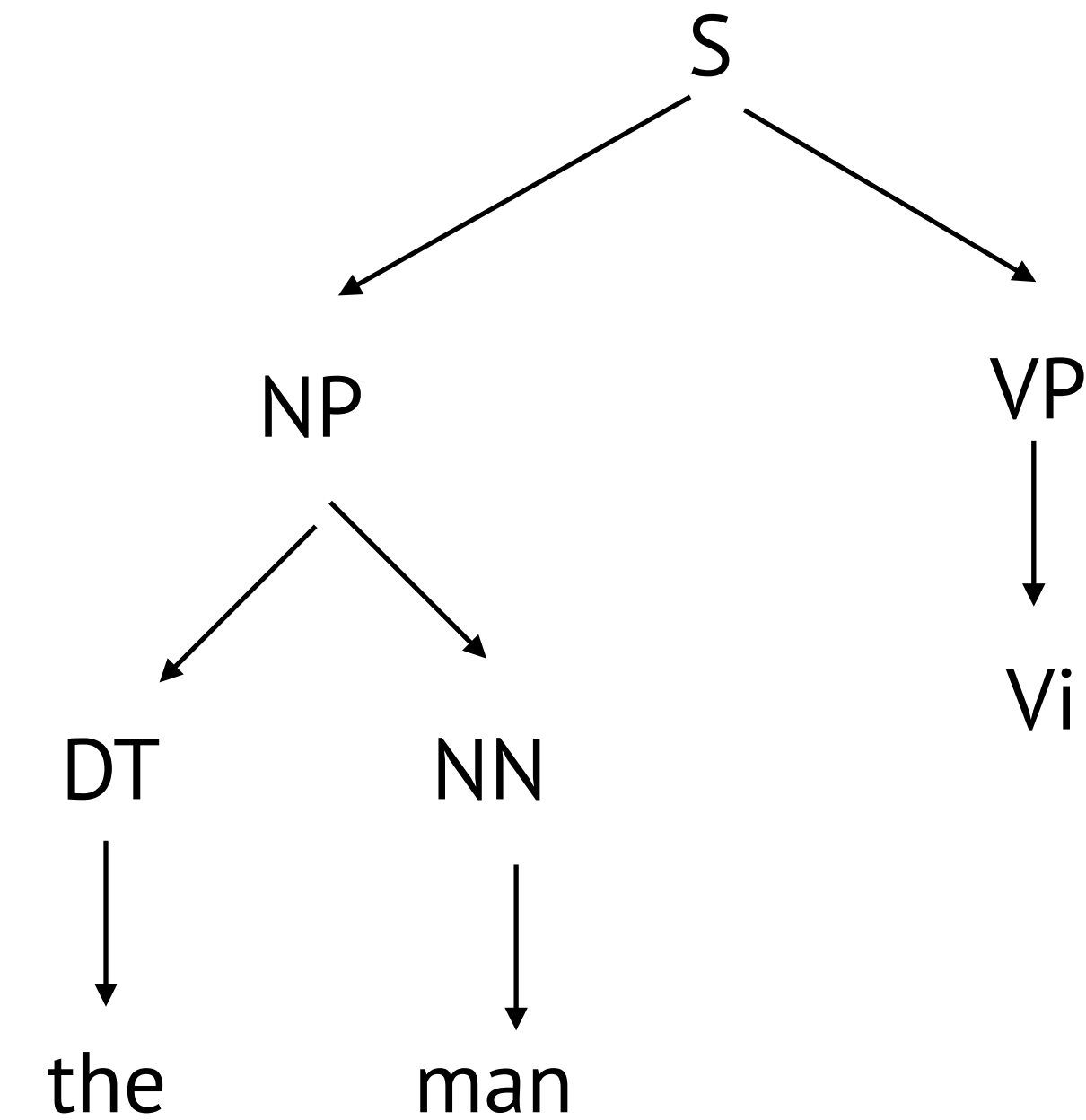
(S (NP ((DT the) (NN man)) VP))

$$P(x, y) = 1 \times 0.3 \times 1 \times 0.7 \times$$

Derivation Example

$R =$

S	→	NP VP	1.0	Vi	→	sleeps	1.0
				Vt	→	saw	1.0
VP	→	Vi	0.4	NN	→	man	0.7
VP	→	Vt NP	0.4	NN	→	woman	0.2
VP	→	VP PP	0.2	NN	→	telescope	0.1
NP	→	DT NN	0.3	DT	→	the	1.0
NP	→	NP PP	0.7	IN	→	with	0.5
PP	→	IN NP	1.0	IN	→	in	0.5



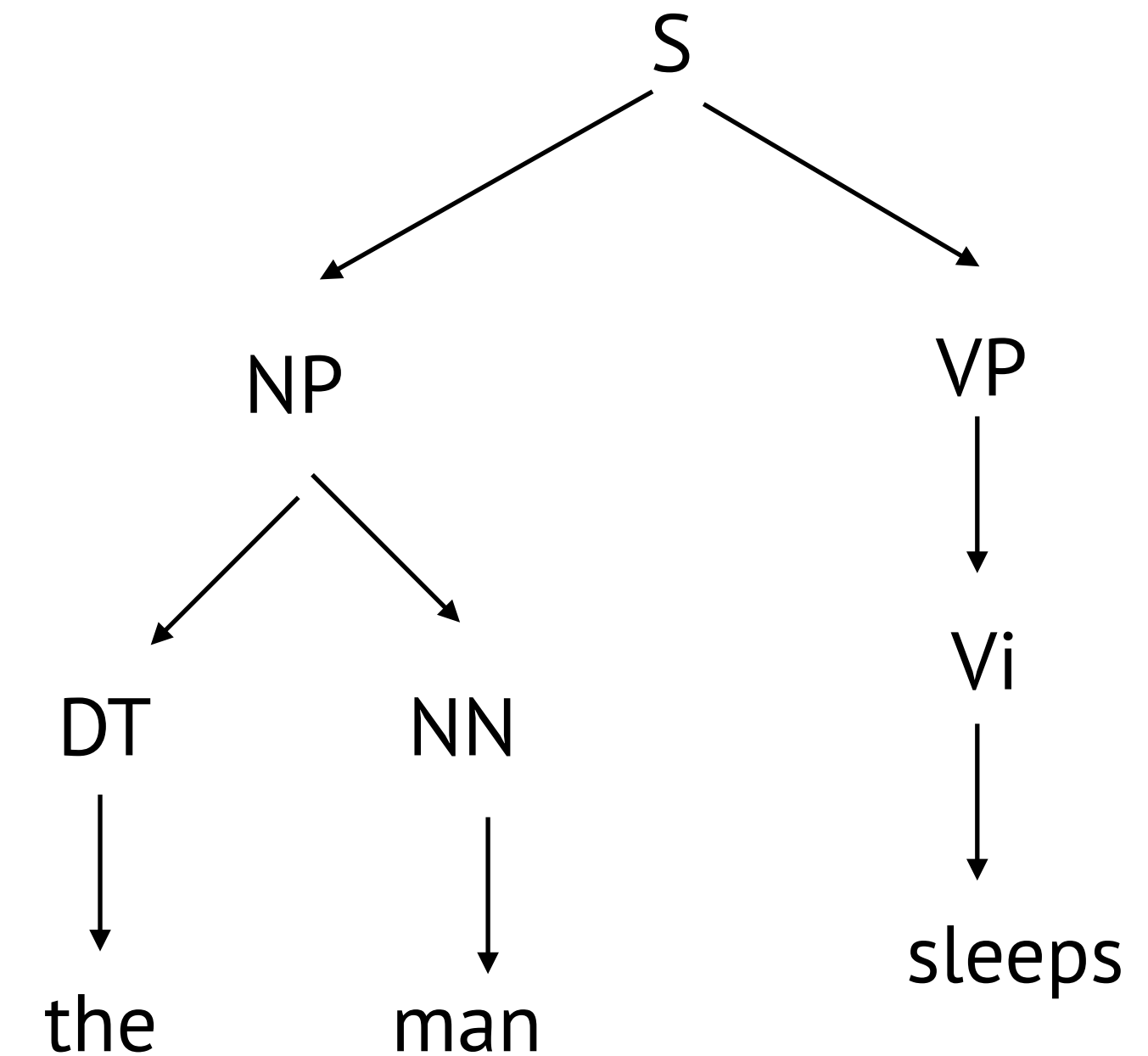
(S (NP ((DT the) (NN man)) (VP (Vi))))

$$P(x, y) = 1 \times 0.3 \times 1 \times 0.7 \times 0.4 \times$$

Derivation Example

$R =$

S	→	NP VP	1.0	Vi	→	sleeps	1.0
				Vt	→	saw	1.0
VP	→	Vi	0.4				
VP	→	Vt NP	0.4	NN	→	man	0.7
VP	→	VP PP	0.2	NN	→	woman	0.2
				NN	→	telescope	0.1
NP	→	DT NN	0.3	DT	→	the	1.0
NP	→	NP PP	0.7	IN	→	with	0.5
PP	→	IN NP	1.0	IN	→	in	0.5



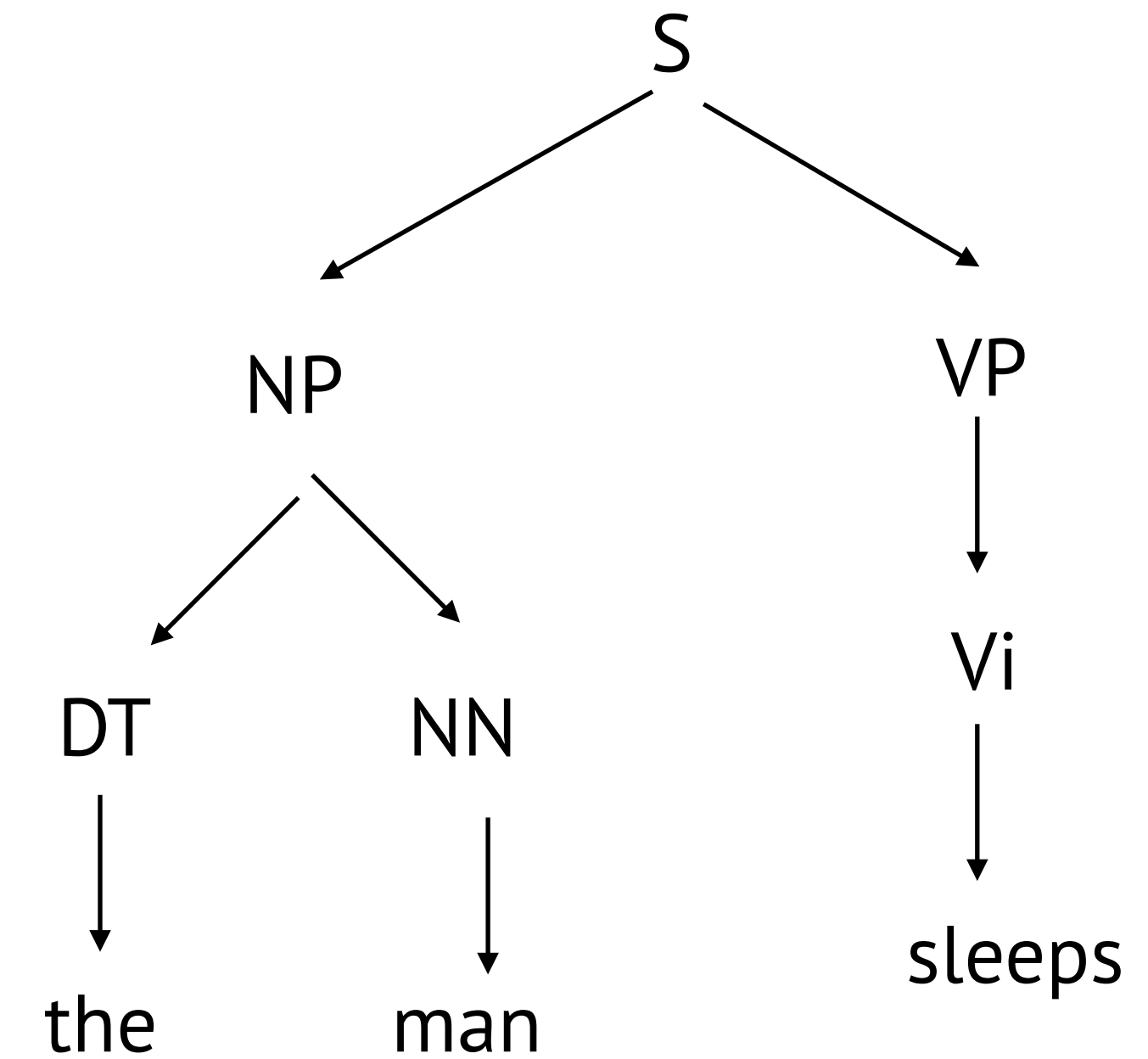
(S (NP ((DT the) (NN man)) (VP (Vi sleeps))))

$$P(\mathbf{x}, \mathbf{y}) = 1 \times 0.3 \times 1 \times 0.7 \times 0.4 \times 1$$

Derivation Example

$R =$

S	→	NP VP	1.0	Vi	→	sleeps	1.0
				Vt	→	saw	1.0
VP	→	Vi	0.4				
VP	→	Vt NP	0.4	NN	→	man	0.7
VP	→	VP PP	0.2	NN	→	woman	0.2
				NN	→	telescope	0.1
NP	→	DT NN	0.3	DT	→	the	1.0
NP	→	NP PP	0.7	IN	→	with	0.5
PP	→	IN NP	1.0	IN	→	in	0.5



(S (NP ((DT the) (NN man)) (VP (Vi sleeps)))))

Probabilistic Context-Free Grammars

$R =$

S	→	NP VP	1.0	Vi	→	sleeps	1.0
				Vt	→	saw	1.0
VP	→	Vi	0.4	NN	→	man	0.7
VP	→	Vt NP	0.4	NN	→	woman	0.2
VP	→	VP PP	0.2	NN	→	telescope	0.1
NP	→	DT NN	0.3	DT	→	the	1.0
NP	→	NP PP	0.7	IN	→	with	0.5
PP	→	IN NP	1.0	IN	→	in	0.5

1. How do we get those weights?

2. How to get the (marginal) probability of this sentence and the most likely parse?

the man saw the woman with a telescope

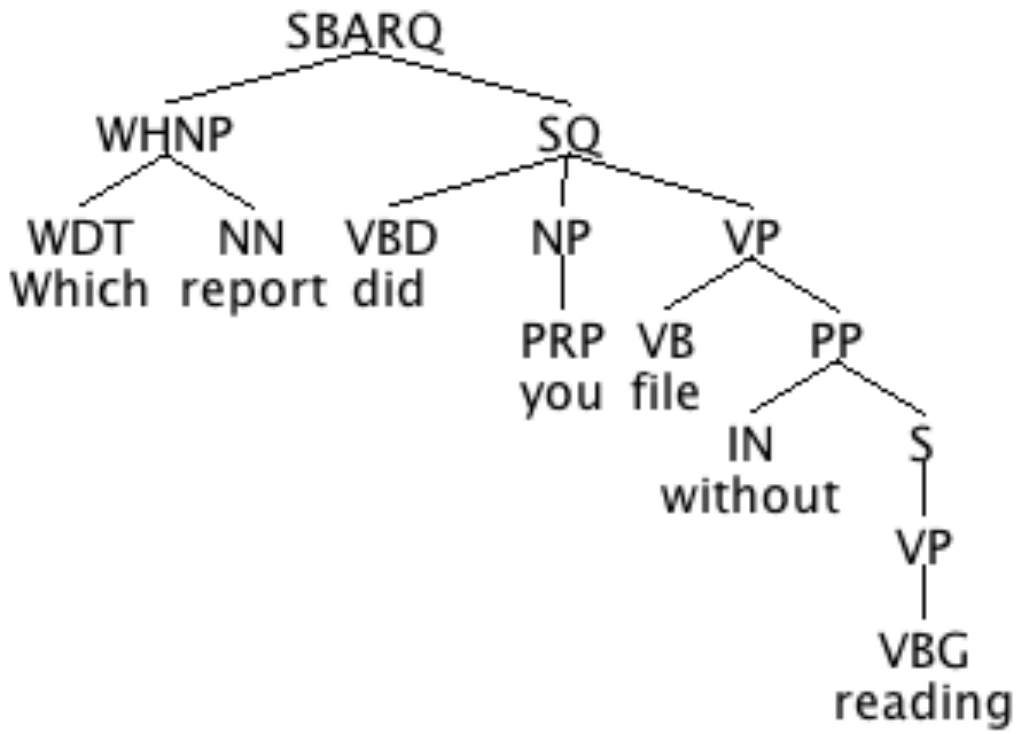
Treebanks (Penn Treebank)

tk treebank viewer

TREEBANK VIEWER Sandiway Fong University of Arizona (dec 2006: freeware version)

Sentence File /Users/sandiway/Desktop/treeprint/lu.lisp Prolog Tree File /Users/sandiway/Desktop/treeprint/lu2.pl Load

((John (NNP)) (said (VBD)) (that (IN)) (his (PRPS)) (brothe
((We (PRP)) (believed (VBD)) (Mary (NNP)) (to (TO)) (like
((He (PRP)) (thinks (VBZ)) (Mary (NNP)) (likes (NNS)) (Joh
((Who (NNP)) (does (VBZ)) (he (PRP)) (like (VB)))
((Who (NNP)) (was (VBD)) (arrested (VBN)))
((John (NNP)) (tried (VBD)) (to (TO)) (win (VB)) (the (DT))
((John (NNP)) (seems (VBZ)) (to (TO)) (be (VB)) (crazy (N
((John (NNP)) (was (VBD)) (arrested (VBN)) (after (IN)) (le
((John (NNP)) (is (VBZ)) (too (RB)) (dumb (JJ)) (to (TO)) (ta
((Who (NN)) (did (VBD)) (he (PRP)) (try (VB)) (to (TO)) (wi
((Which (NNP)) (report (NN)) (did (VBD)) (you (PRP)) (file
((Which (NNP)) (book (NN)) (did (VBD)) (you (PRP)) (file (V
((Who (NNP)) (filed (VBN)) (which (WDT)) (report (NN)) (v
((The (DT)) (report (NN)) (was (VBD)) (filed (VBN)) (withc
((The (DT)) (report (NN)) (fell (VBD)) (on (IN)) (the (DT))
((The (DT)) (teacher (NN)) (fell (VBD)) (on (IN)) (the (DT))
((Which (NNP)) (report (NN)) (did (VBD)) (you (PRP)) (file
((The (DT)) (report (NN)) (was (VBD)) (filed (VBN)) (after
((What (WP)) (was (VBD)) (filed (VBN)) (without (IN)) (beir
((The (DT)) (report (NN)) (was (VBD)) (filed (VBN)) (withc
((The (DT)) (report (NN)) (disappeared (VBD)) (without (IN))
((The (DT)) (teacher (NN)) (was (VBD)) (fired (VBN)) (with
((The (DT)) (teacher (NN)) (was (VBD)) (fired (VBN)) (afte
((The (DT)) (teacher (NN)) (resigned (VBD)) (after (IN)) (t
((Who (NNP)) (resigned (VBD)) (before (IN)) (we (PRP)) (c
((Who (NNP)) (resigned (VBD)) (before (IN)) (we (PRP)) (c
((Who (NNP)) (did (VBD)) (you (PRP)) (hire (VBD)) (becau



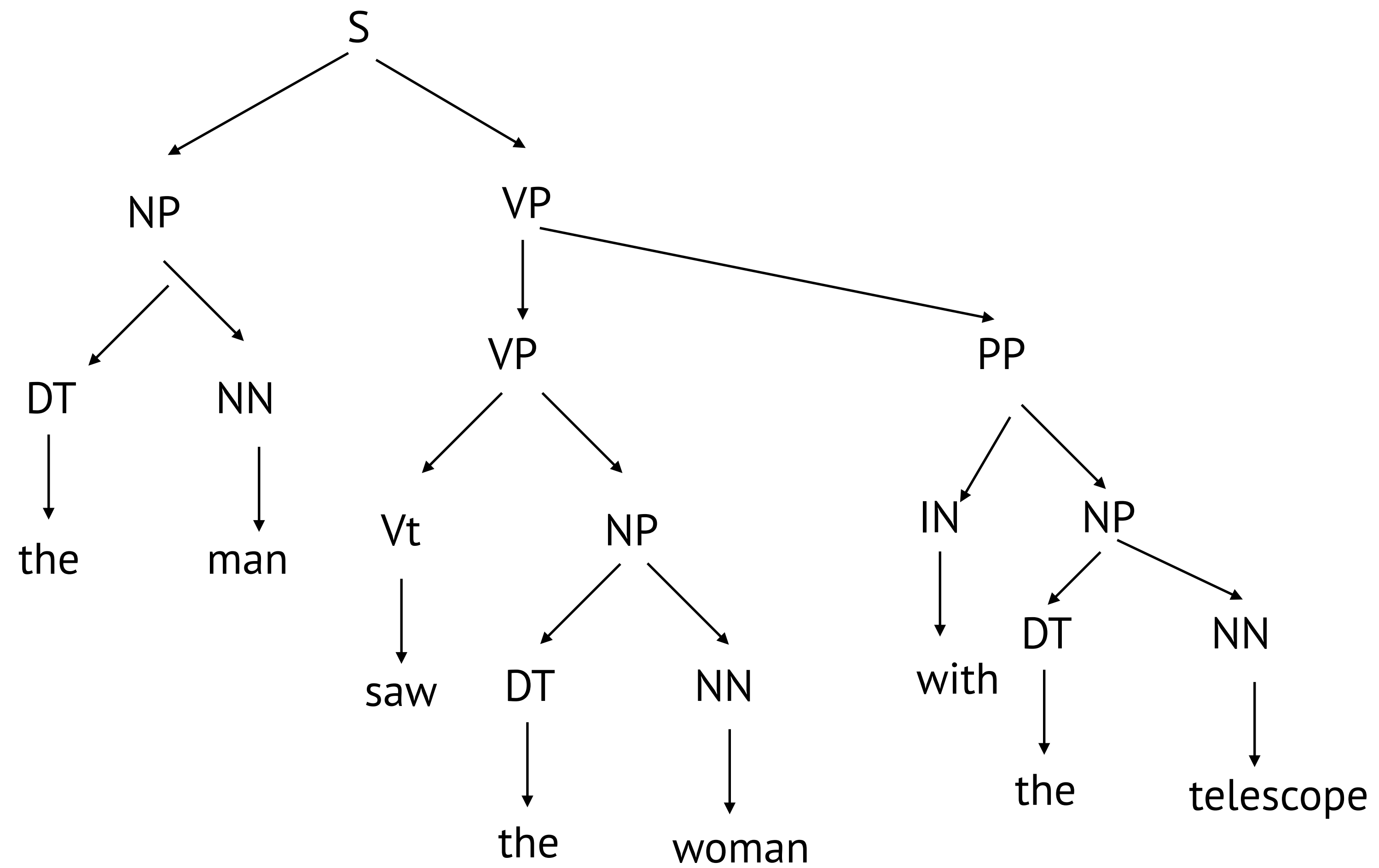
```
graph TD
    SBARQ --> WHNP[WHNP]
    SBARQ --> SQ[SQ]
    WHNP --> WDT[WDT]
    WHNP --> NN[NN]
    WDT --- Which[Which]
    NN --- report[report]
    SQ --> NP[NP]
    SQ --> VP1[VP]
    NP --> PRP[PRP]
    PRP --- you[you]
    VP1 --> VB[VB]
    VB --- file[file]
    VP1 --> PP[PP]
    PP --> IN[IN]
    IN --- without[without]
    PP --> S[S]
    S --> VP2[VP]
    VP2 --> VBG[VBG]
    VBG --- reading[reading]
```

4.5 million words of
American English



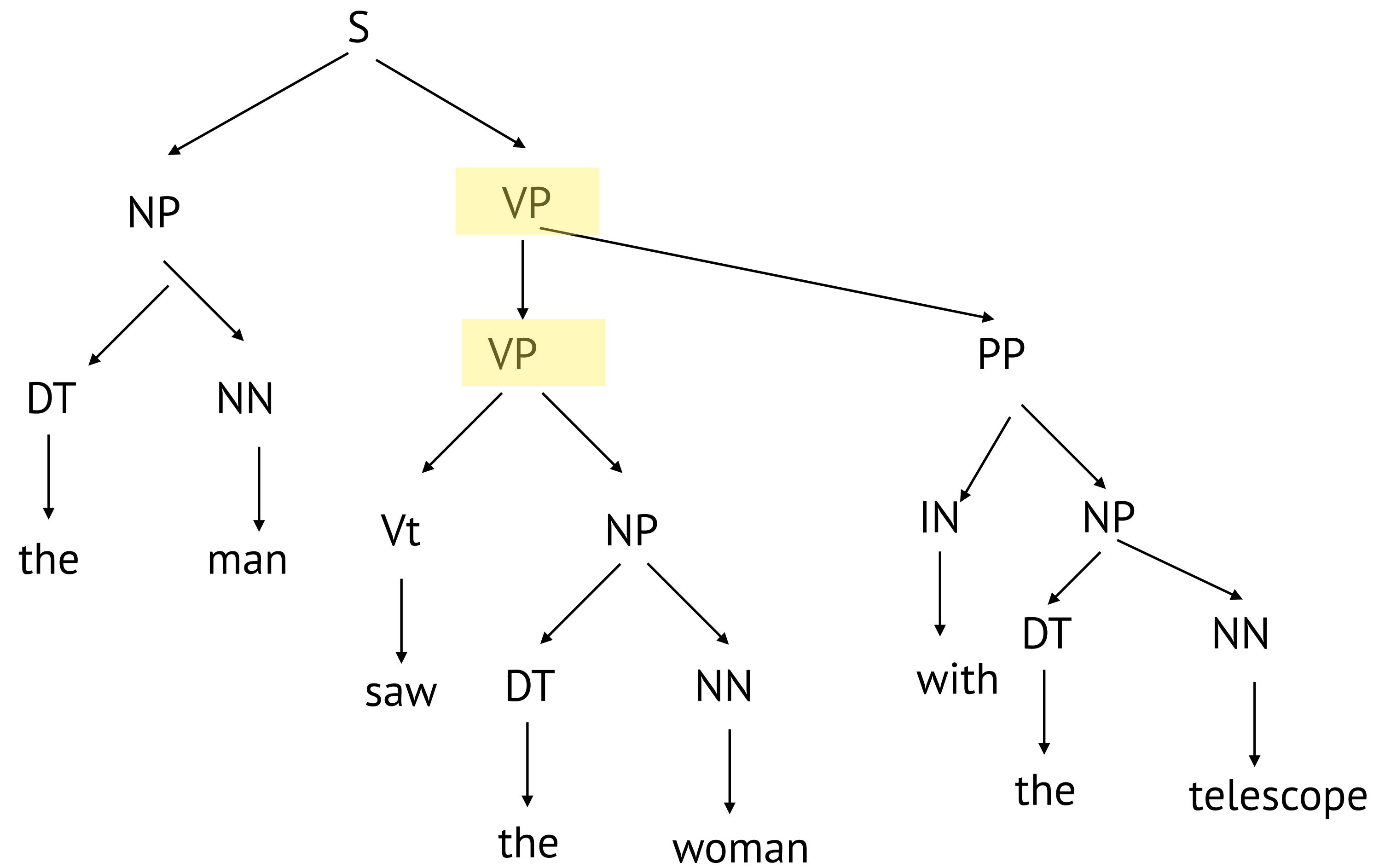
Mitch Marcus

Estimating the Probabilities from the Treebank



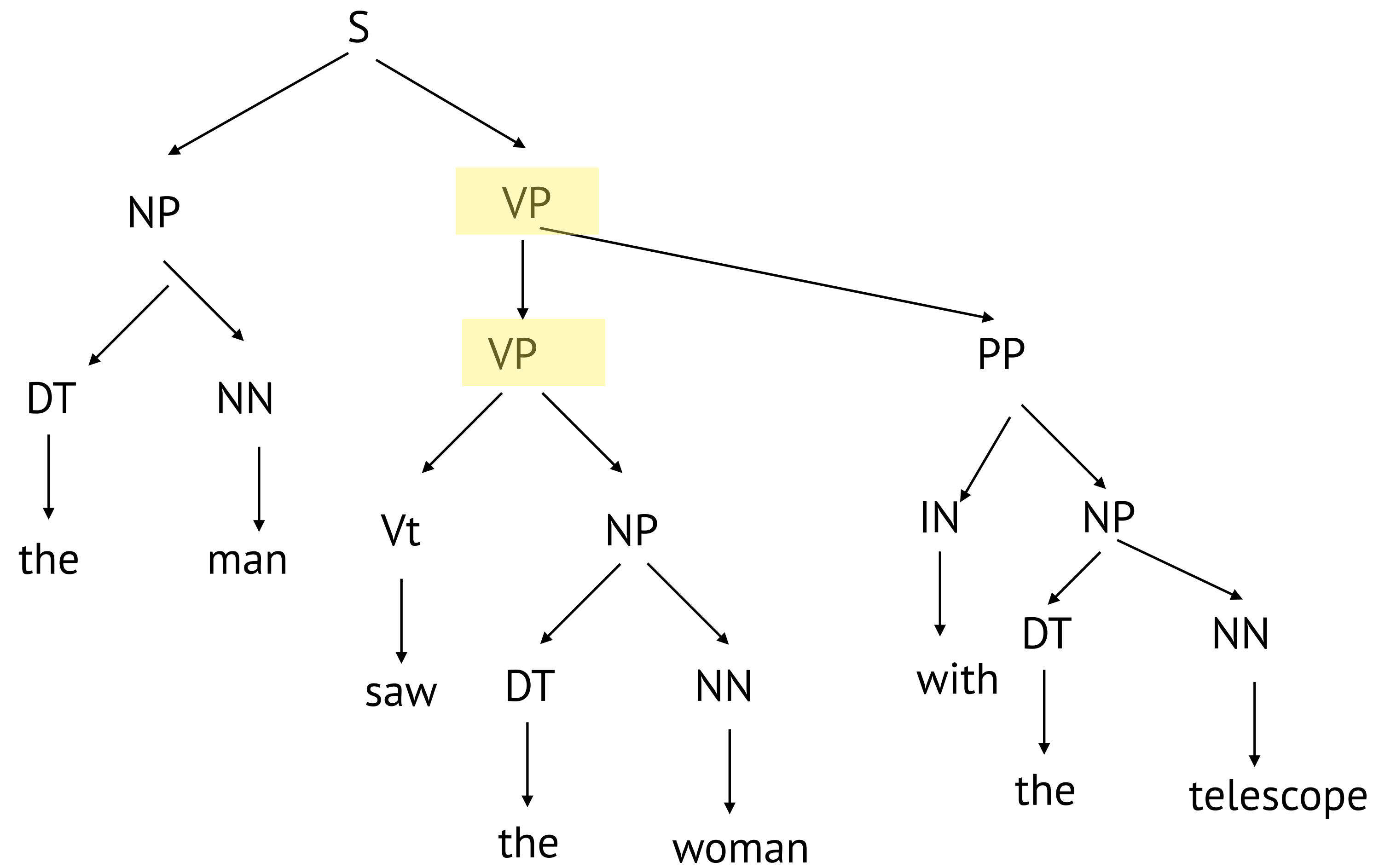
$$p(\text{VP} \rightarrow \text{VP PP}) = ?$$

Estimating the Probabilities from the Treebank



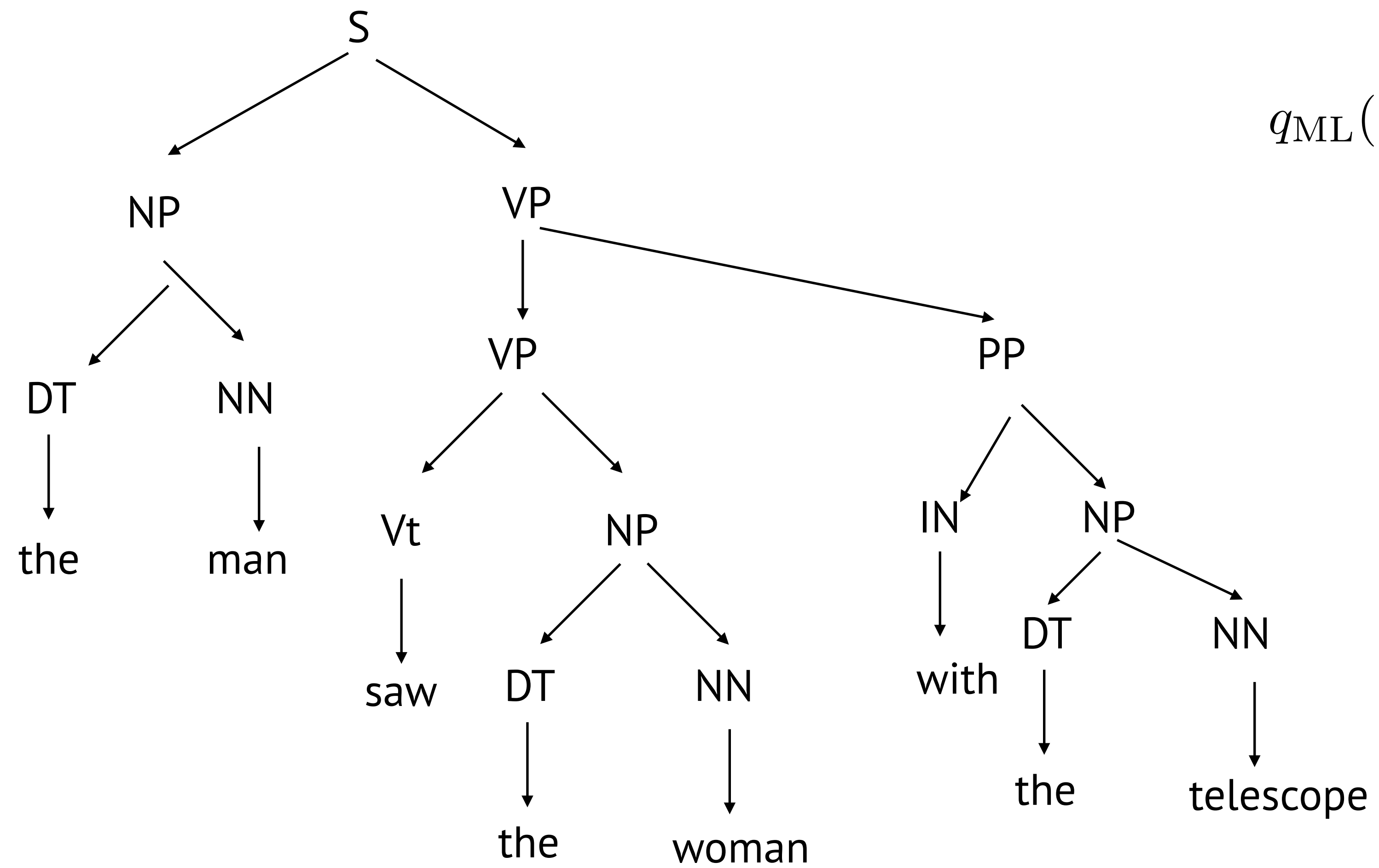
$$p(\text{VP} \rightarrow \text{VP PP}) = ?$$

Estimating the Probabilities from the Treebank



$$p(\text{VP} \rightarrow \text{VP PP}) = \frac{1}{2}$$

Estimating the Probabilities from the Treebank

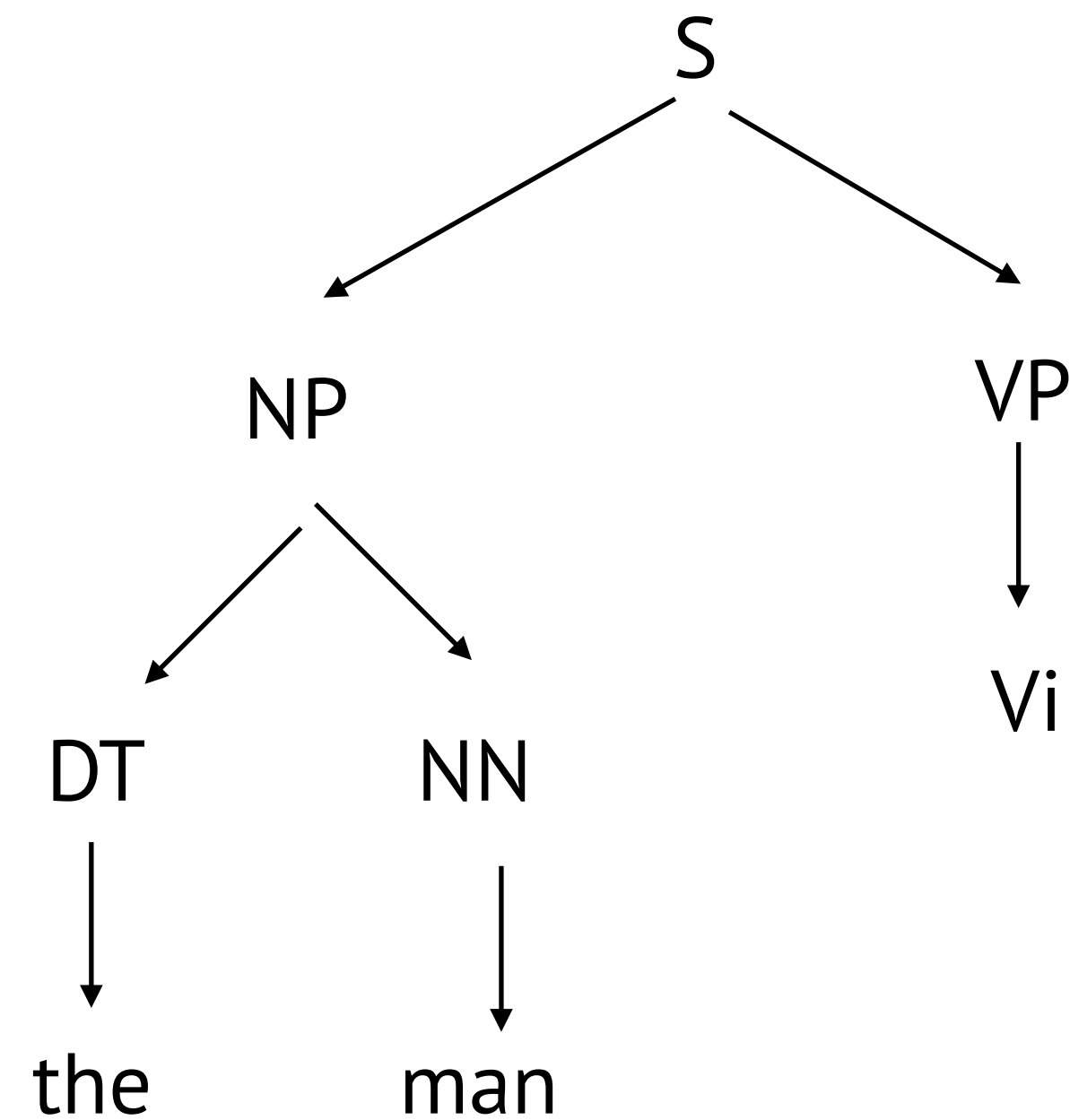


$$q_{\text{ML}}(\alpha \rightarrow \beta) = \frac{\text{Count}(\alpha \rightarrow \beta)}{\text{Count}(\alpha)}$$

MLE estimation!

Parsing with PCFGs

Parsing: $\arg \max_{y \in Y} p(x, y)$



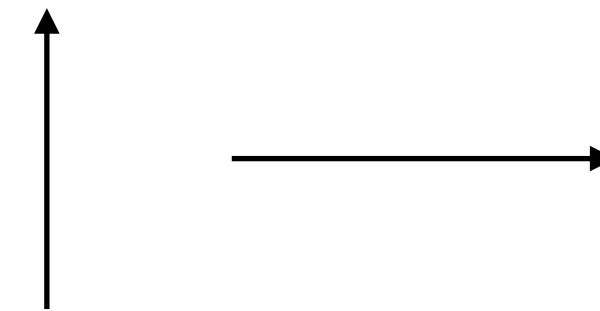
(S (NP ((DT the) (NN man)) (VP (Vi sleeps)))))

$$P(x, y) = 1 \times 0.3 \times 1 \times 0.7 \times 0.4 \times 1$$


Dynamic Programming

8	2	9	7
5	4	3	1
2	6	1	1
 2	5	4	2

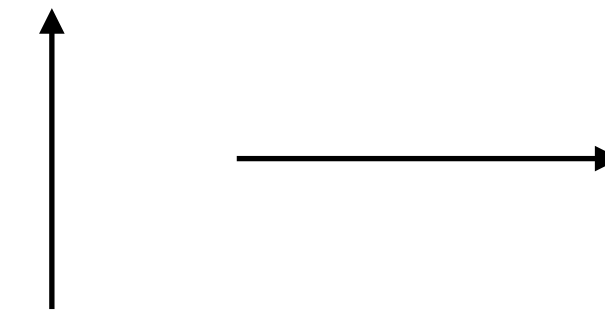
Find the lowest cost path from
bottom left corner to the upper
right corner



Dynamic Programming


8	2	9	7
5	4	3	1
2	6	1	1
 2	5	4	2

Find the lowest cost path from bottom left corner to the upper right corner

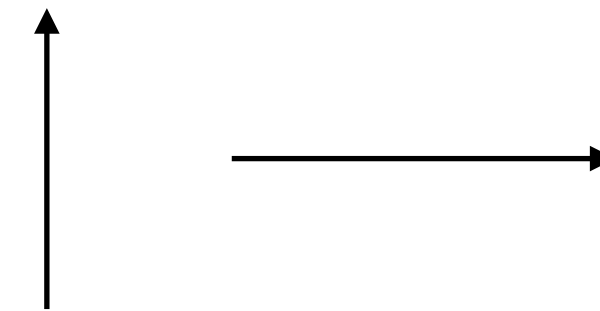


$$2 + 2 + 5 + 4 + 2 + 9 + 7 = 31$$

Dynamic Programming

8	2	9	7
5	4	3	1
2	6	1	1
 2	5	4	2

Find the lowest cost path from
bottom left corner to the upper
right corner



$$2 + 2 + 6 + 1 + 1 + 1 + 7 = 20$$

Dynamic Programming

8	2	9	7
5	4	3	1
2	6	1	1
2	5	4	2

2			

Dynamic Programming

8	2	9	7
5	4	3	1
2	6	1	1
2	5	4	2

17 (d)			
9 (d)			
4 (d)			
2	7 (l)	11 (l)	13 (l)

Dynamic Programming

8	2	9	7
5	4	3	1
2	6	1	1
2	5	4	2

17 (d)			
9 (d)			
4 (d)			
2	7 (l)	11 (l)	13 (l)

Dynamic Programming

8	2	9	7
5	4	3	1
2	6	1	1
2	5	4	2

17 (d)			
9 (d)			
4 (d)	10 (l)		
2	7 (l)	11 (l)	13 (l)

Dynamic Programming

8	2	9	7
5	4	3	1
2	6	1	1
2	5	4	2

17 (d)			
9 (d)	13 (l)		
4 (d)	10 (l)	11 (l)	
2	7 (l)	11 (l)	13 (l)

Dynamic Programming

8	2	9	7
5	4	3	1
2	6	1	1
2	5	4	2

17 (d)	15 (d)		
9 (d)	13 (l)	14 (d)	
4 (d)	10 (l)	11 (l)	12 (l)
2	7 (l)	11 (l)	13 (l)

Dynamic Programming

8	2	9	7
5	4	3	1
2	6	1	1
2	5	4	2

17 (d)	15 (d)	23 (d)	
9 (d)	13 (l)	14 (d)	13 (d)
4 (d)	10 (l)	11 (l)	12 (l)
2	7 (l)	11 (l)	13 (l)

Dynamic Programming

8	2	9	7
5	4	3	1
2	6	1	1
2	5	4	2

17 (d)	15 (d)	23 (d)	20 (d)
9 (d)	13 (l)	14 (d)	13 (d)
4 (d)	10 (l)	11 (l)	12 (l)
2	7 (l)	11 (l)	13 (l)

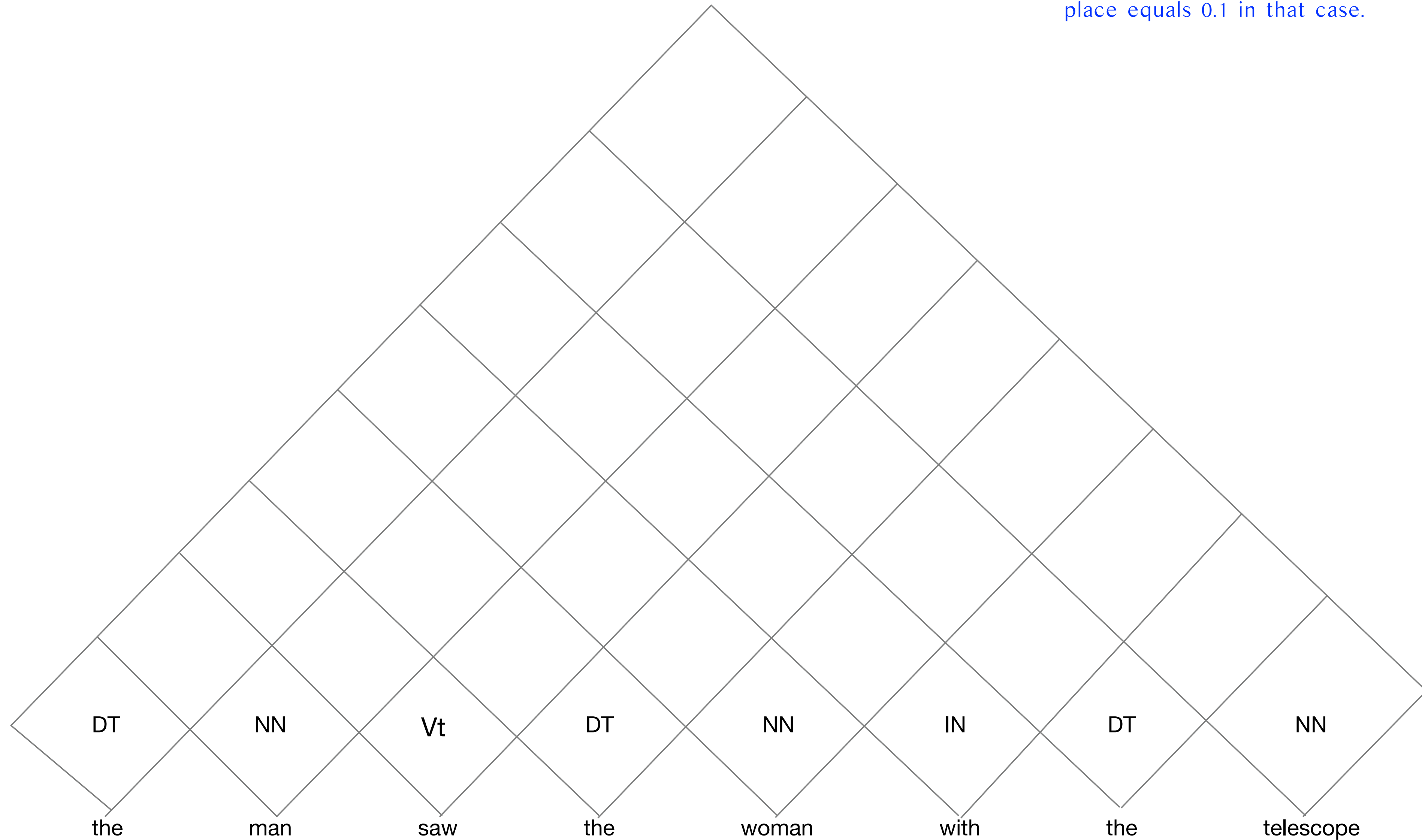
Parsing with PCFGs

$R =$

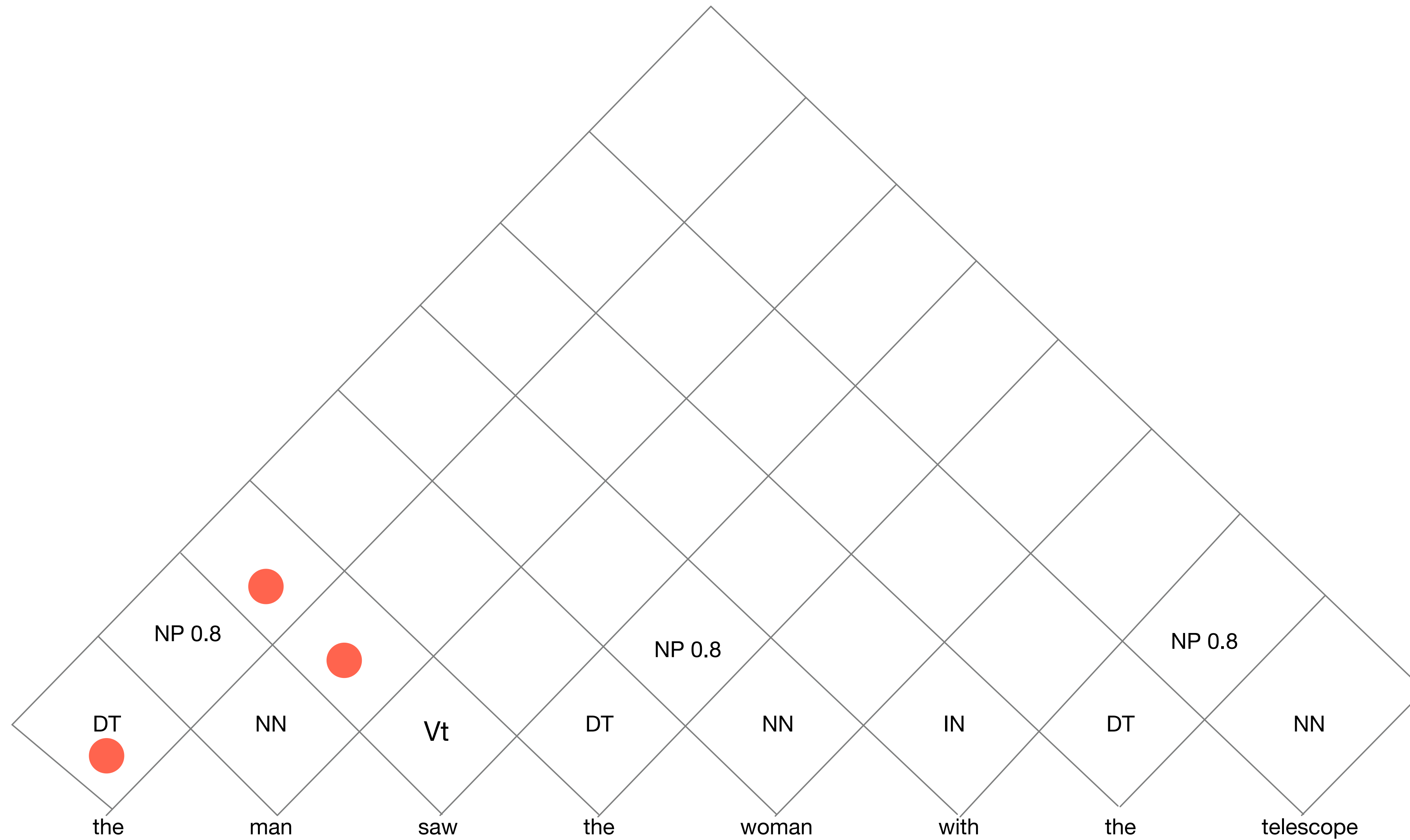
S	→	NP VP	1.0	Vt	→	saw	1.0
				NN	→	man	0.1
VP	→	Vt NP	0.8	NN	→	woman	0.1
VP	→	VP PP	0.2	NN	→	telescope	0.3
				NN	→	dog	0.5
NP	→	DT NN	0.8				
NP	→	NP PP	0.2	DT	→	the	1.0
PP	→	IN NP	1.0	IN	→	with	0.6
				IN	→	in	0.4

Parsing with PCFGs

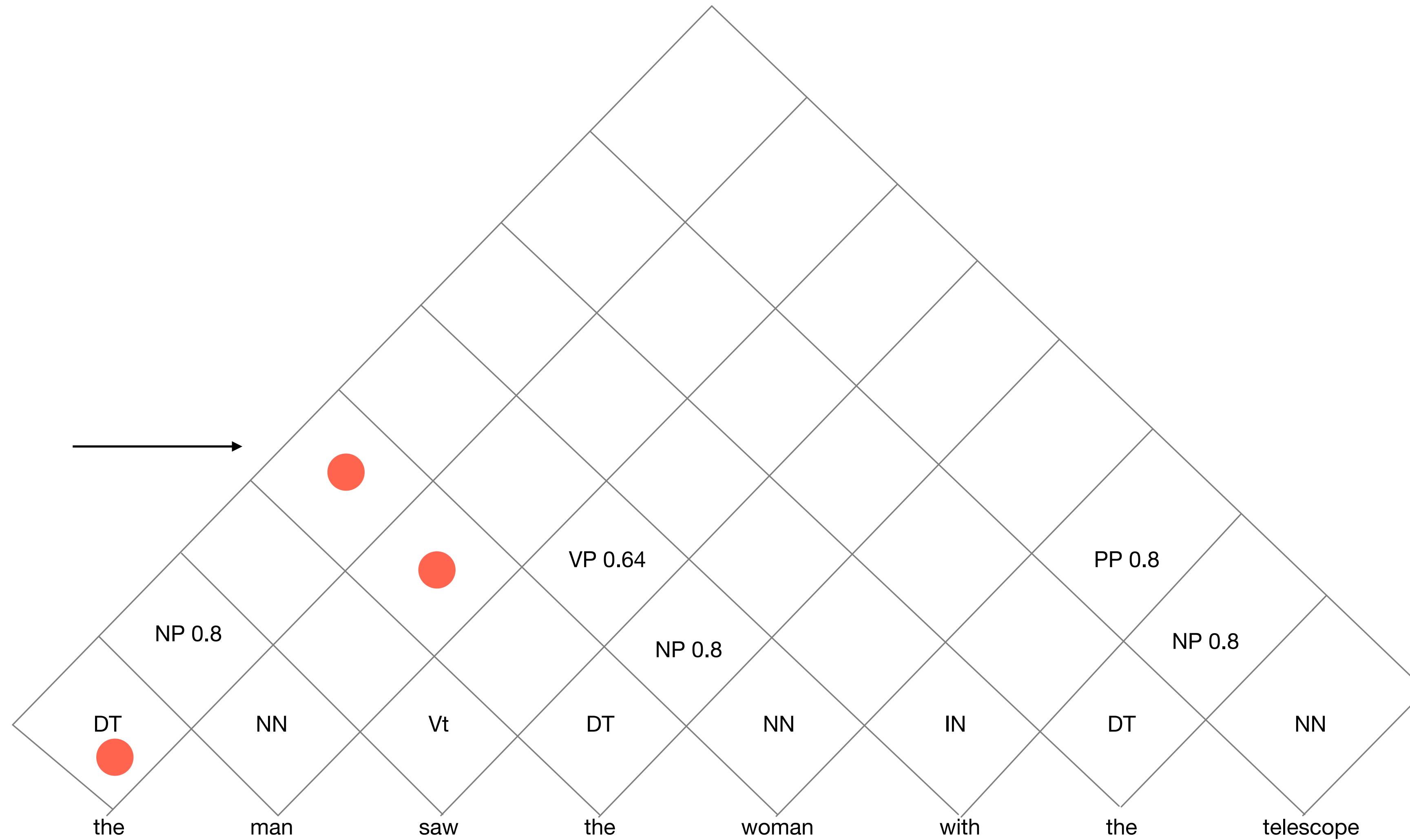
** For simplicity – Let's assume all these pre-terminals are built with probability 1 (this is obviously wrong) – remember that in reality you need to use rules like NN -> man 0.1 to build it. The probability of NN in that place equals 0.1 in that case.



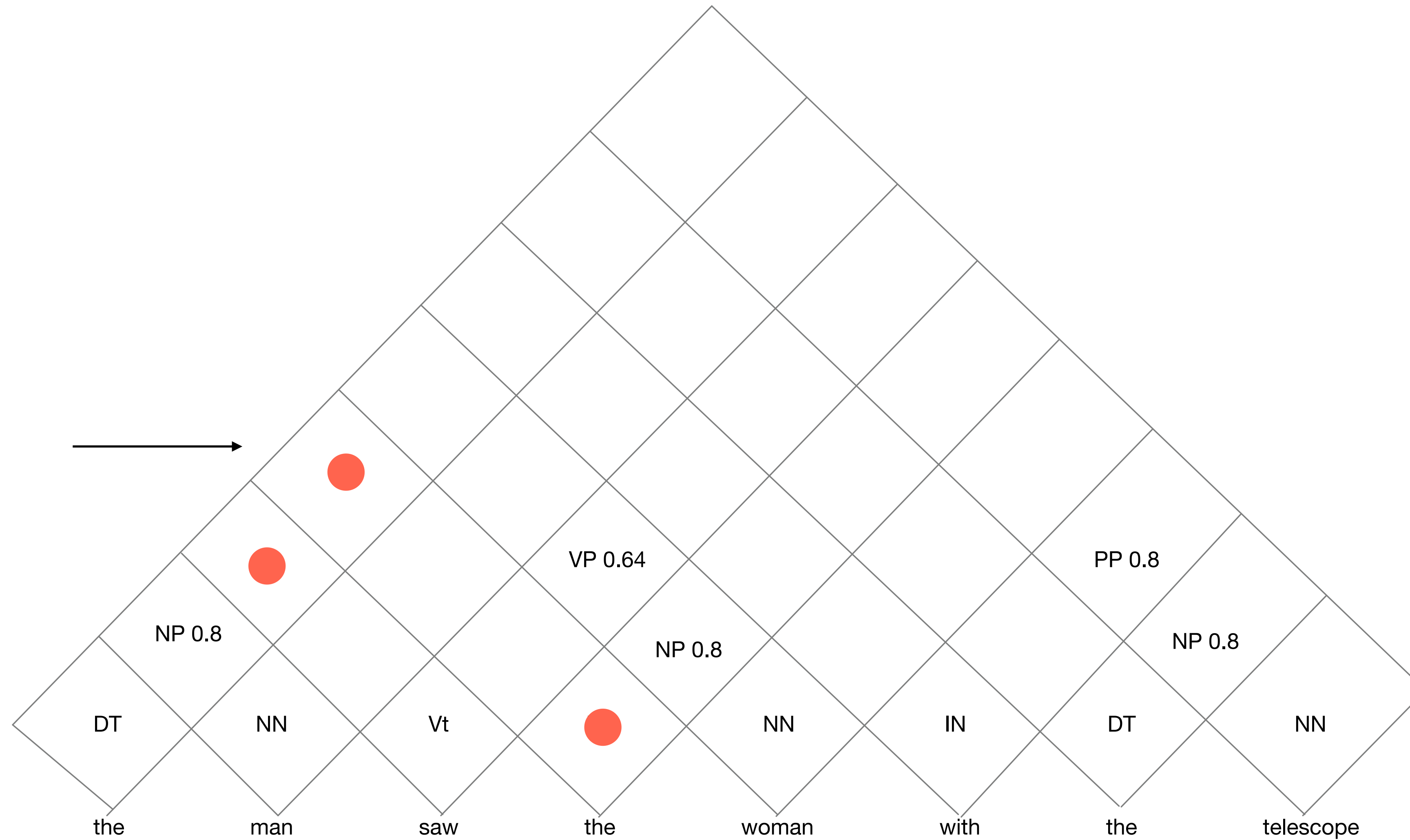
Parsing with PCFGs



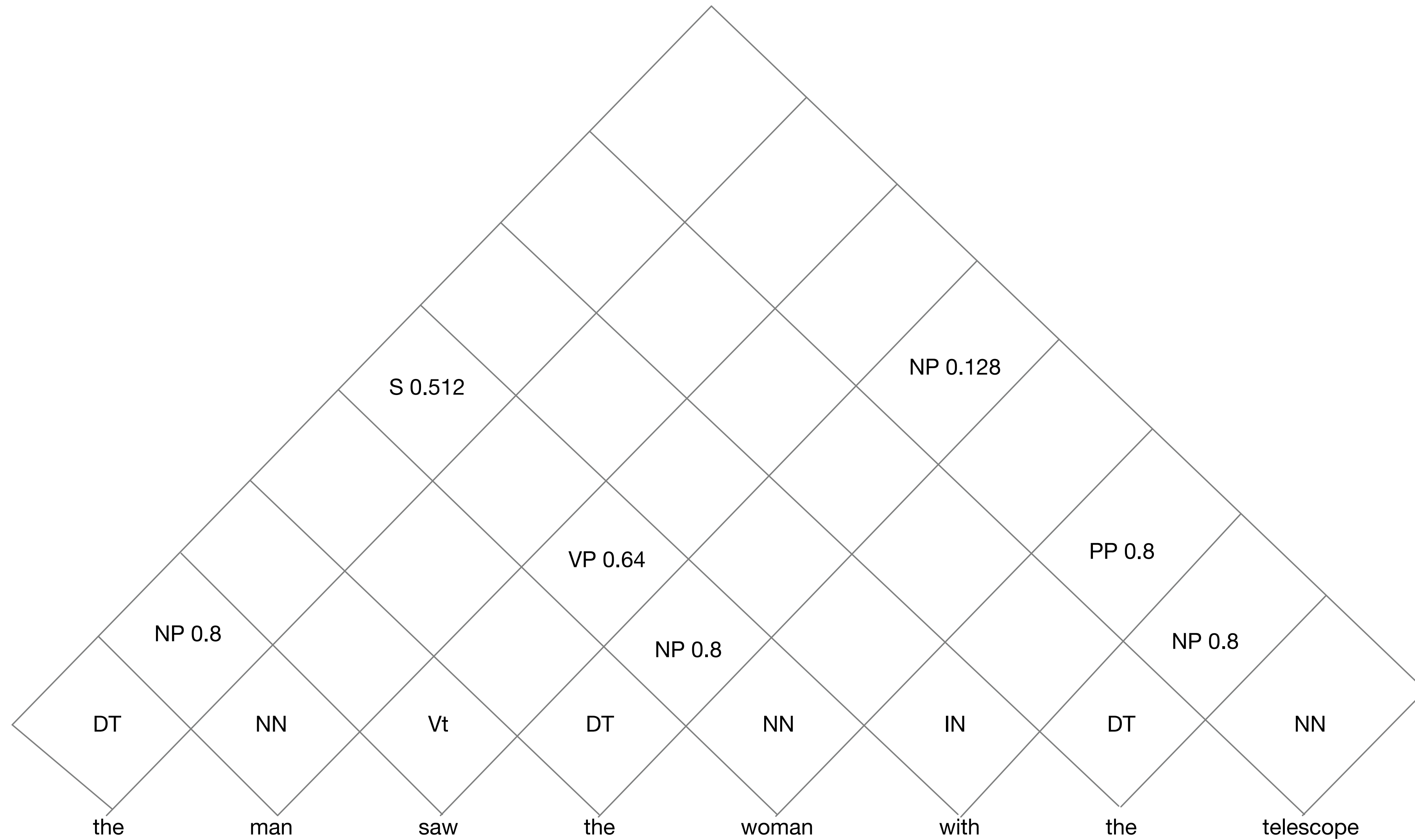
Parsing with PCFGs



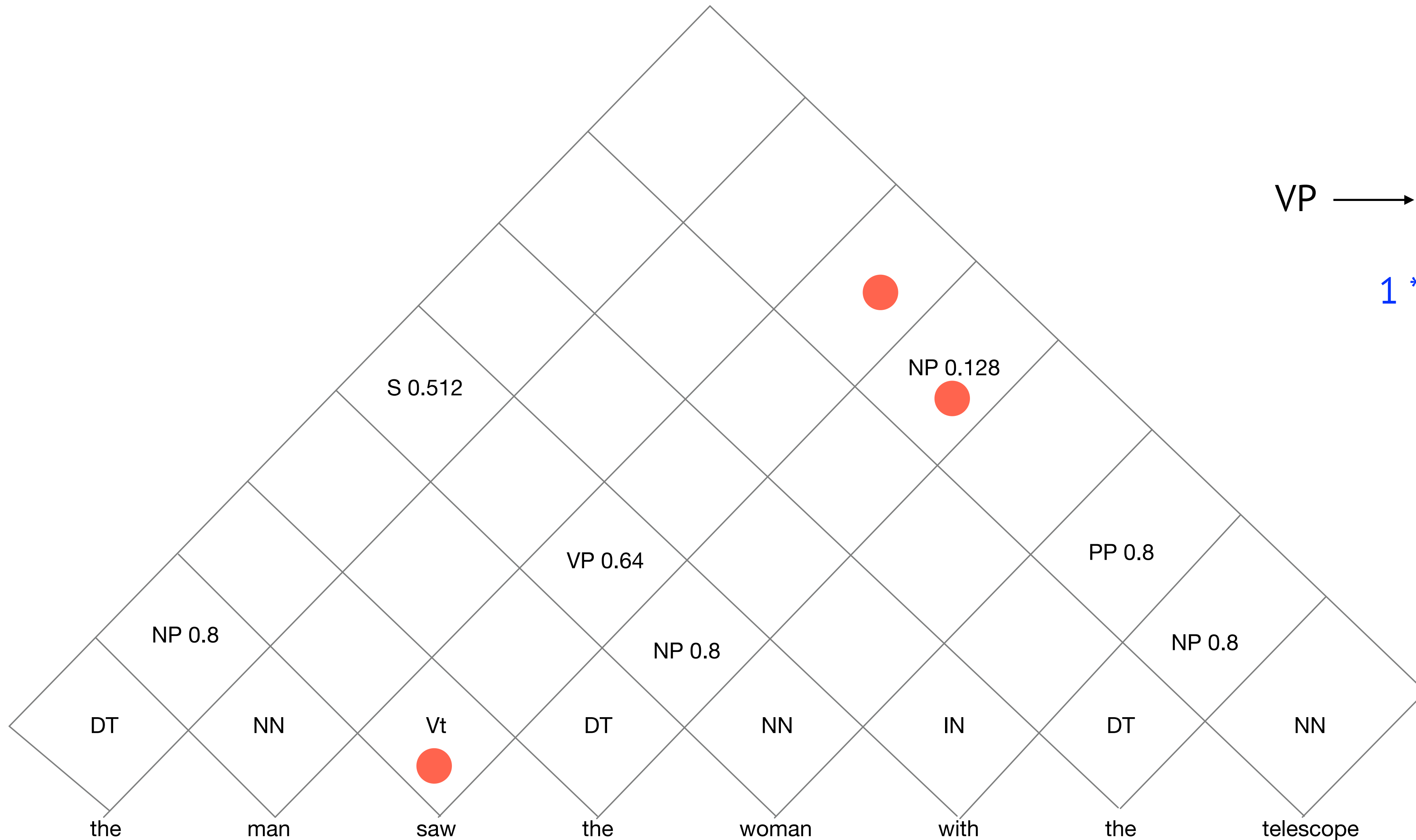
Parsing with PCFGs



Parsing with PCFGs



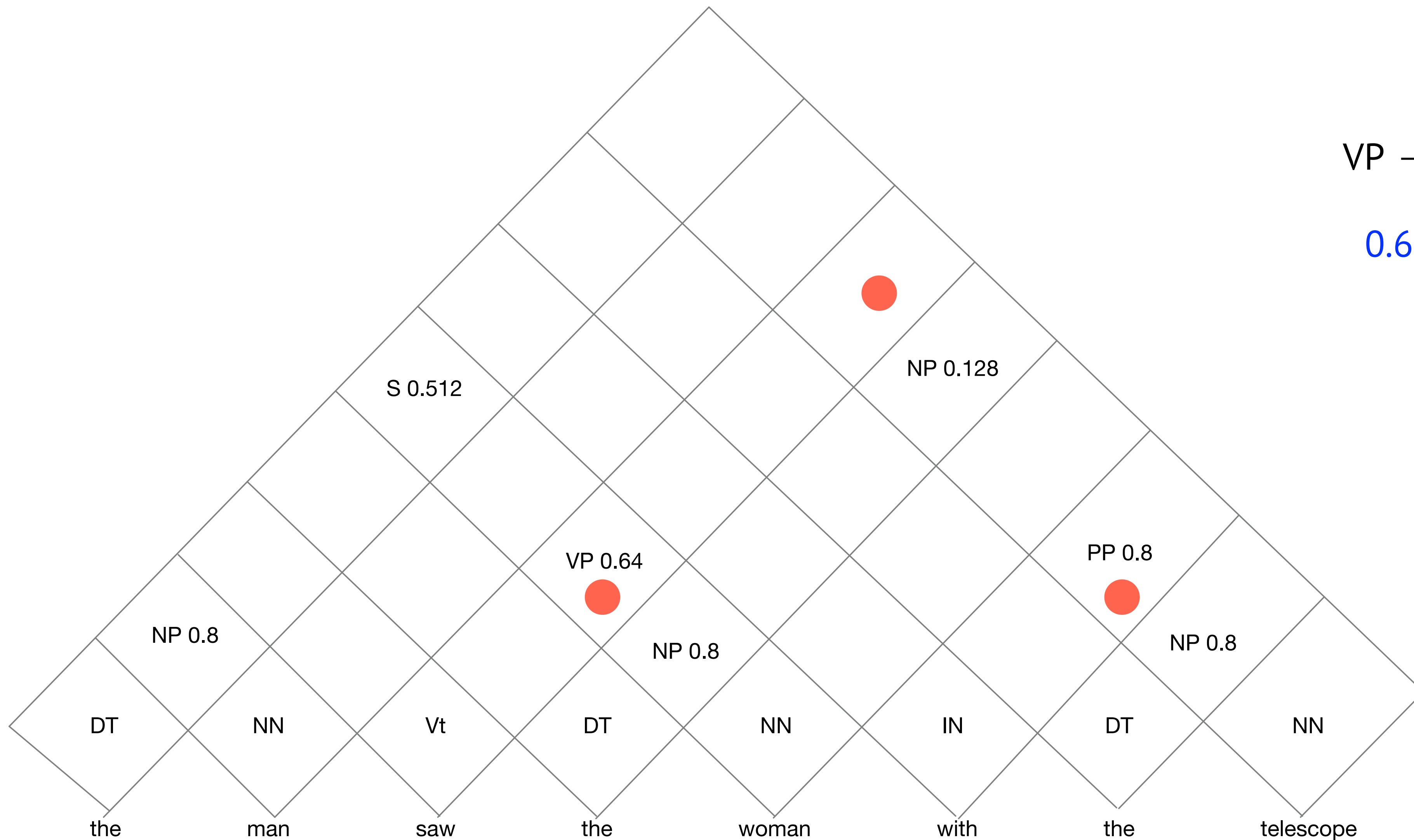
Parsing with PCFGs



VP \longrightarrow Vt NP 0.8

$$1 * 0.128 * 0.8 = 0.1024$$

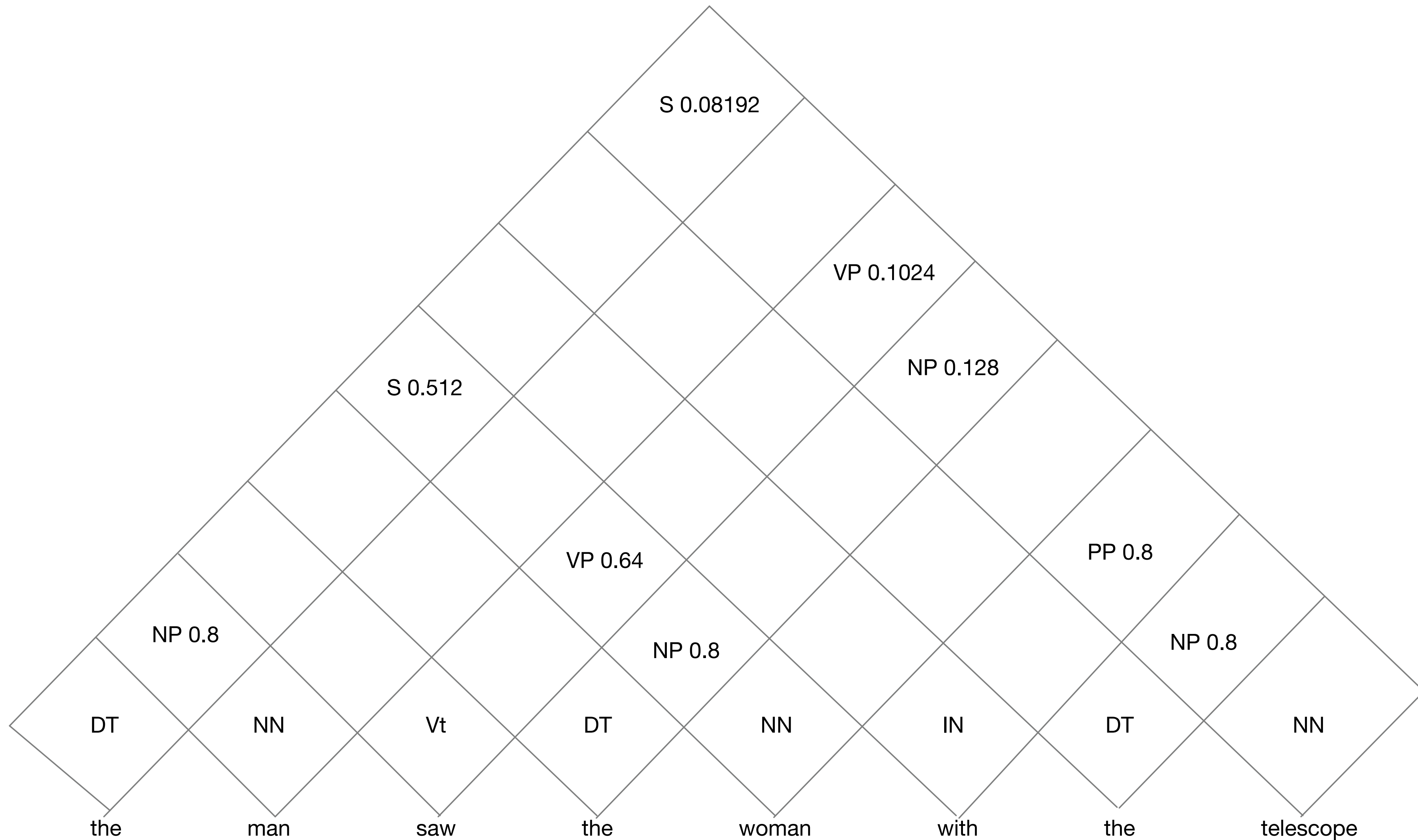
Parsing with PCFGs



VP \longrightarrow VP PP 0.2

$$0.64 * 0.8 * 0.2 = 0.1024$$

Parsing with PCFGs (CYK Algorithm)

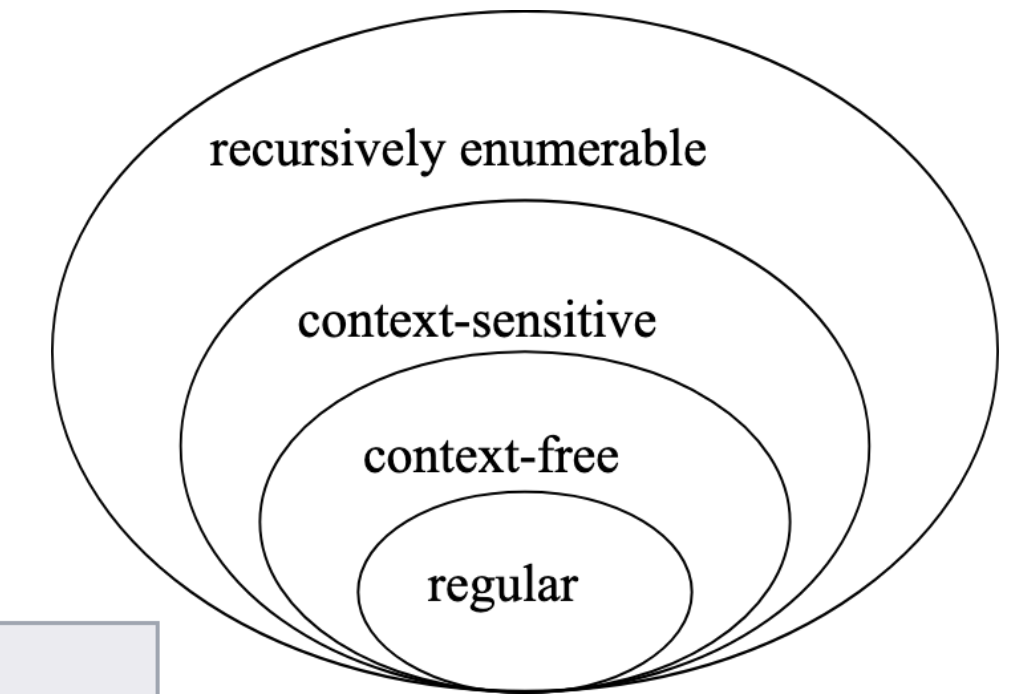


Revisit Question

Match strings with equal number of a and b.

e.g., aaabbb, aabb, aaaabbbb...

Chomsky Hierarchy



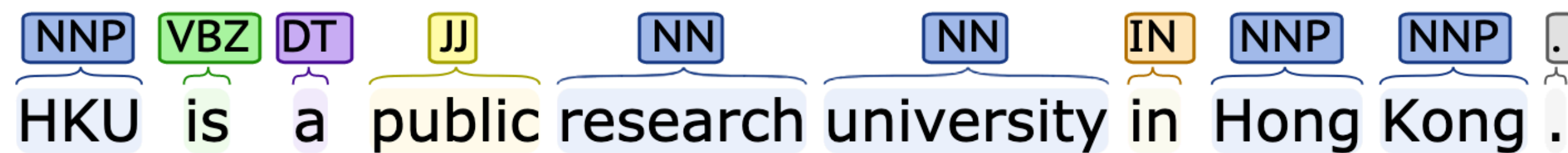
Grammar ⇄	Languages ⇄	Recognizing Automaton ⇄	Production rules (constraints) ^[a] ⇄	Examples ^{[5][6]} ⇄
Type-3	Regular	Finite-state automaton	$A \rightarrow a$ $A \rightarrow aB$ (right regular) or $A \rightarrow a$ $A \rightarrow Ba$ (left regular)	$L = \{a^n n > 0\}$
Type-2	Context-free	Non-deterministic pushdown automaton	$A \rightarrow \alpha$	$L = \{a^n b^n n > 0\}$
Type-1	Context-sensitive	Linear-bounded non-deterministic Turing machine	$\alpha A \beta \rightarrow \alpha \gamma \beta$	$L = \{a^n b^n c^n n > 0\}$
Type-0	Recursively enumerable	Turing machine	$\gamma \rightarrow \alpha$ (γ non-empty)	$L = \{w w \text{ describes a terminating Turing machine}\}$

a. ^ Meaning of symbols:

- a = terminal
- A, B = non-terminal
- α, β, γ = string of terminals and/or non-terminals

Linguistic Structures

HKU is a public research university in Hong Kong.

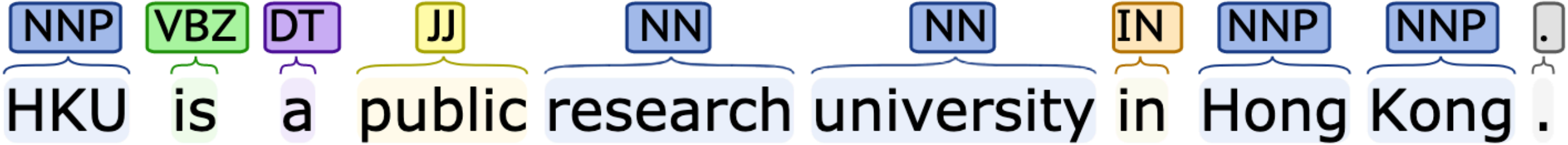


Part-of-speech tagging
(word class)

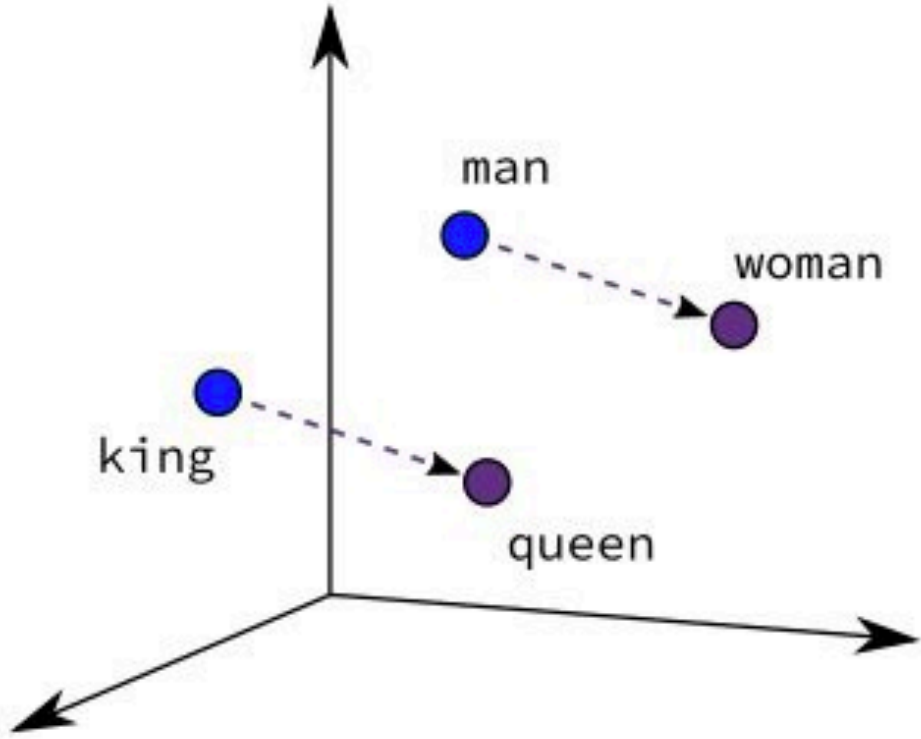


Named entity recognition

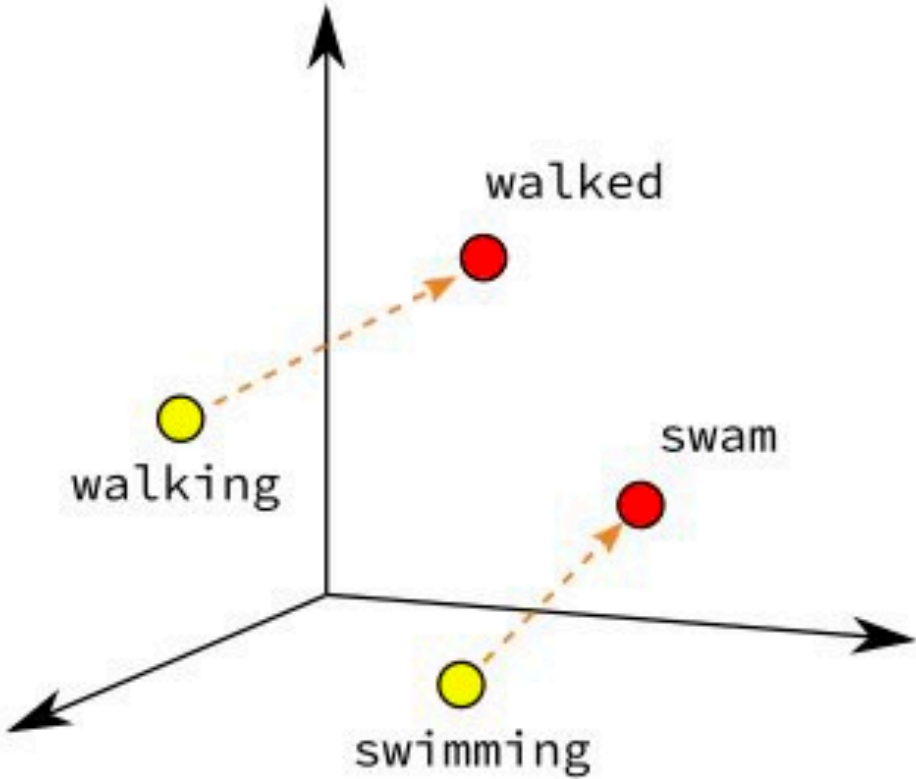
Linguistic Structures



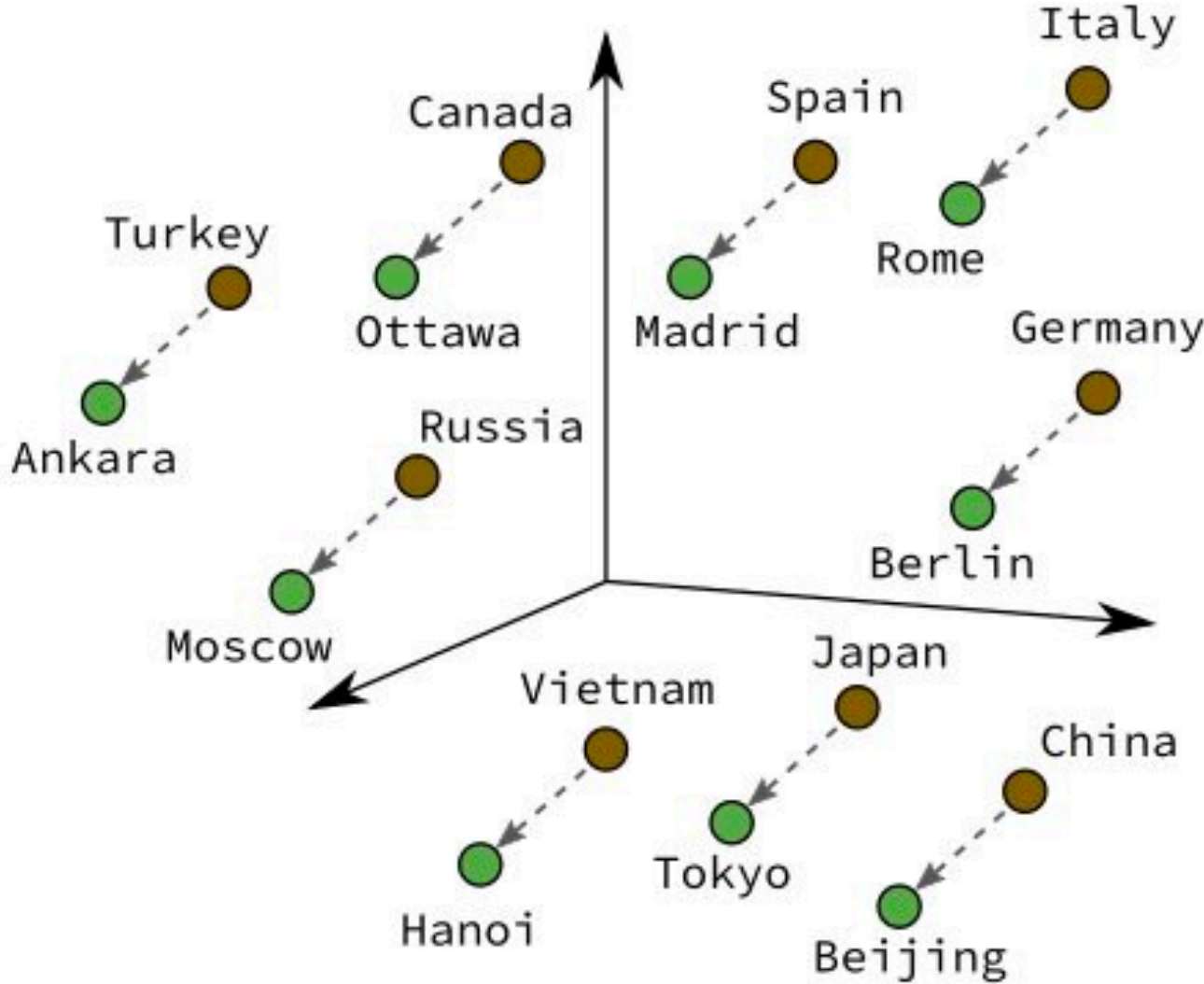
Part-of-speech tagging
(word class)



Male-Female

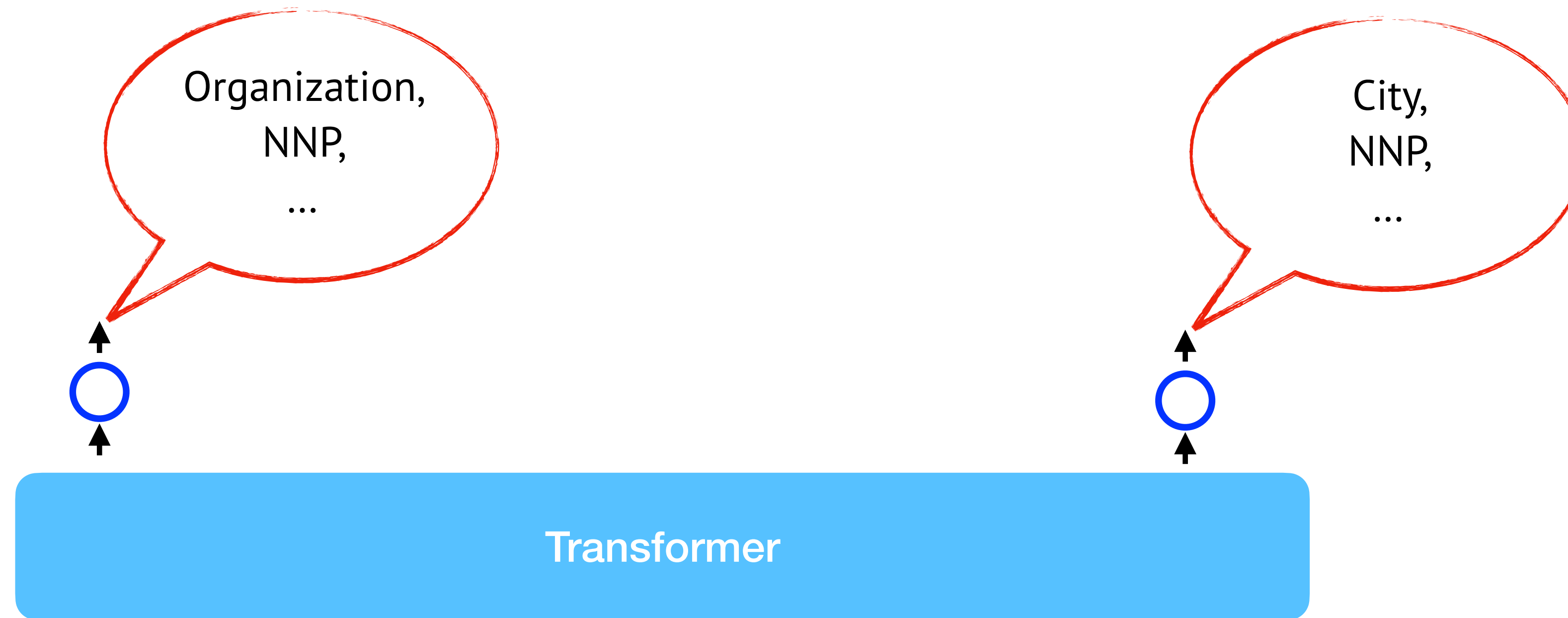


Verb Tense



Country-Capital

Linguistic Structures



HKU is a public research university in Hong Kong.