

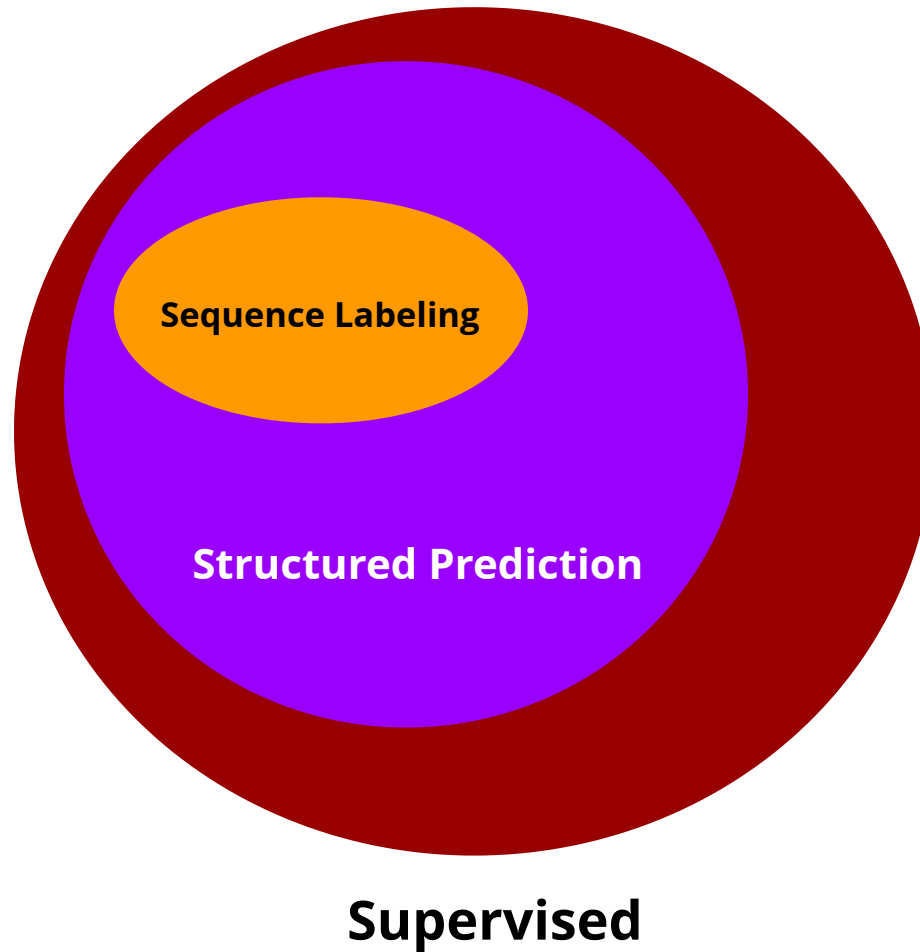
50.040

Natural Language Processing

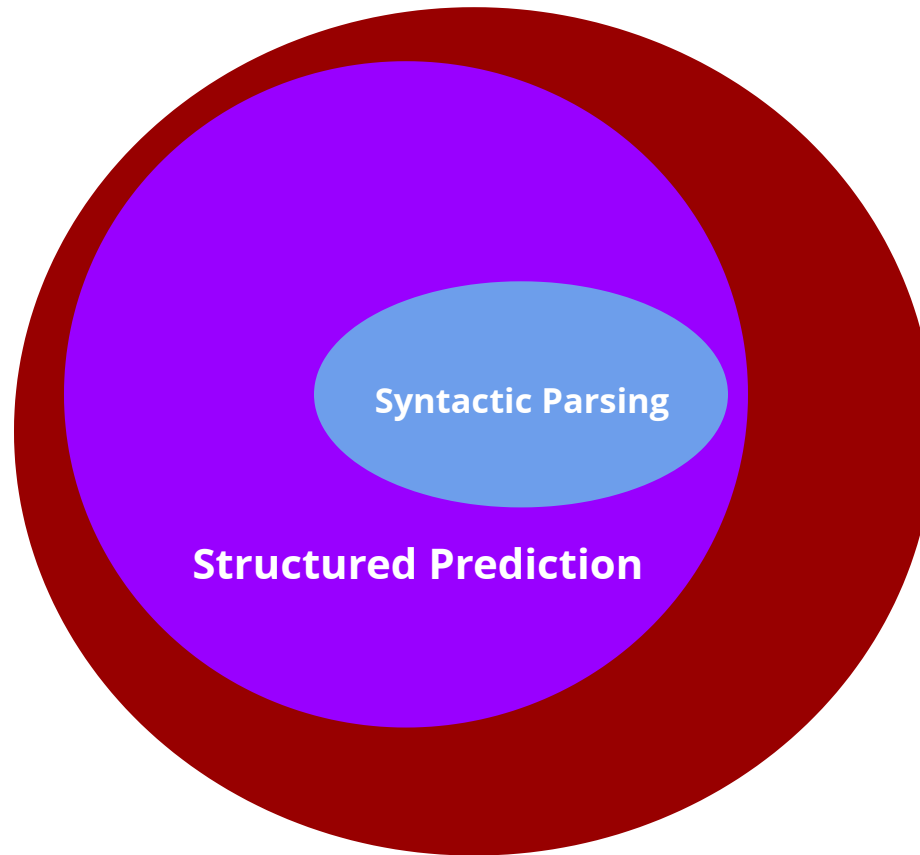
Lu, Wei



Tasks in NLP

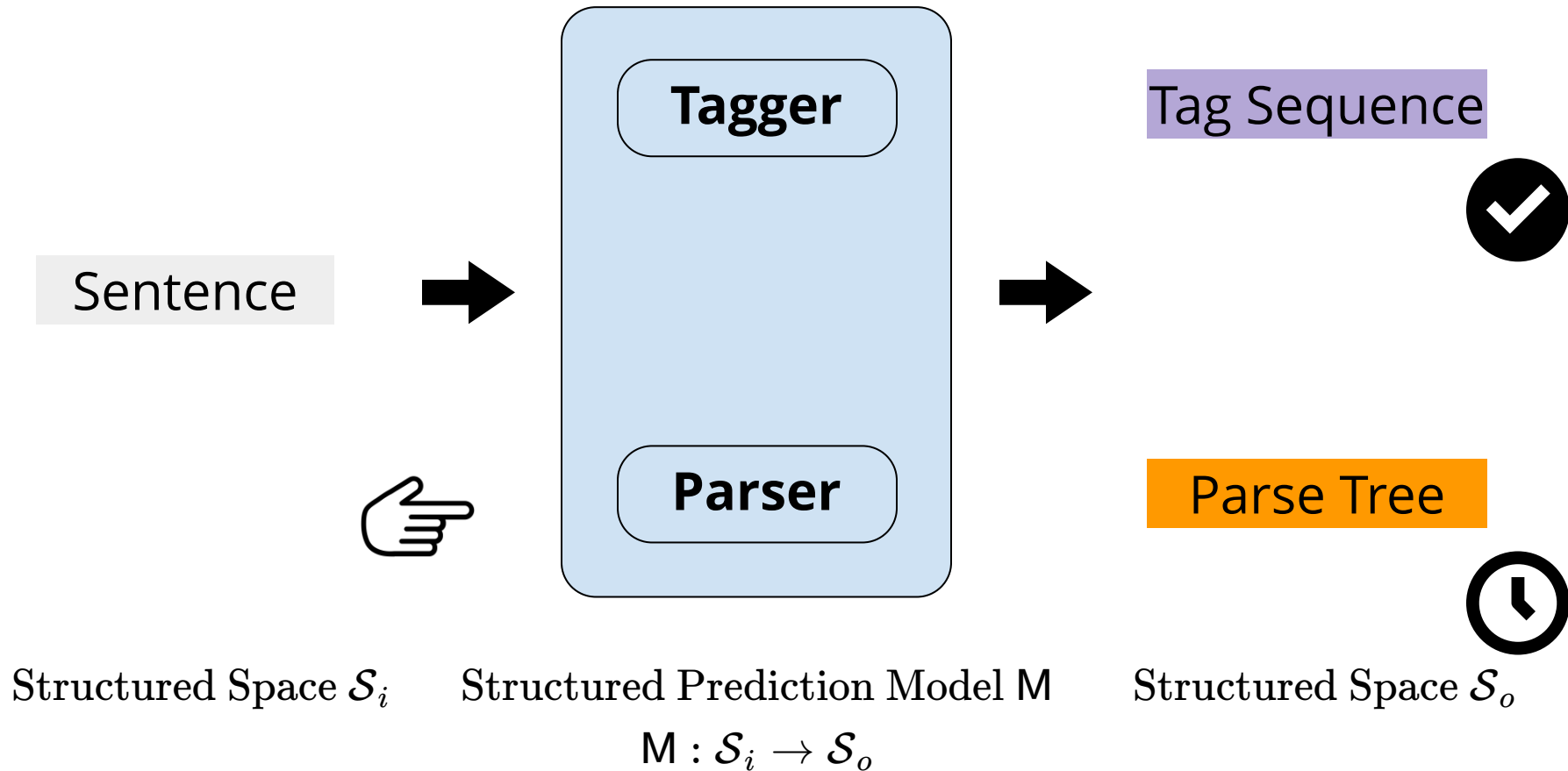


Tasks in NLP



Supervised

Structured Prediction



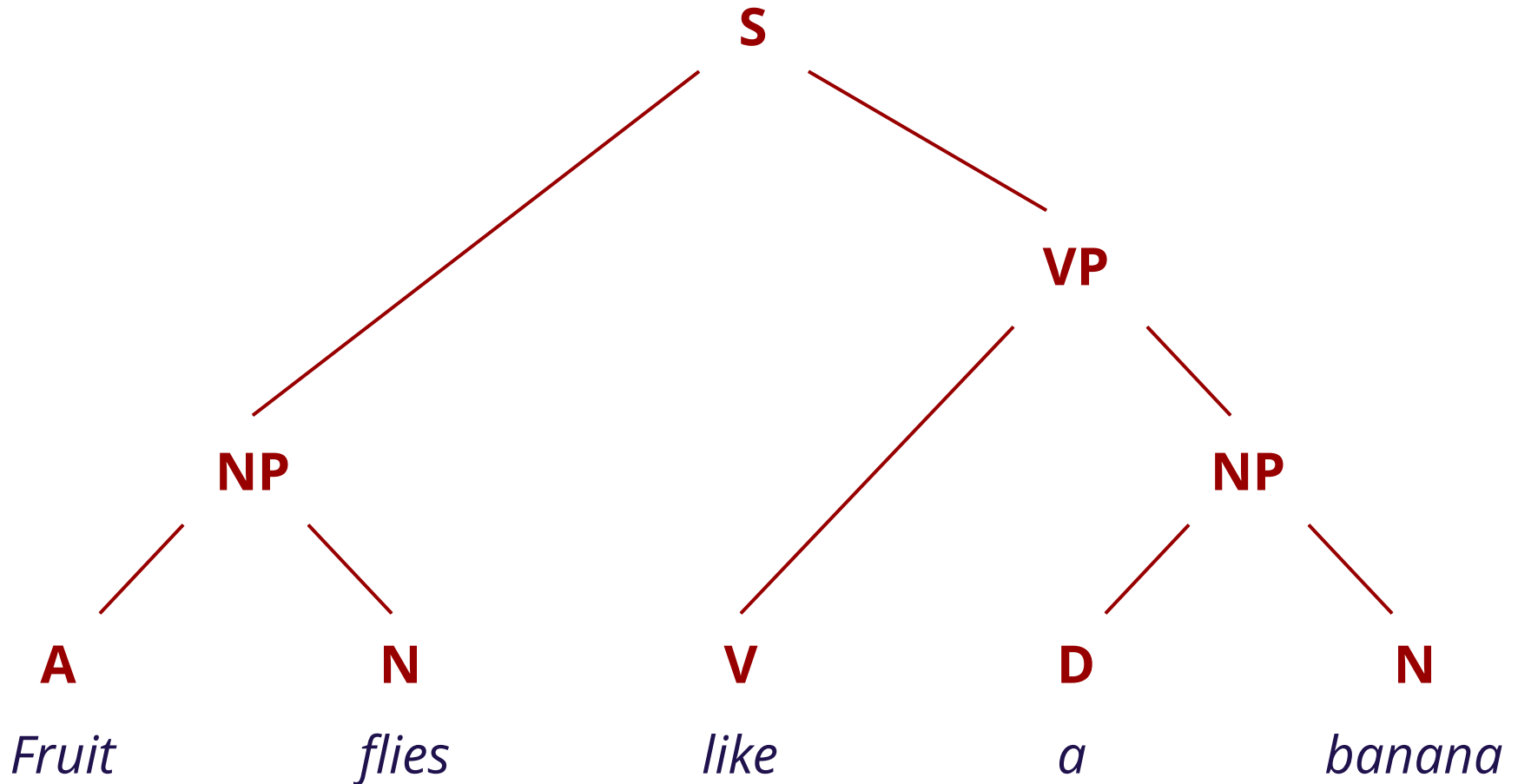
Syntactic Parsing

The task of mapping a sentence into its syntactic structure (usually in the form of a tree or a graph).



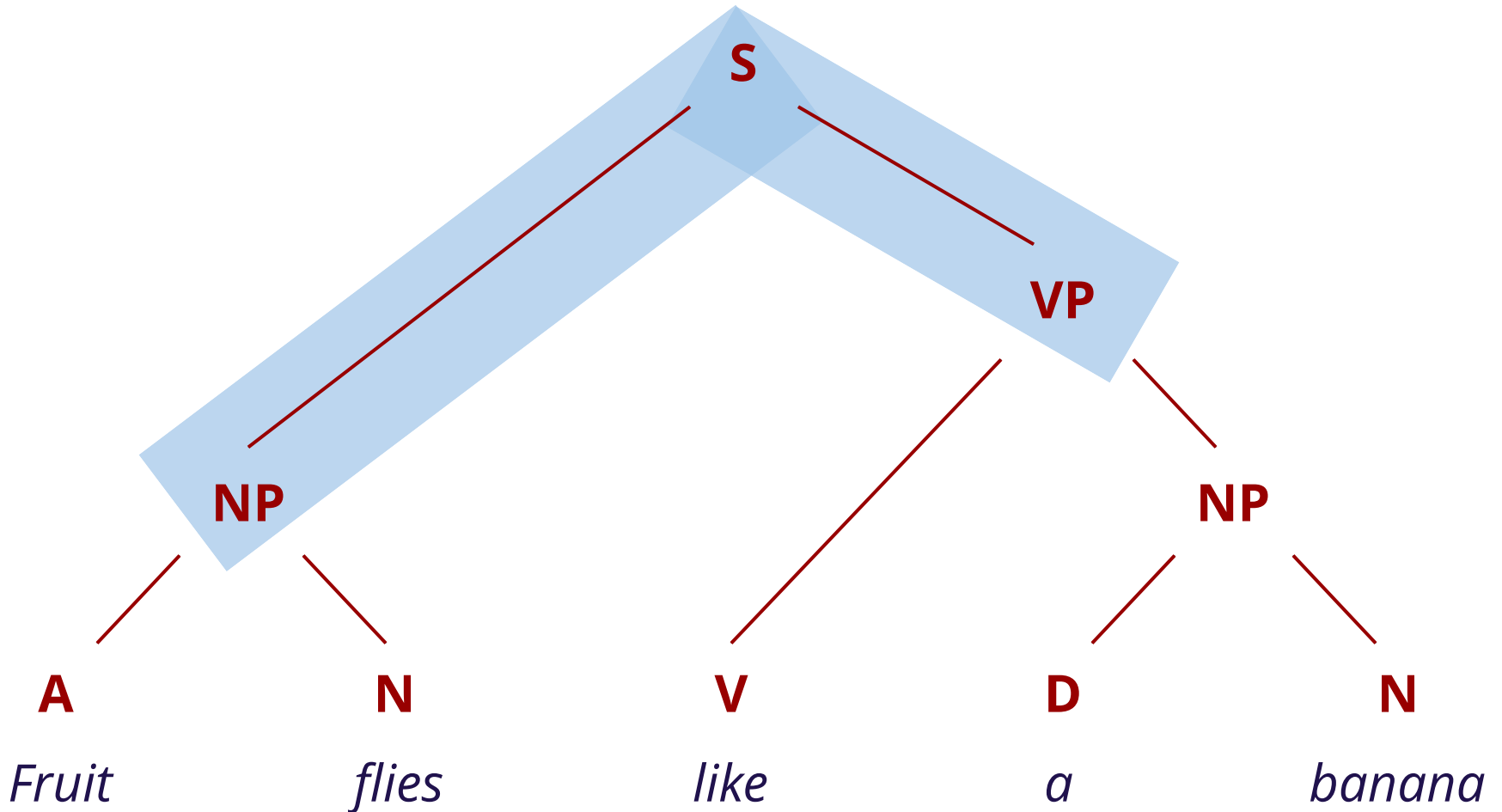
In this course

Constituency Parsing



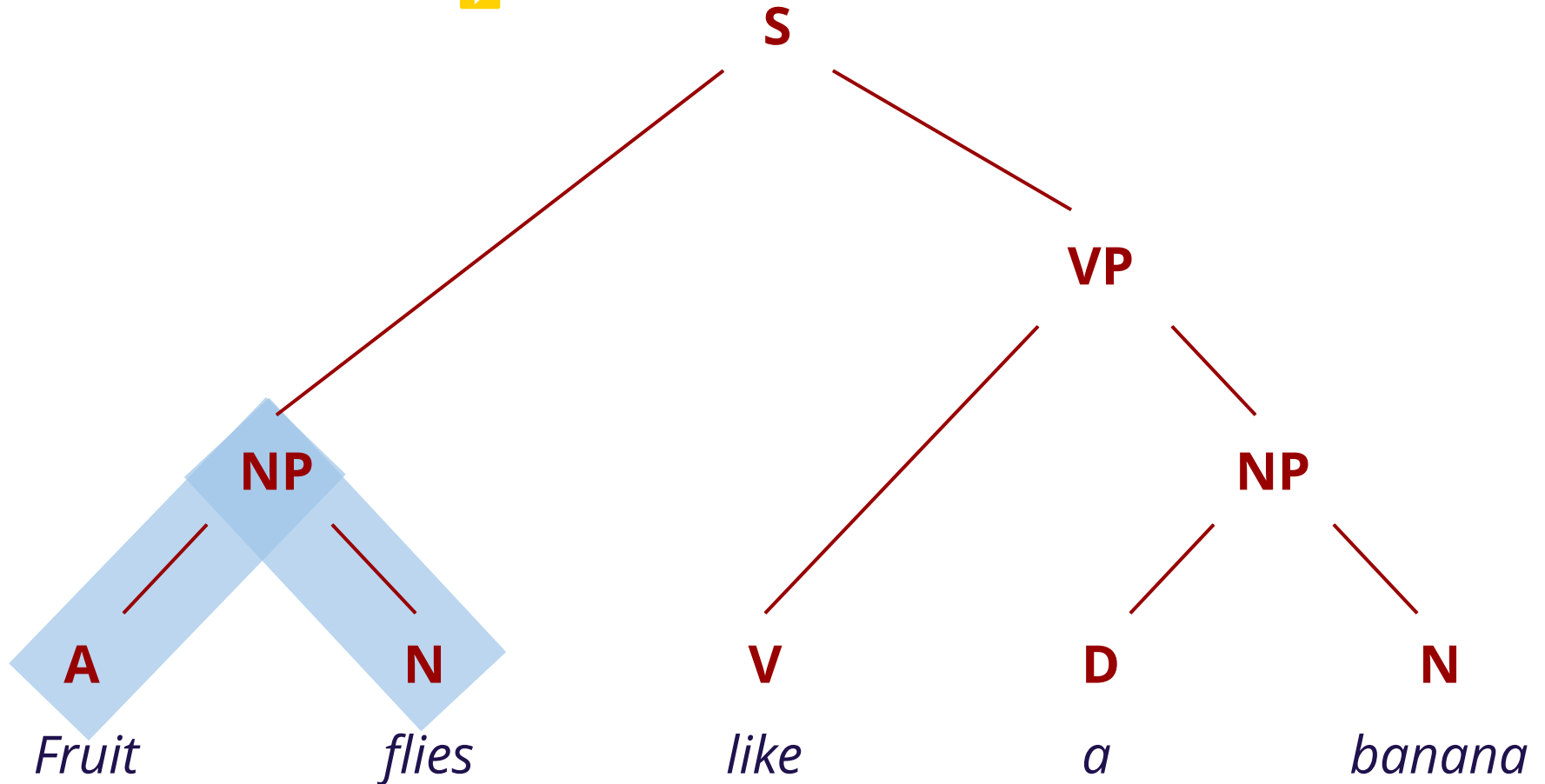
Grammar

S  **NP VP**
→



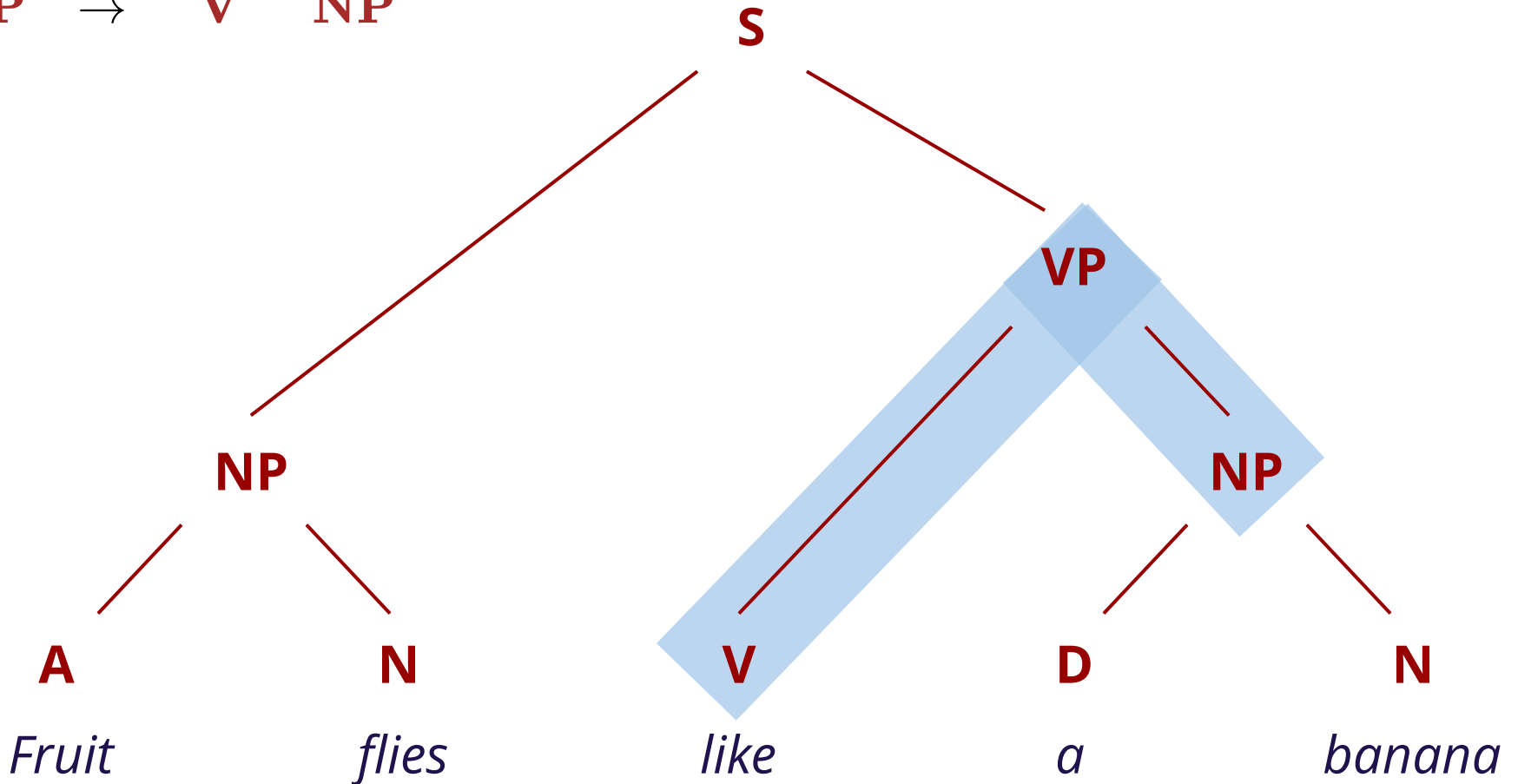
Grammar

S → **NP** **VP**
NP → **A** **N**



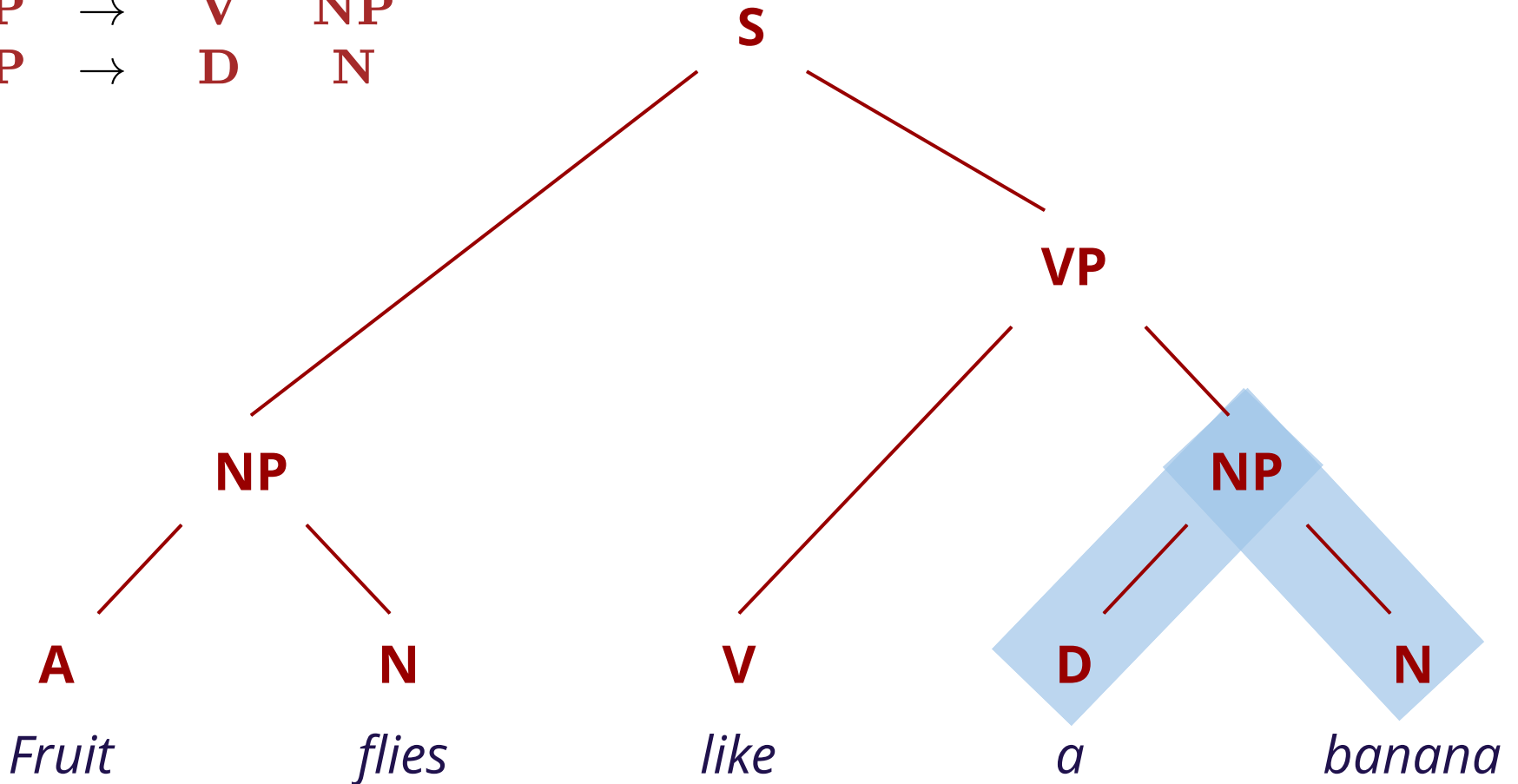
Grammar

S → **NP** **VP**
NP → **A** **N**
VP → **V** **NP**



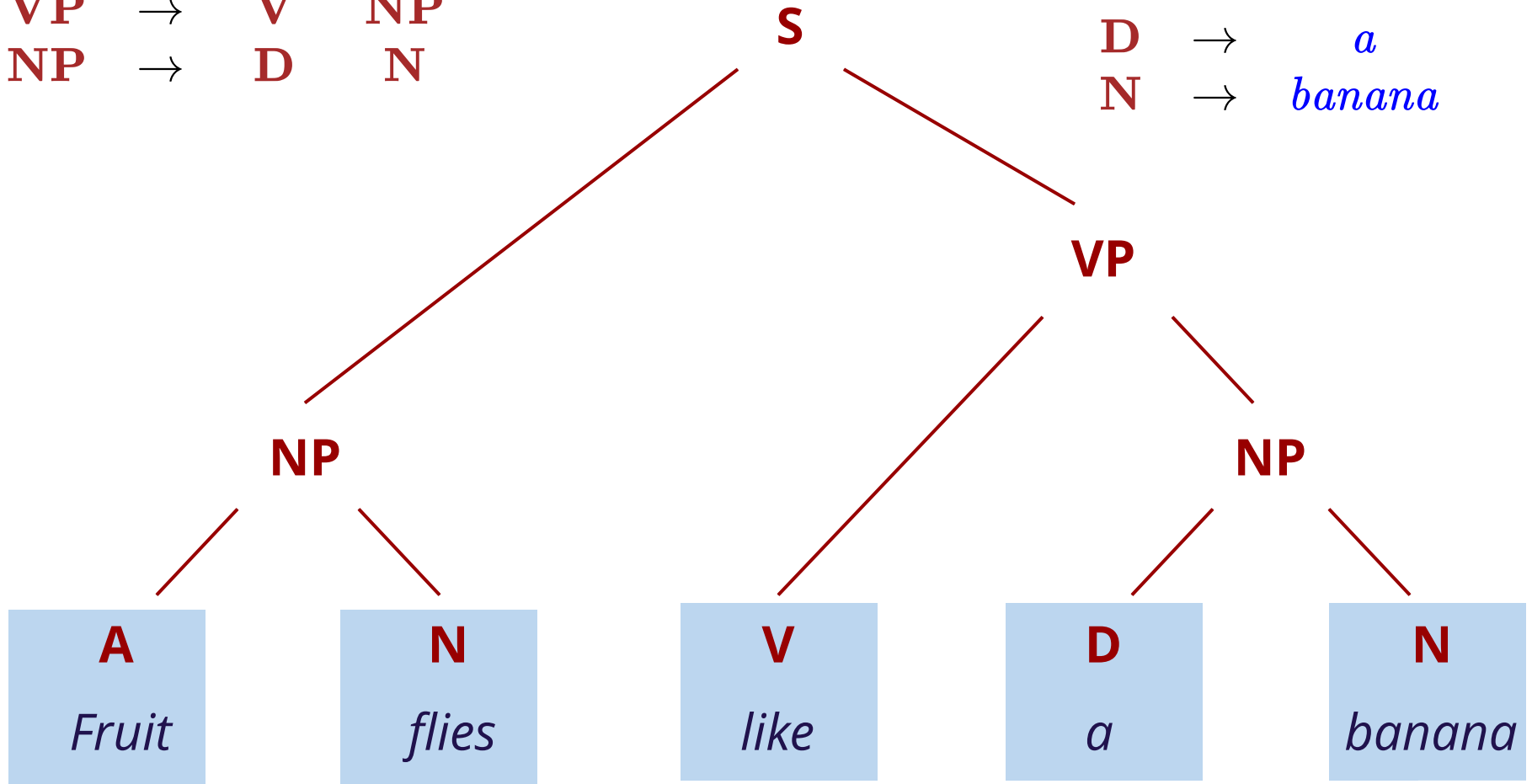
Grammar

S → **NP** **VP**
NP → **A** **N**
VP → **V** **NP**
NP → **D** **N**

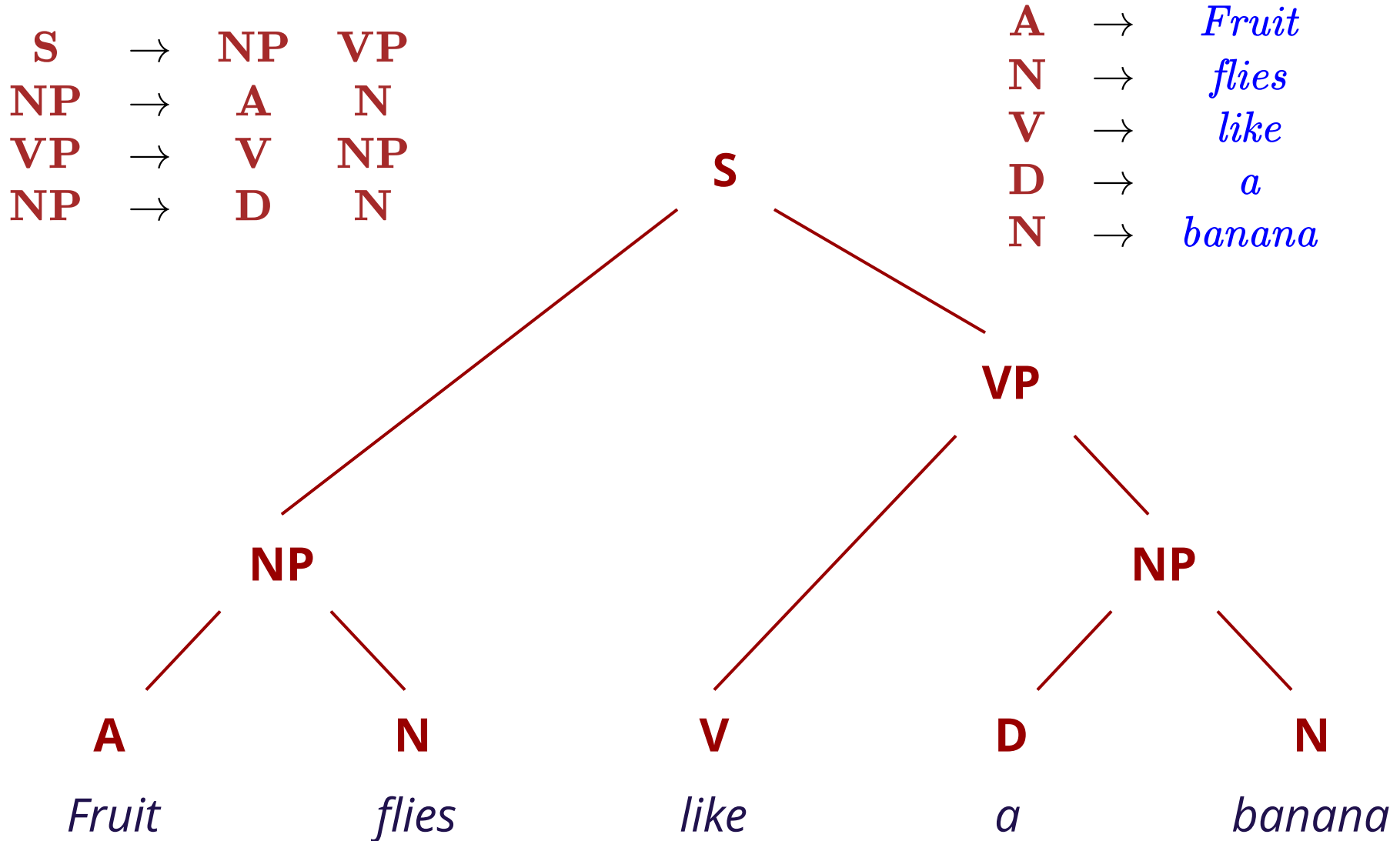


Grammar

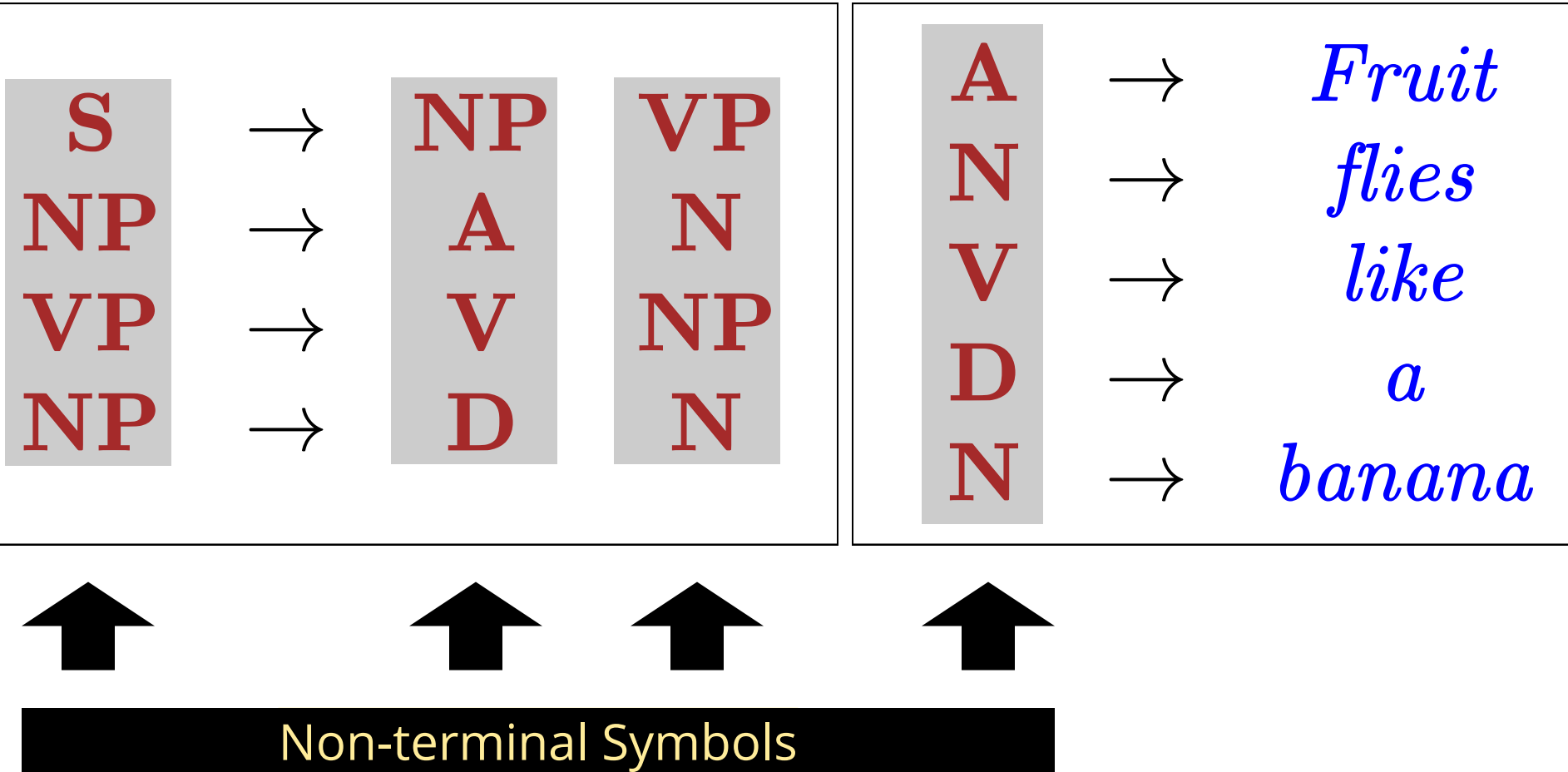
S	→	NP	VP	A	→	<i>Fruit</i>
NP	→	A	N	N	→	<i>flies</i>
VP	→	V	NP	V	→	<i>like</i>
NP	→	D	N	D	→	<i>a</i>
				N	→	<i>banana</i>



Context Free Grammar



Context Free Grammar



Context Free Grammar

S	→	NP	VP
NP	→	A	N
VP	→	V	NP
NP	→	D	N

A	→	<i>Fruit</i>
N	→	<i>flies</i>
V	→	<i>like</i>
D	→	<i>a</i>
N	→	<i>banana</i>

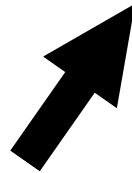


Terminal Symbols

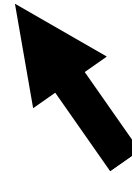
Context Free Grammar

Grammar with rules of the form

$A \rightarrow \text{exp}$

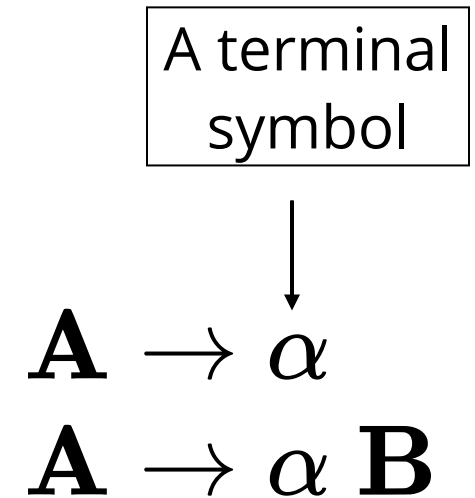
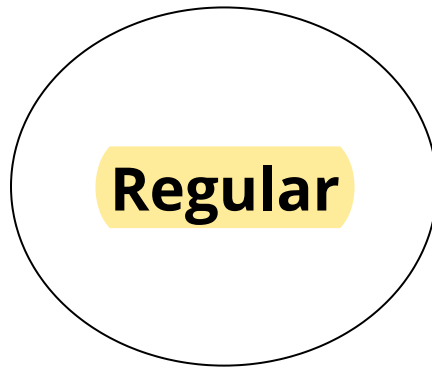


A non-terminal
symbol

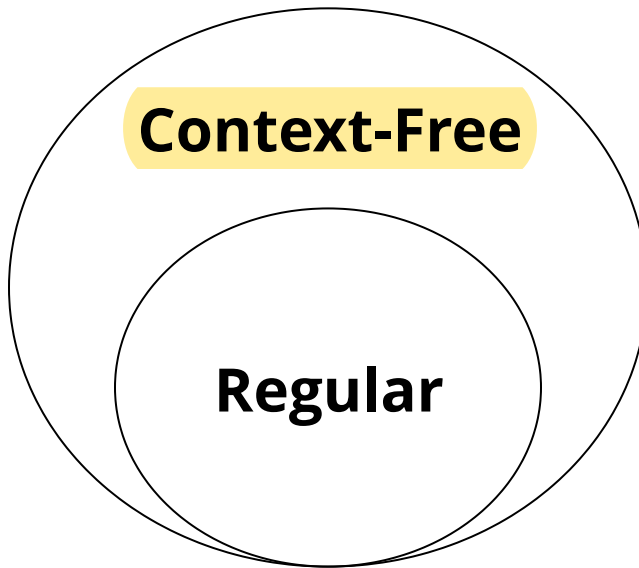


A list of non-terminal
and terminal symbols

Languages



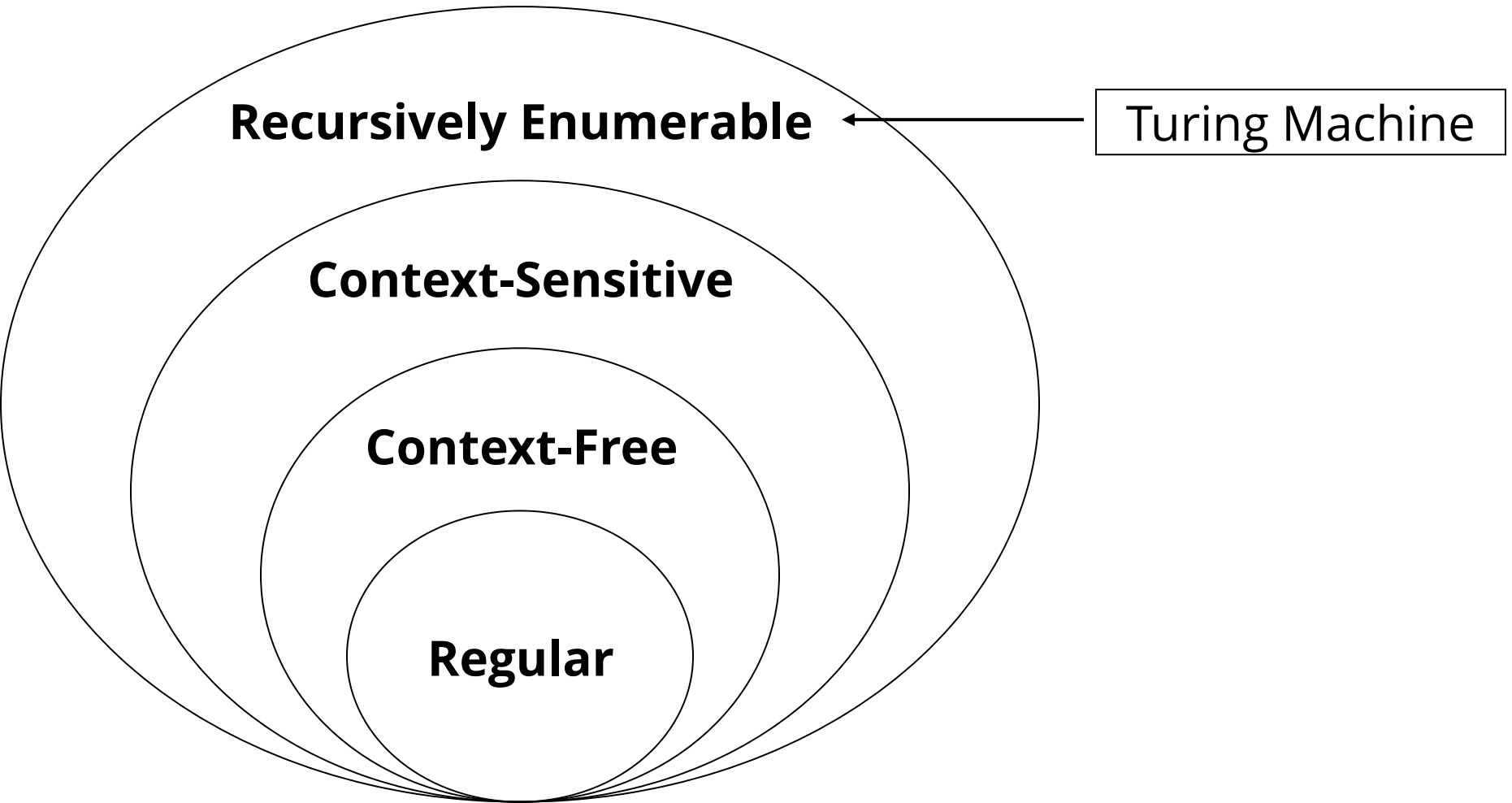
Languages



A list of non-terminal
and terminal symbols

$\mathbf{A} \rightarrow \mathbf{exp}$

Languages



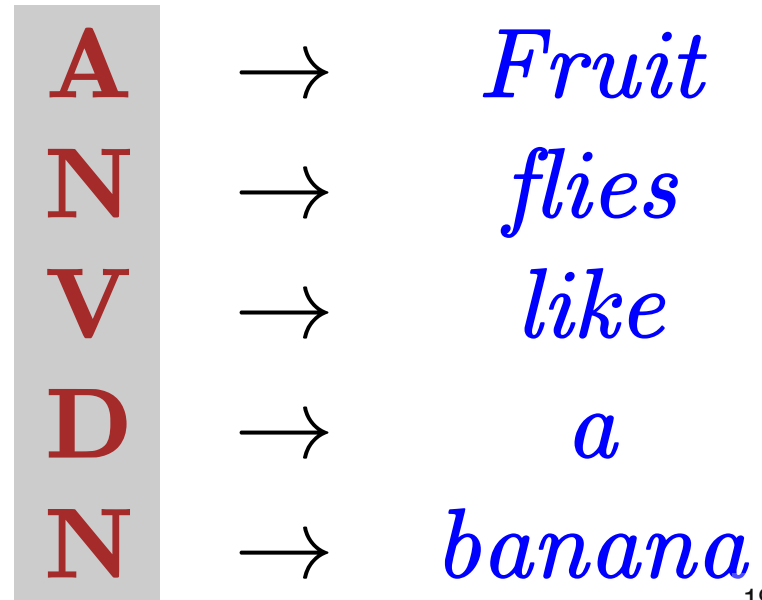
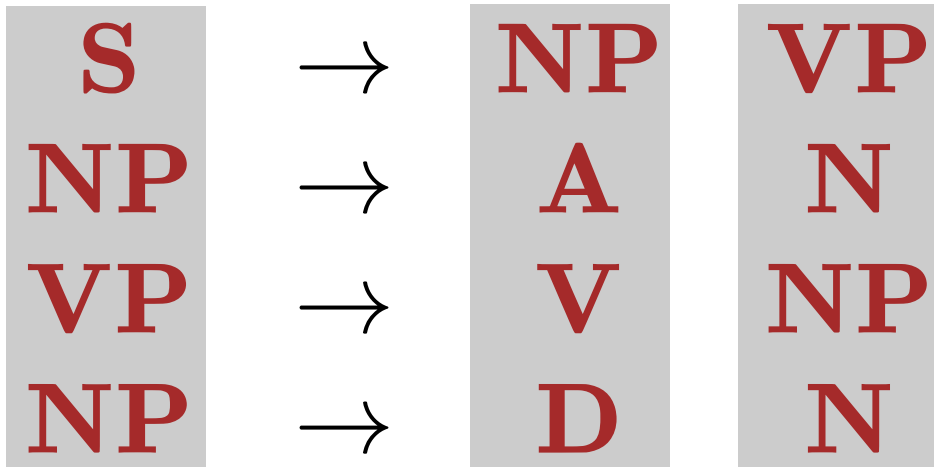
Chomsky Normal Form

A CFG is said to be in Chomsky normal form (CNF) if all its production rules are of either of the following forms:

$A \rightarrow BC$

$A \rightarrow \alpha$

Some textbooks also consider epsilon rules



Chomsky Normal Form

A CFG is said to be in Chomsky normal form (CNF) if all its production rules are of either of the following forms:

$$A \rightarrow BC$$
$$A \rightarrow \alpha$$

Parsing with a CFG in CNF will be convenient.

S
NP
VP
NP

→
→
→
→

NP
A
V
D

VP
N
NP
N

A
N
V
D
N

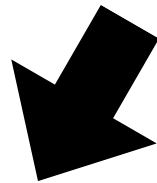
→
→
→
→
→

Fruit
flies
like
a
banana

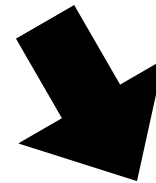
Parsing with CFG



The boy saw the man with the telescope

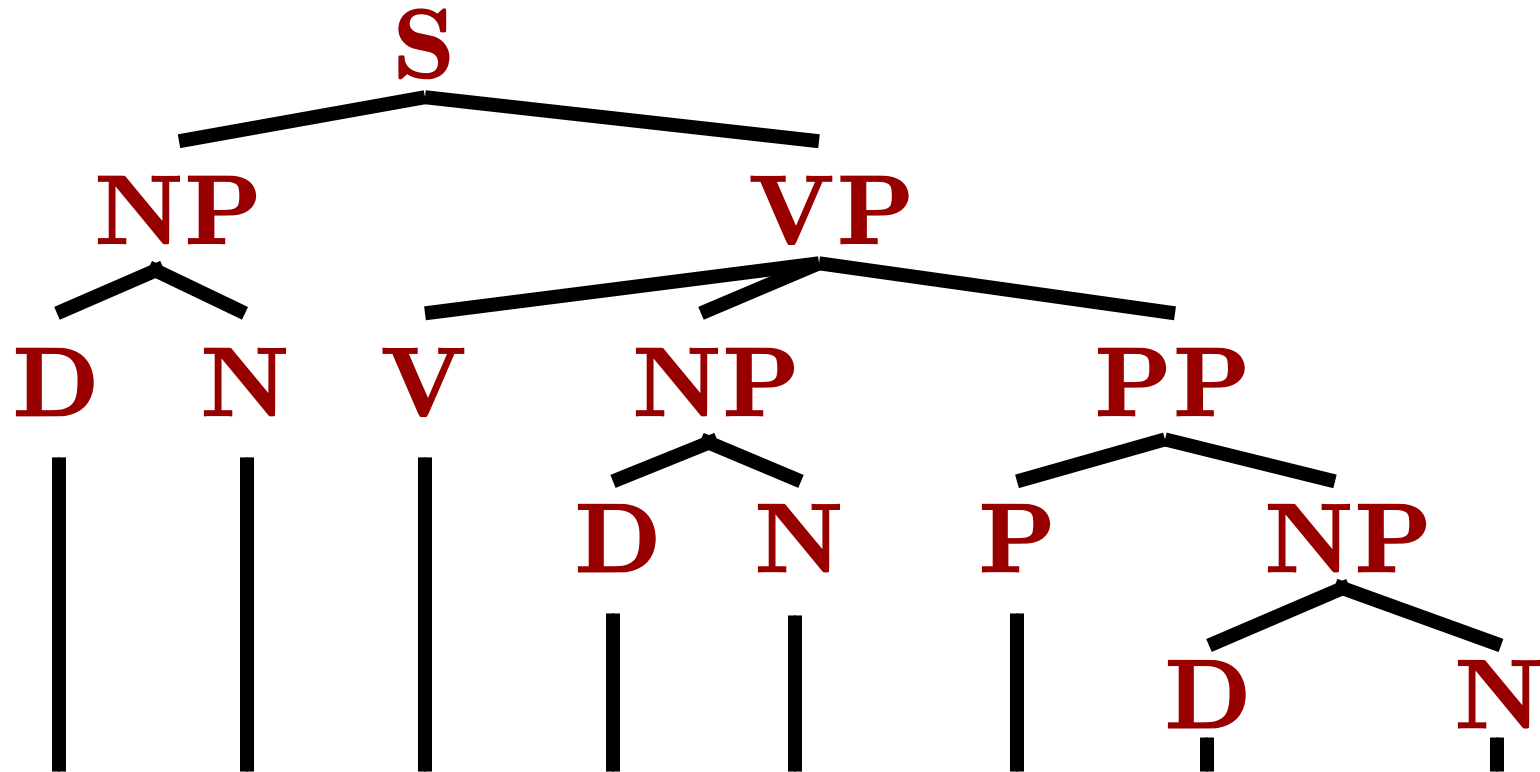


Using the telescope, the
boy saw the man



The boy saw the man.
The man had a telescope

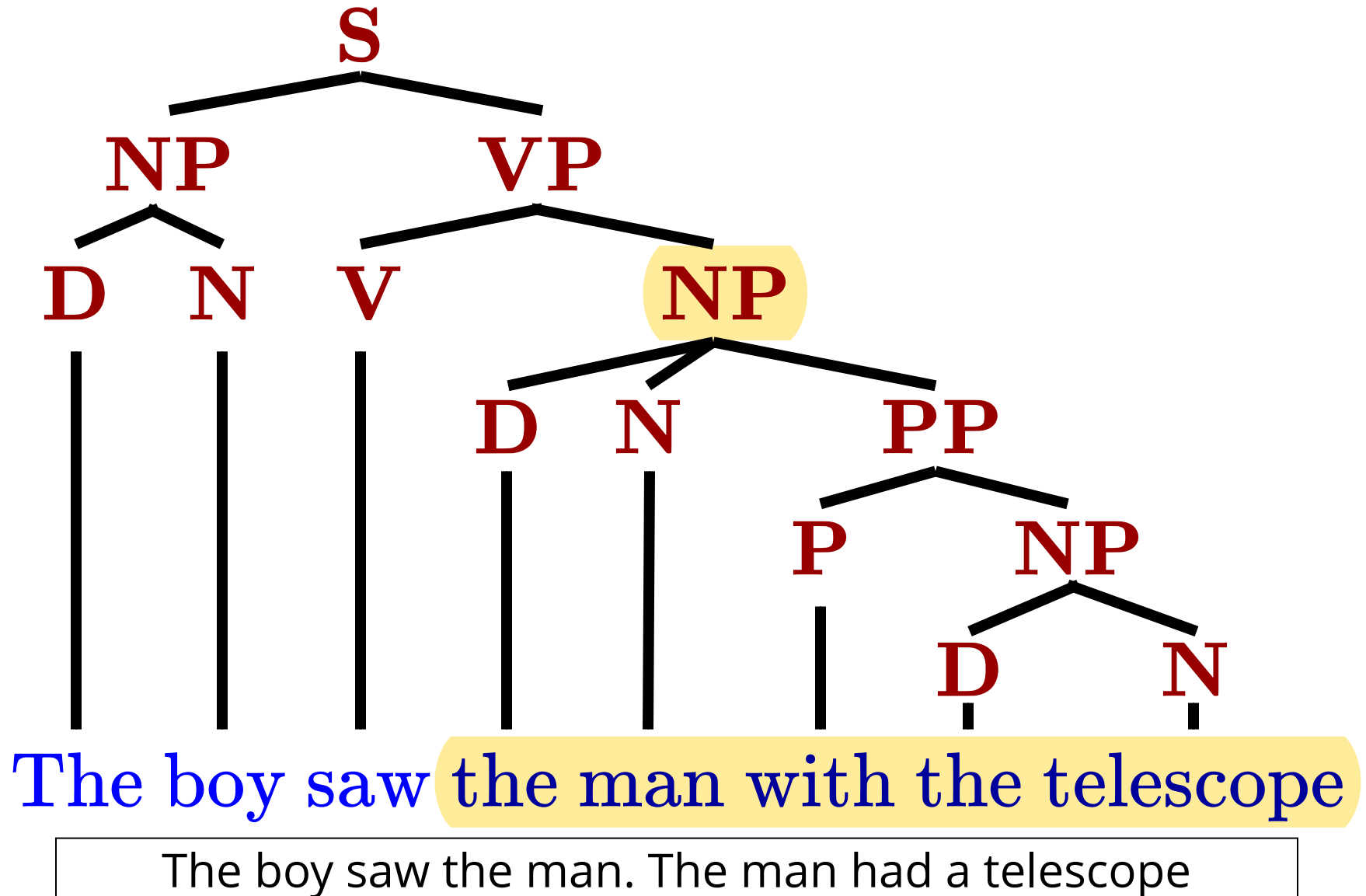
Parsing with CFG



The boy saw the man with the telescope

Using the telescope, the boy saw the man

Parsing with CFG

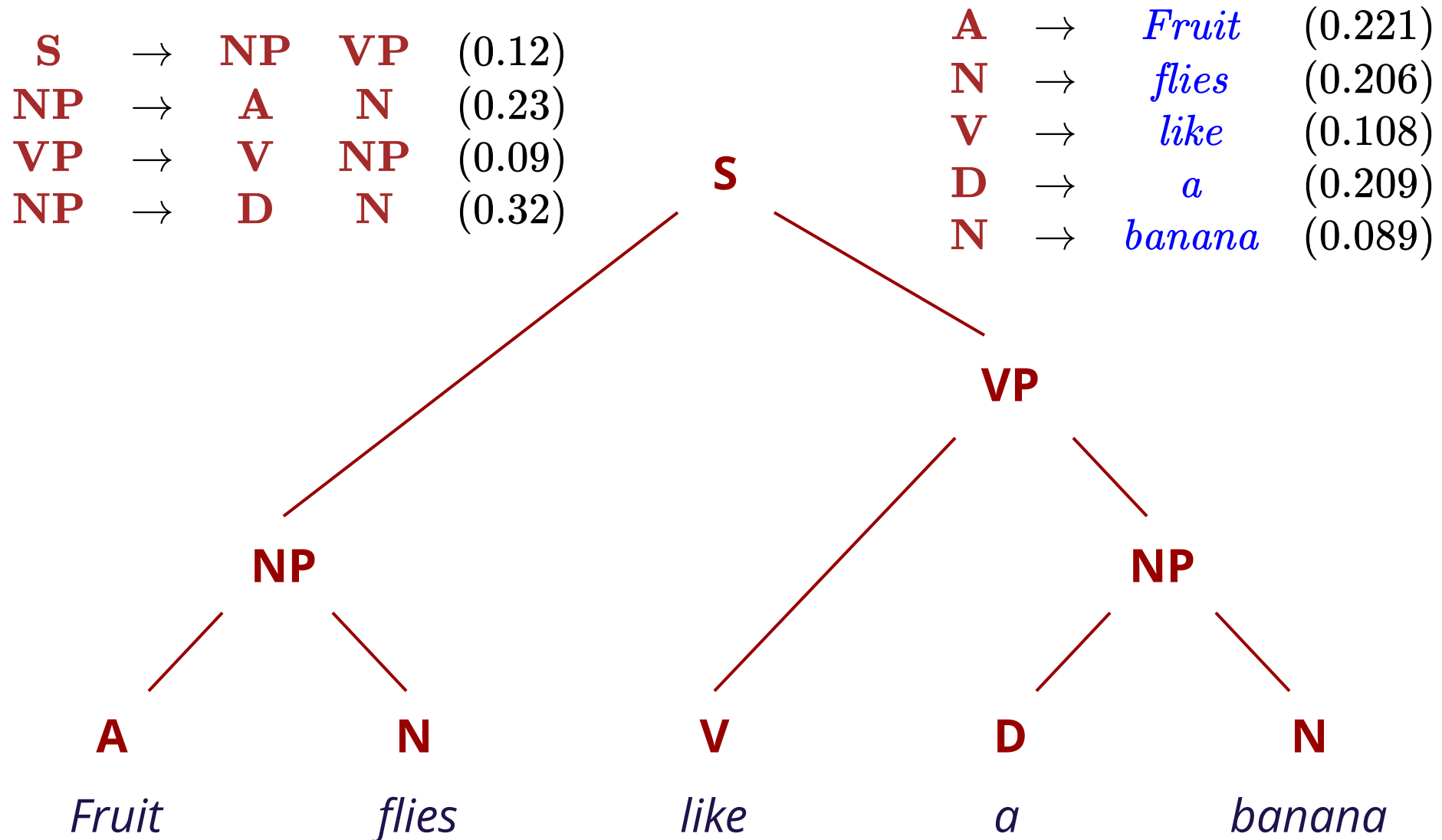


Question

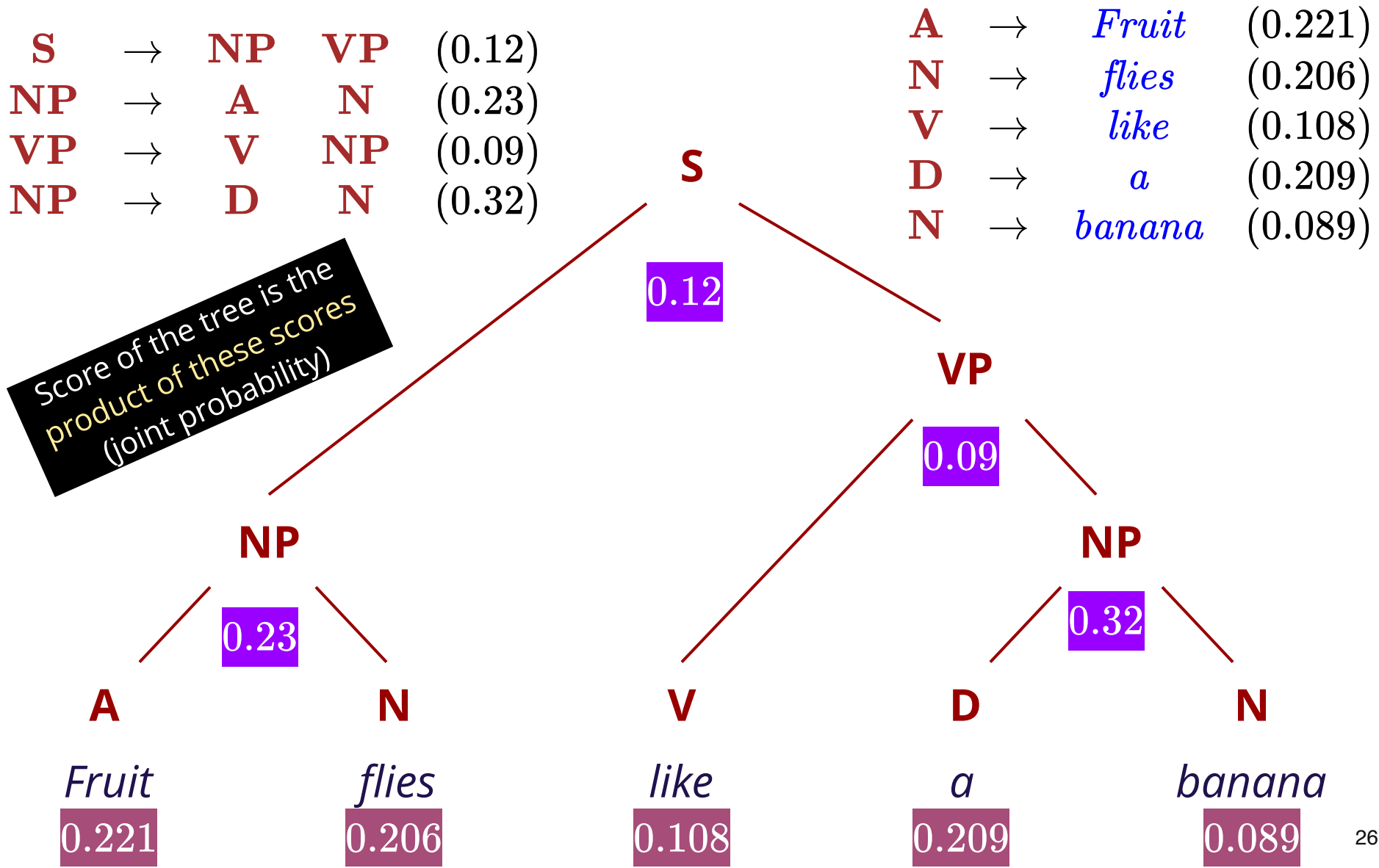
How to know which parse
is better?

We need to assign scores to such trees.

Probabilistic CFG



Probabilistic CFG



PCFG Learning

Where do we get the scores for the rules?

Given	Find
A collection of sentences annotated with their parse trees.	The probability for each rule that appears in these parse trees.



How do we learn such probabilities?

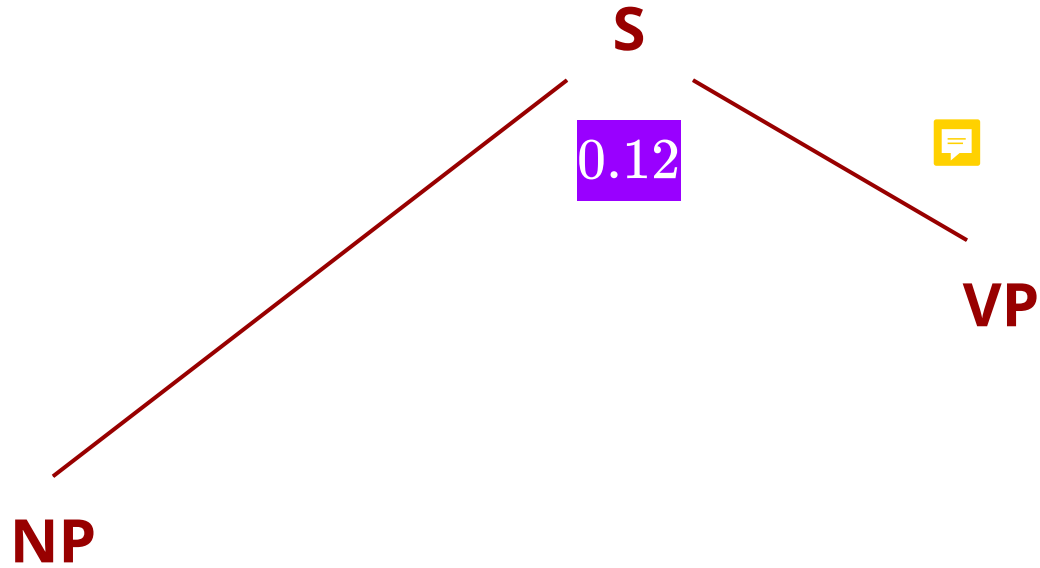
How is each tree generated?

Generative Model



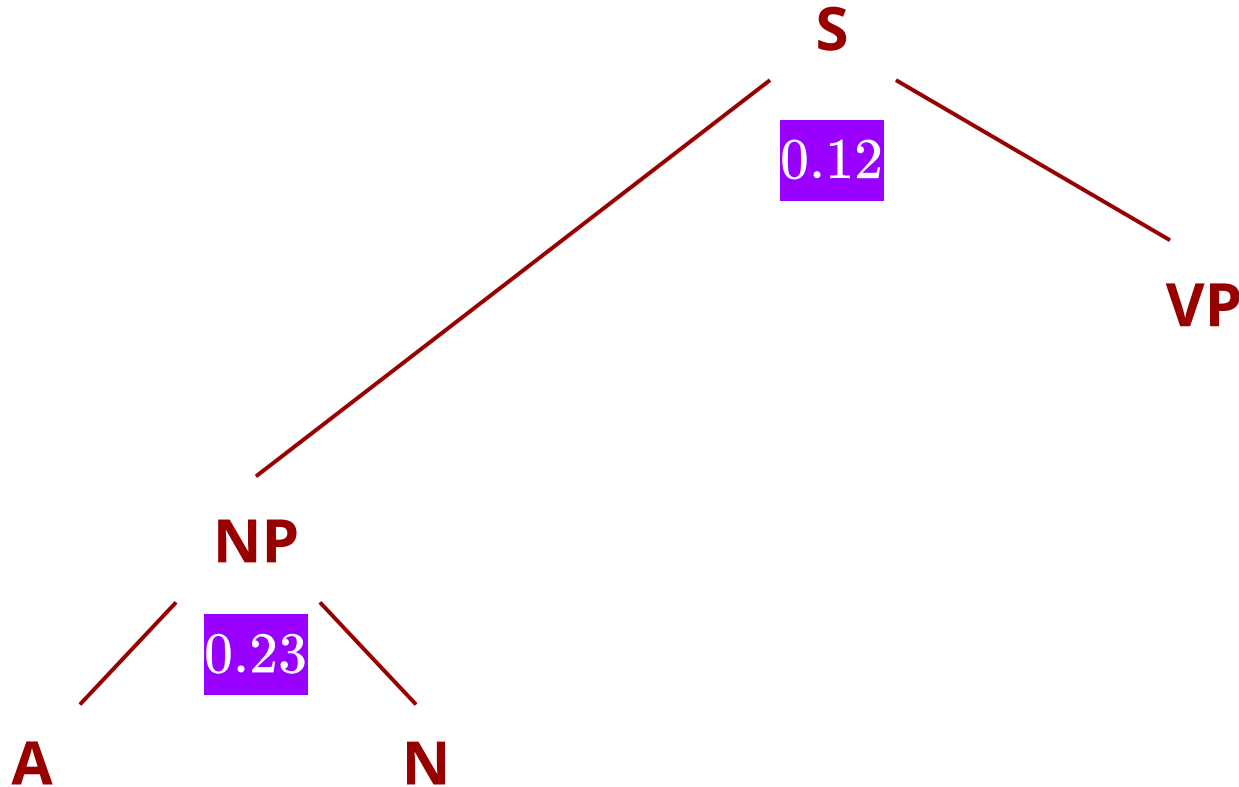
$$p(\textit{tree}) = \dots$$

Generative Model



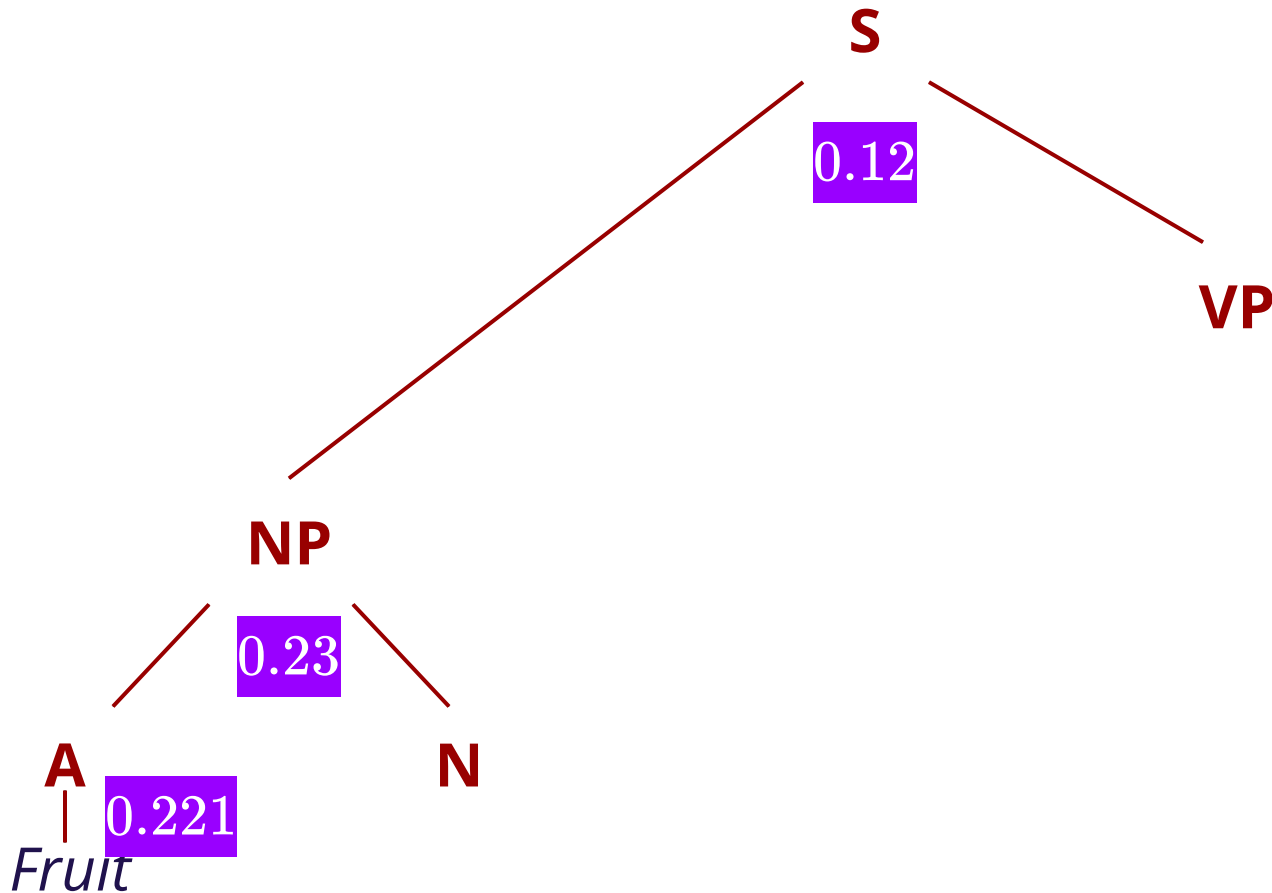
$$p(\text{tree}) = 0.12 \times \dots$$

Generative Model



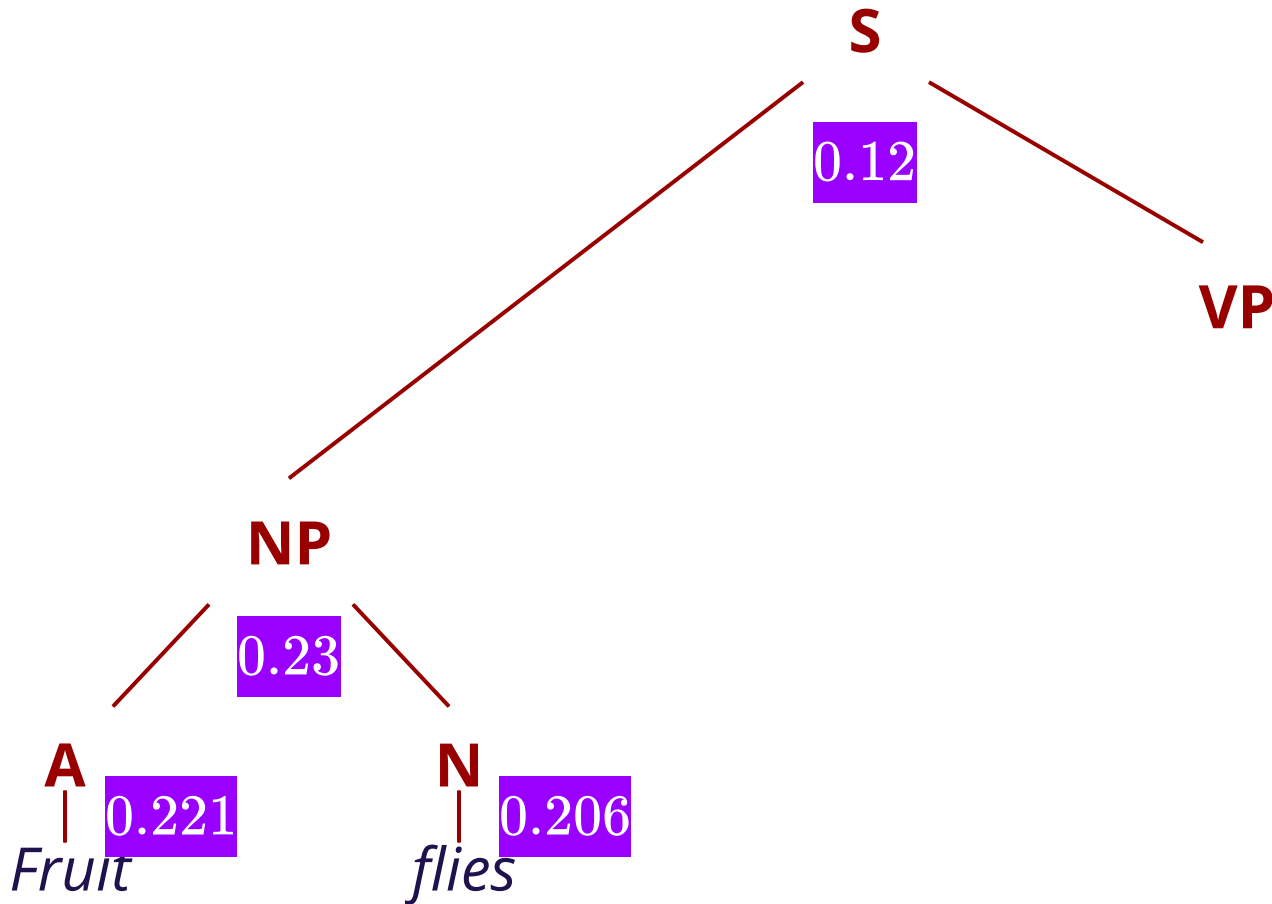
$$p(\text{tree}) = 0.12 \times 0.23 \times \dots$$

Generative Model



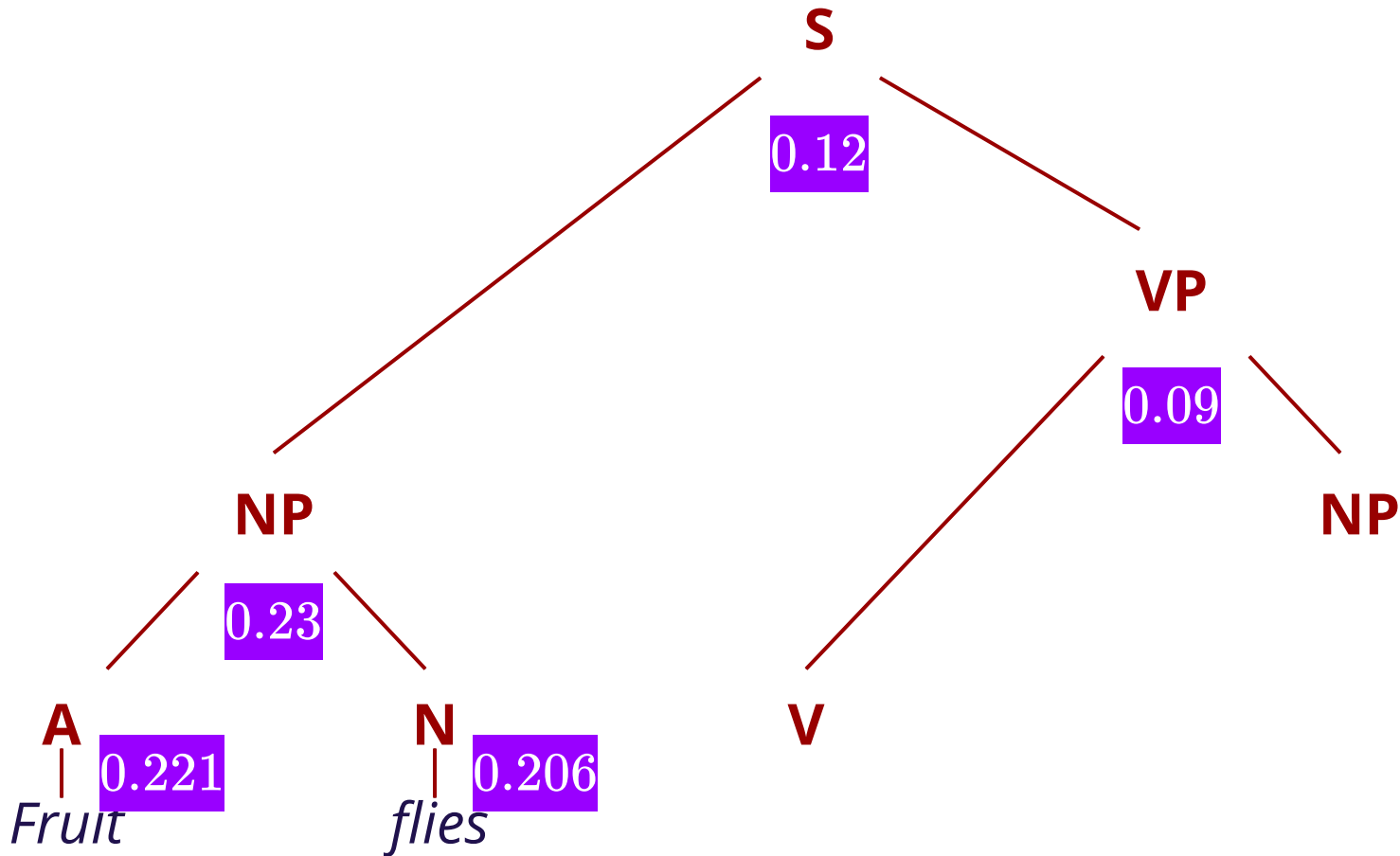
$$p(\text{tree}) = 0.12 \times 0.23 \times 0.221 \times \dots$$

Generative Model



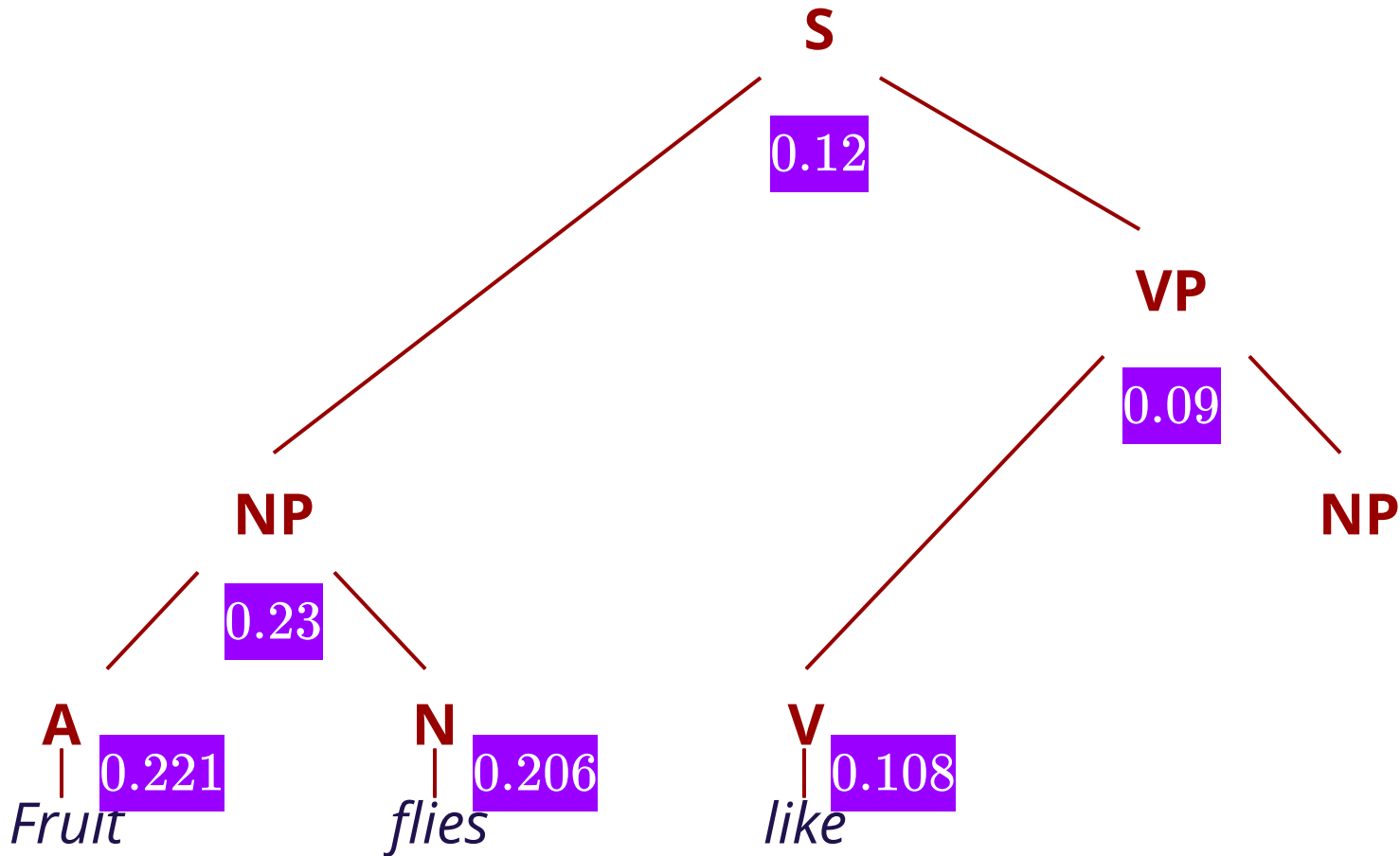
$$p(\text{tree}) = 0.12 \times 0.23 \times 0.221 \times 0.206 \times \dots$$

Generative Model



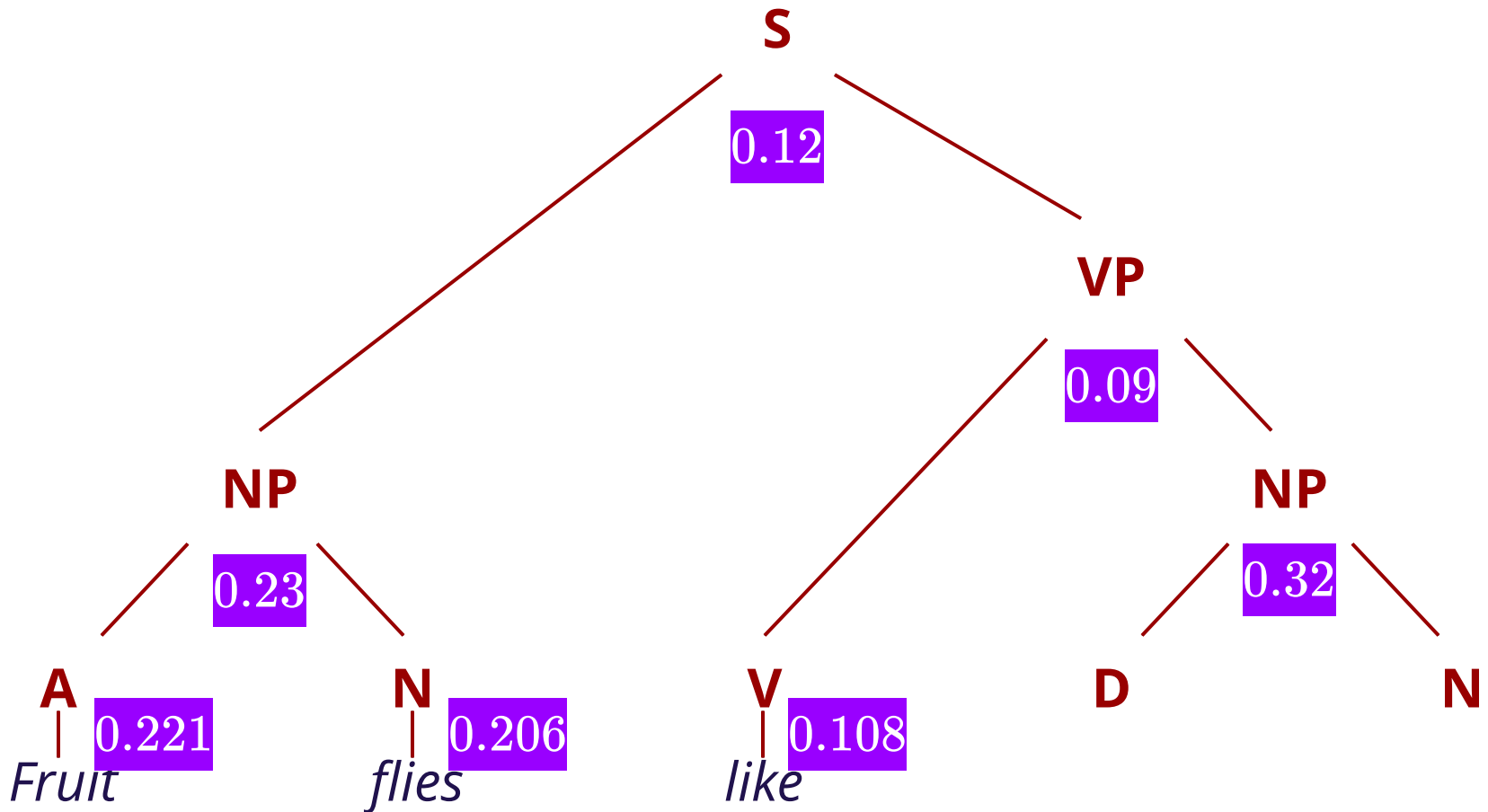
$$p(\text{tree}) = 0.12 \times 0.23 \times 0.221 \times 0.206 \times 0.09 \times \dots$$

Generative Model



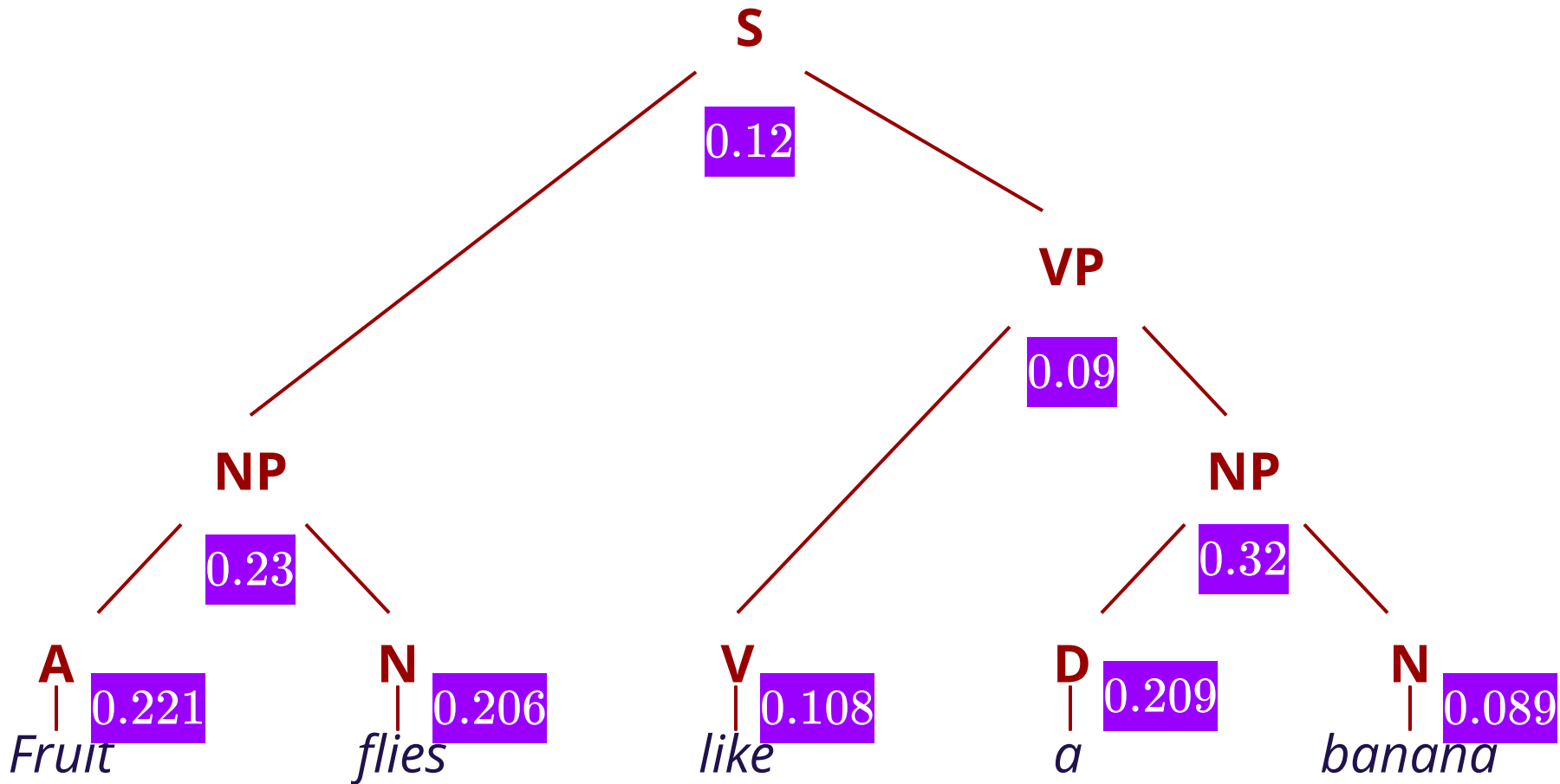
$$p(\text{tree}) = 0.12 \times 0.23 \times 0.221 \times 0.206 \times 0.09 \times 0.108 \times \dots$$

Generative Model



$$p(\text{tree}) = 0.12 \times 0.23 \times 0.221 \times 0.206 \times 0.09 \times 0.108 \times 0.32 \times \dots$$

Generative Model

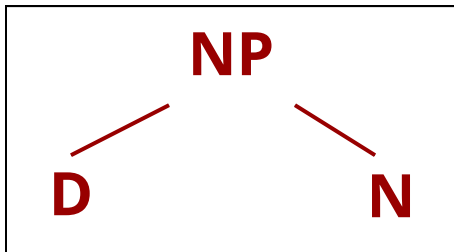


$$p(\text{tree}) = 0.12 \times 0.23 \times 0.221 \times 0.206 \times 0.09 \times 0.108 \times 0.32 \times 0.209 \times 0.089$$

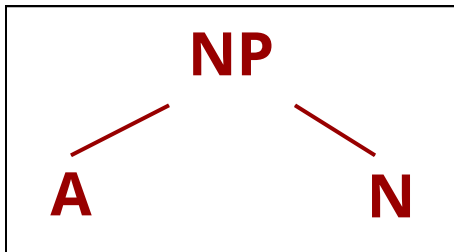
Question

How to learn the probability for each PCFG rule based on the generative process?

PCFG Learning



This rule appears 54 times in the training set



This rule appears 37 times in the training set



What is the probability for the rule **NP** \rightarrow **A N**?

$$\frac{37}{37+54}$$

PCFG Learning

Maximum Likelihood
Estimator!!

The number of times we see the rule
 $\mathbf{A} \rightarrow \mathbf{exp}$ in the training set.



$$p(\mathbf{A} \rightarrow \mathbf{exp}) = \frac{\text{count}(\mathbf{A} \rightarrow \mathbf{exp})}{\text{count}(\mathbf{A})}$$



The number of times we see the
non-terminal \mathbf{A} in the training set.

PCFG Decoding

Given	Find
A probabilistic CFG and an input sentence.	The most probable parse tree for the given sentence.



Hmm... seems we need a procedure similar to Viterbi, but works for PCFG?

Cocke-Kasami-Younger (CKY) Algorithm

S	→	NP	VP	(0.12)
NP	→	A	N	(0.23)
VP	→	V	NP	(0.09)
NP	→	D	N	(0.32)

A	→	<i>Fruit</i>	(0.221)
N	→	<i>flies</i>	(0.206)
V	→	<i>like</i>	(0.108)
D	→	<i>a</i>	(0.209)
N	→	<i>banana</i>	(0.089)

Fruit

flies

like

a

banana



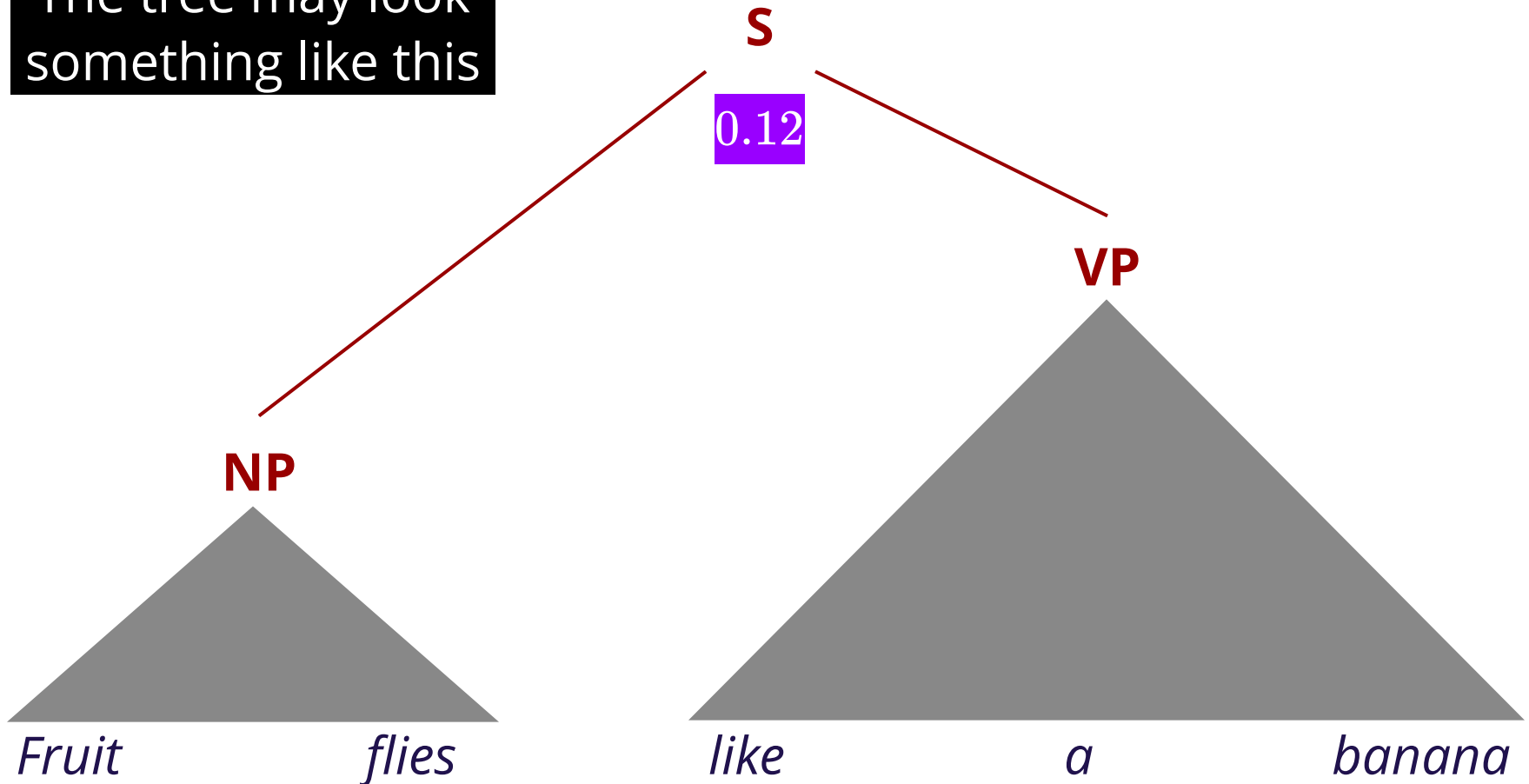
Parse Tree

CKY Algorithm

S \rightarrow **NP** **VP** (0.12)



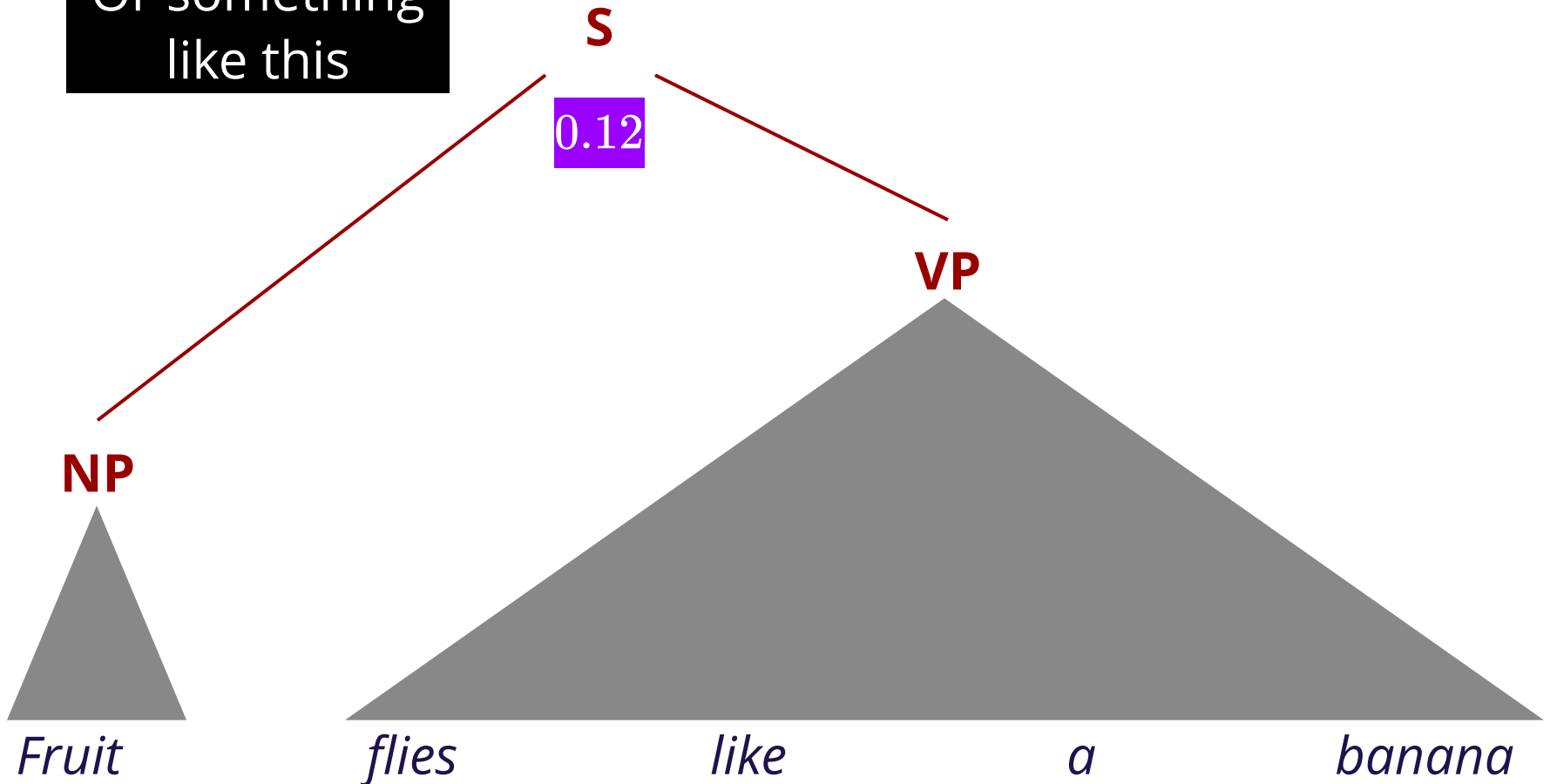
The tree may look something like this



CKY Algorithm

S \rightarrow **NP** **VP** (0.12)

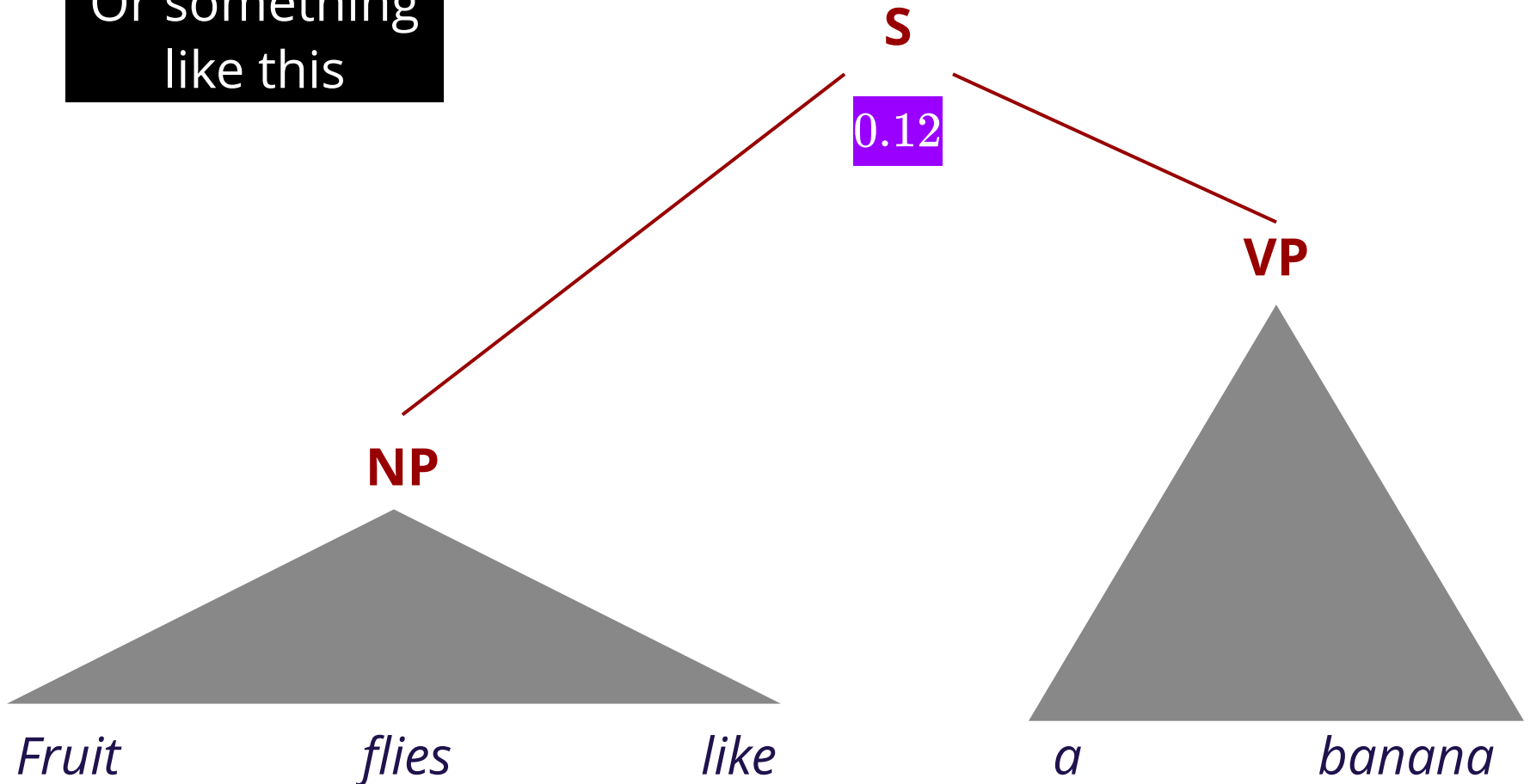
Or something
like this



CKY Algorithm

S \rightarrow **NP** **VP** (0.12)

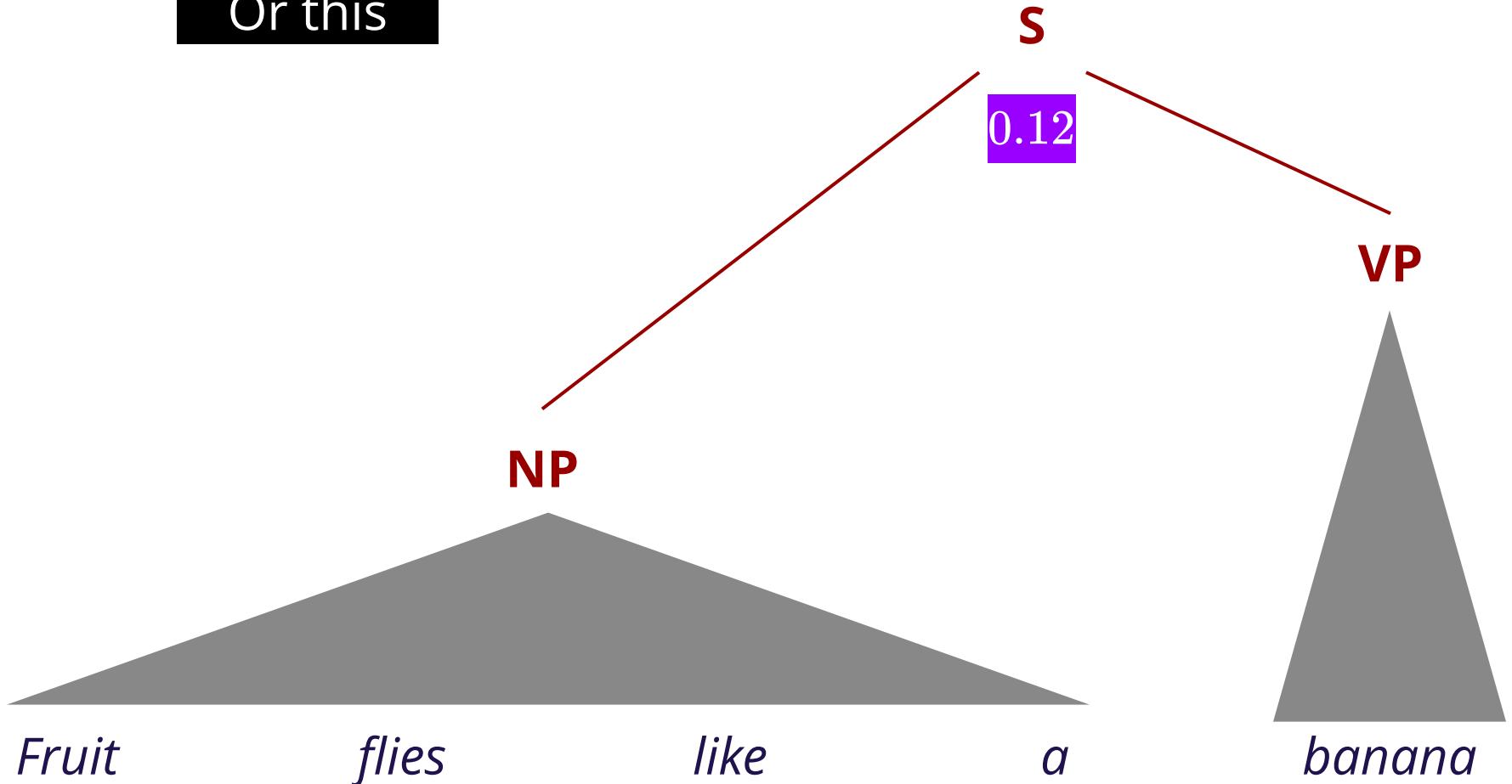
Or something
like this



CKY Algorithm

S \rightarrow **NP** **VP** (0.12)

Or this



CKY Algorithm

S \rightarrow **NP** **VP** (0.12)

Partition position: 1

$0.12 \times \text{bestScore}[0, 1, \text{NP}] \times \text{bestScore}[1, 5, \text{VP}]$

S

0.12

VP

NP

$\text{bestScore}[0, 1, \text{NP}]$

$\text{bestScore}[1, 5, \text{VP}]$

The score of the best subtree that covers the word span $[0, 1)$ with the root non-terminal **NP**.

Fruit

flies

like

a

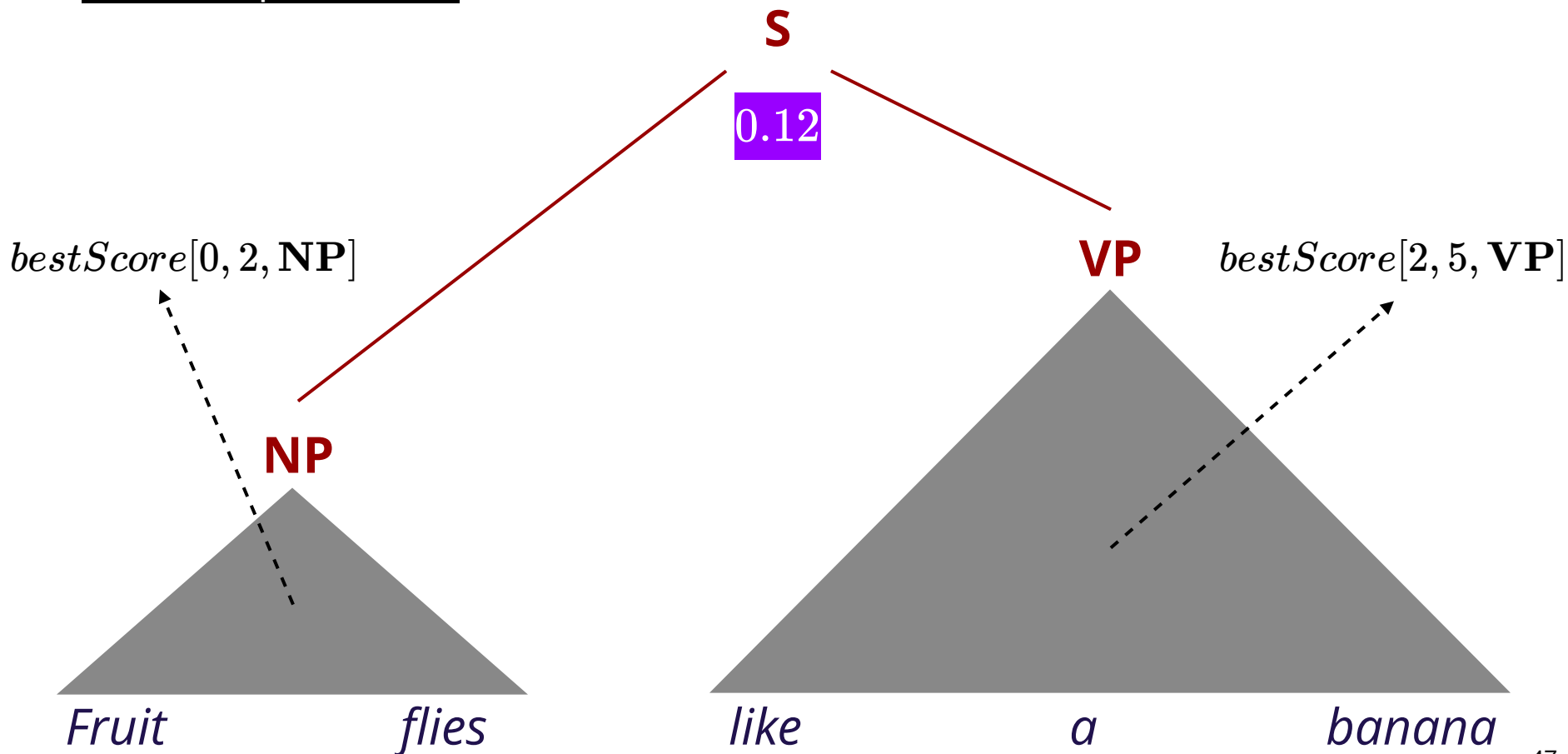
banana

CKY Algorithm

S \rightarrow **NP** **VP** (0.12)

Partition position: 2

$0.12 \times \text{bestScore}[0, 2, \mathbf{NP}] \times \text{bestScore}[2, 5, \mathbf{VP}]$

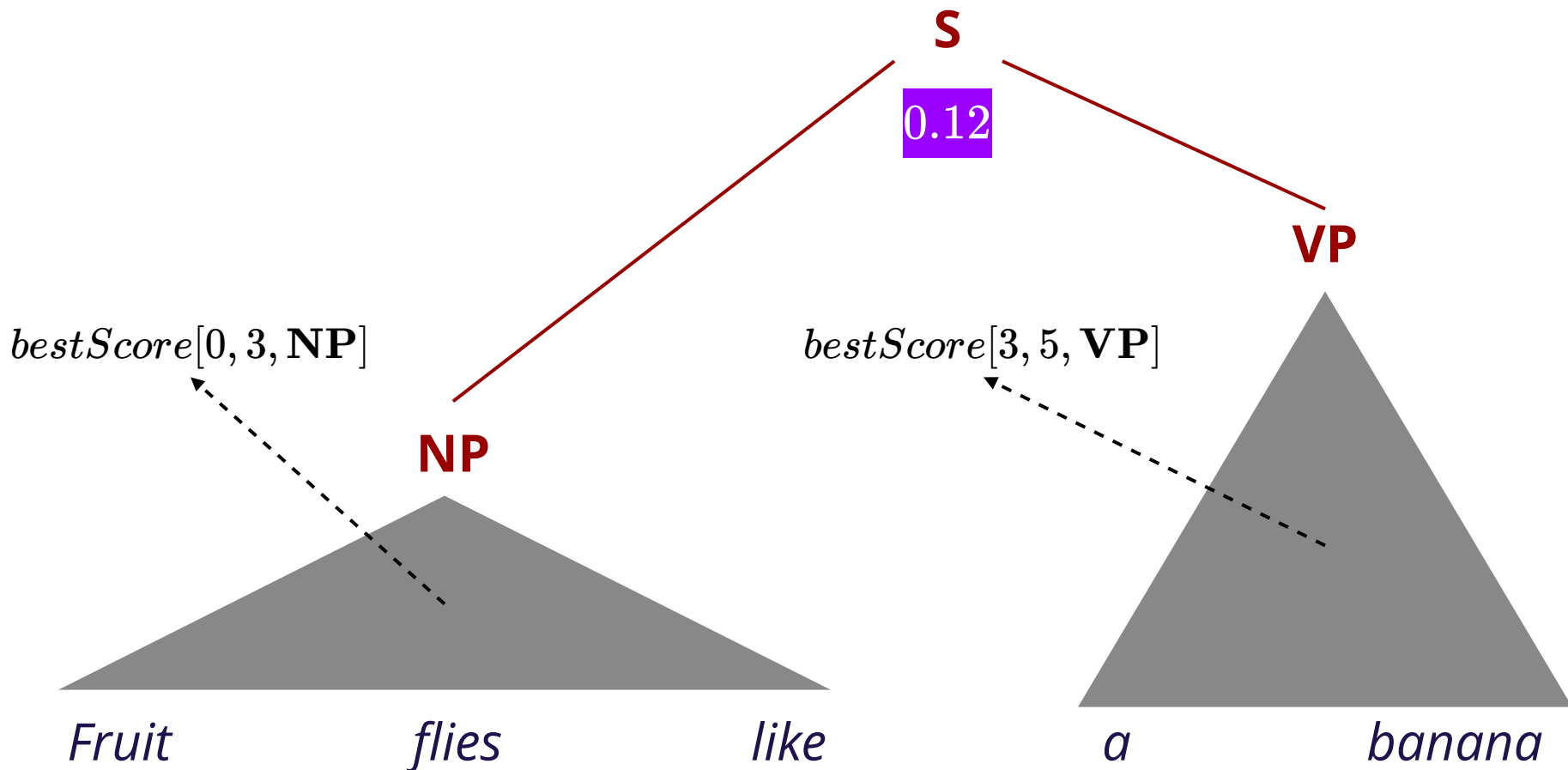


CKY Algorithm

S \rightarrow **NP** **VP** (0.12)

Partition position: 3

$0.12 \times \text{bestScore}[0, 3, \mathbf{NP}] \times \text{bestScore}[3, 5, \mathbf{VP}]$

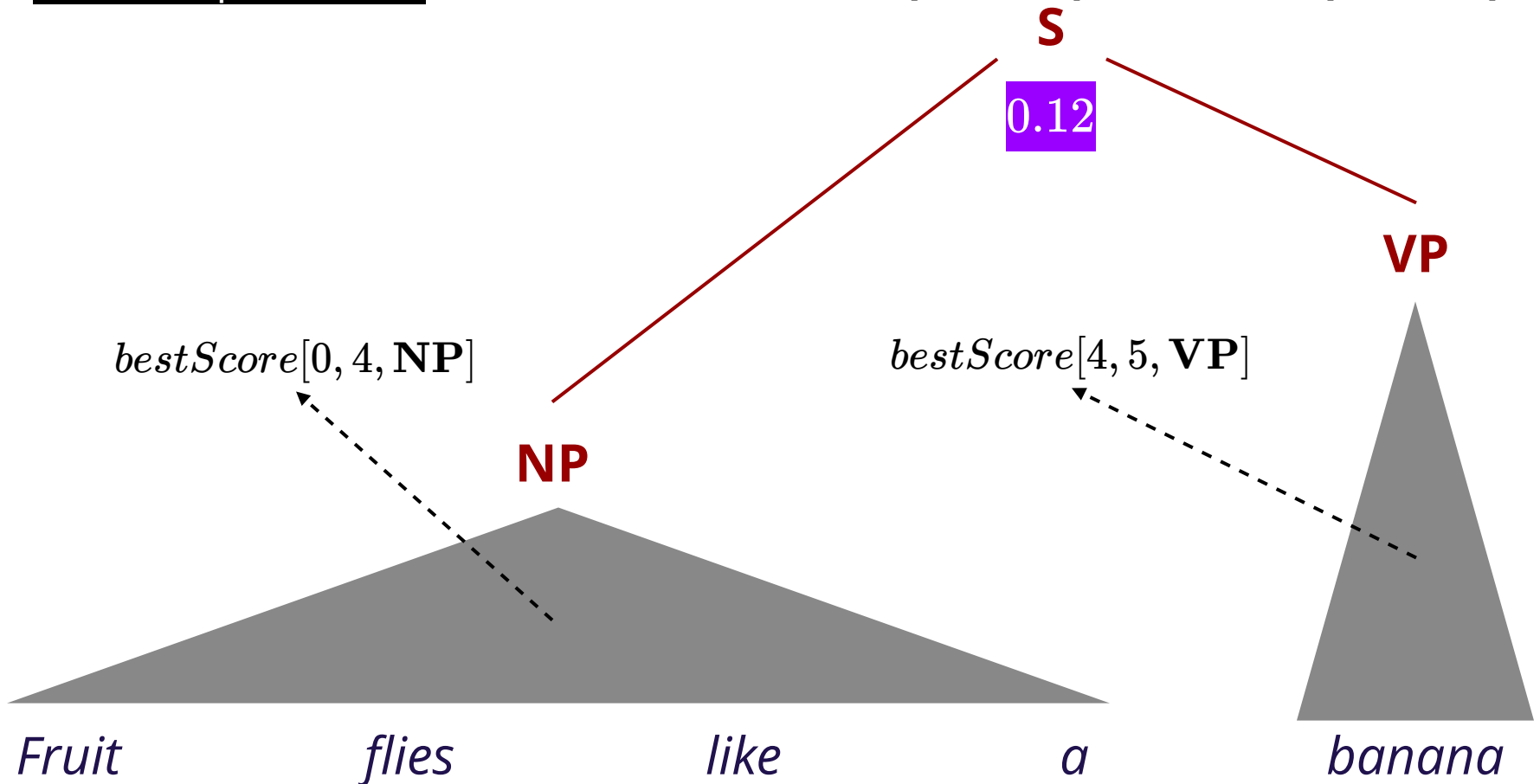


CKY Algorithm

S \rightarrow **NP** **VP** (0.12)

Partition position: 4

$0.12 \times \text{bestScore}[0, 4, \mathbf{NP}] \times \text{bestScore}[4, 5, \mathbf{VP}]$

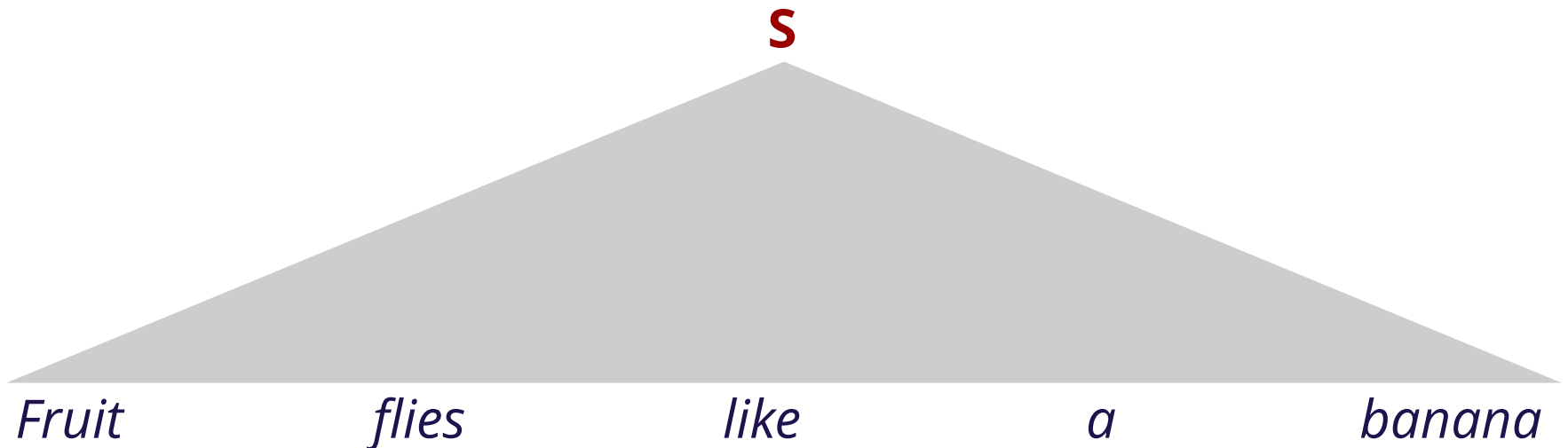


CKY Algorithm

$$\mathbf{S} \rightarrow \mathbf{NP} \mathbf{VP} \quad (0.12)$$

We shall pick the split point that gives the highest score.

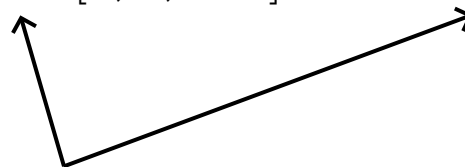
$$bestScore[0, 5, \mathbf{S}] = \max_{1 \leq k \leq 4} (0.12 \times bestScore[0, k, \mathbf{NP}] \times bestScore[k, 5, \mathbf{VP}])$$



CKY Algorithm

S \rightarrow **NP** **VP** (0.12)

$$bestScore[0, 5, \mathbf{S}] = \max_{1 \leq k \leq 4} (0.12 \times bestScore[0, k, \mathbf{NP}] \times bestScore[k, 5, \mathbf{VP}])$$



Q1. How to find such *bestScore* values?

Dynamic programming!

S

Fruit

flies

like

a


banana

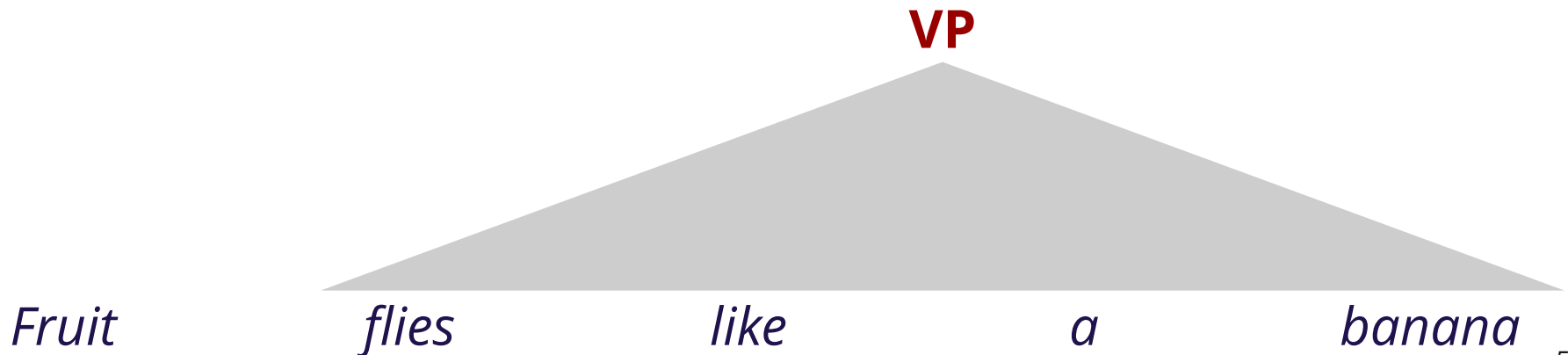
CKY Algorithm

$\text{VP} \rightarrow \text{V NP} \quad (0.29)$
 $\text{VP} \rightarrow \text{V VP} \quad (0.12)$
 $\text{VP} \rightarrow \text{V PP} \quad (0.08)$

$\text{bestScore}[1, 5, \text{VP}] = \max\{\max_{1 \leq k \leq 4} (0.29 \times \text{bestScore}[1, k, \text{V}] \times \text{bestScore}[k, 5, \text{NP}]),$
 $\max_{1 \leq k \leq 4} (0.12 \times \text{bestScore}[1, k, \text{V}] \times \text{bestScore}[k, 5, \text{VP}]),$
 $\max_{1 \leq k \leq 4} (0.08 \times \text{bestScore}[1, k, \text{V}] \times \text{bestScore}[k, 5, \text{PP}])\}$

You need two 'for' loops!!

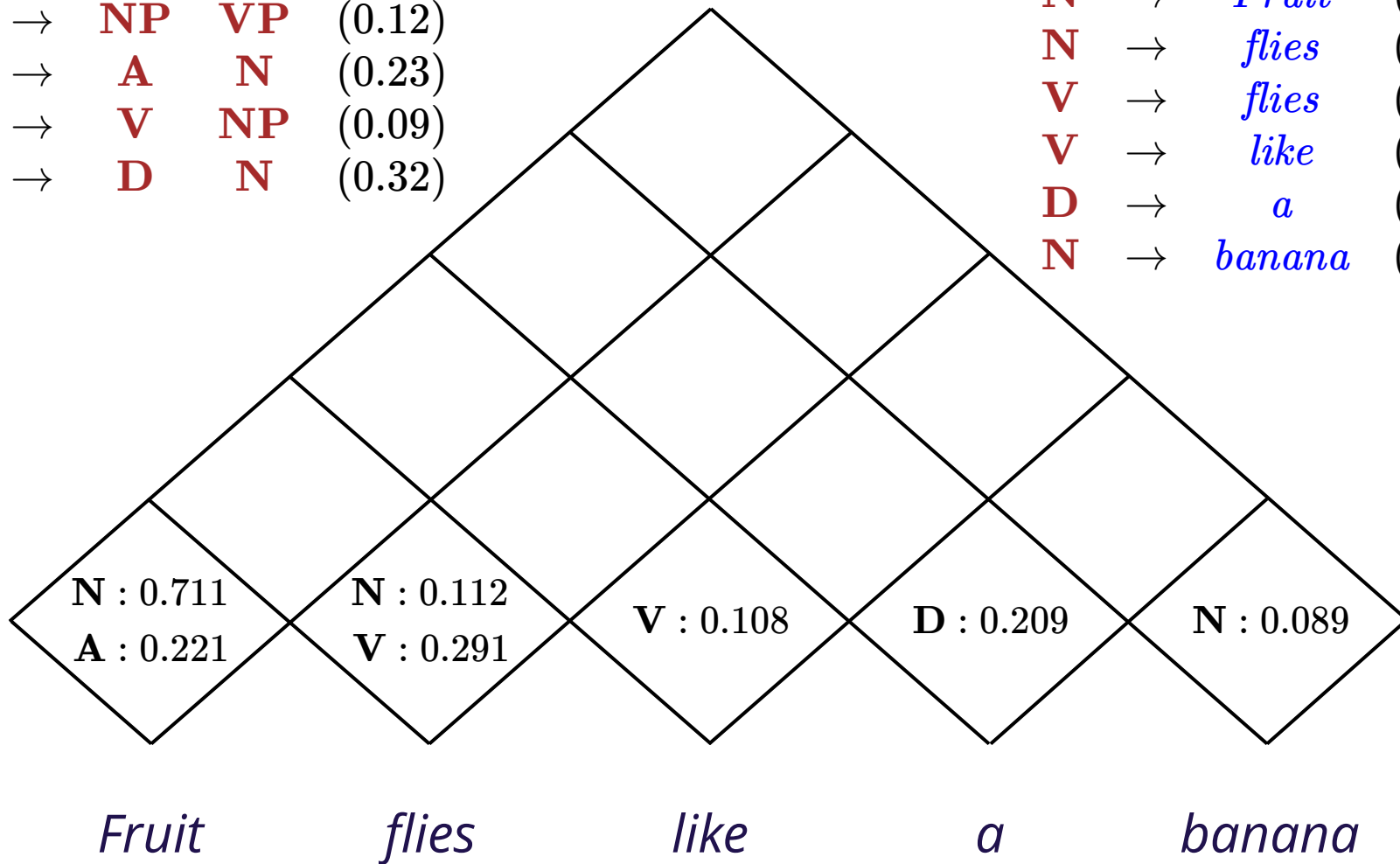
Q2. What if we have multiple rules that start with the same non-terminal? 



CKY Algorithm

S → **NP** **VP** (0.12)
NP → **A** **N** (0.23)
VP → **V** **NP** (0.09)
NP → **D** **N** (0.32)

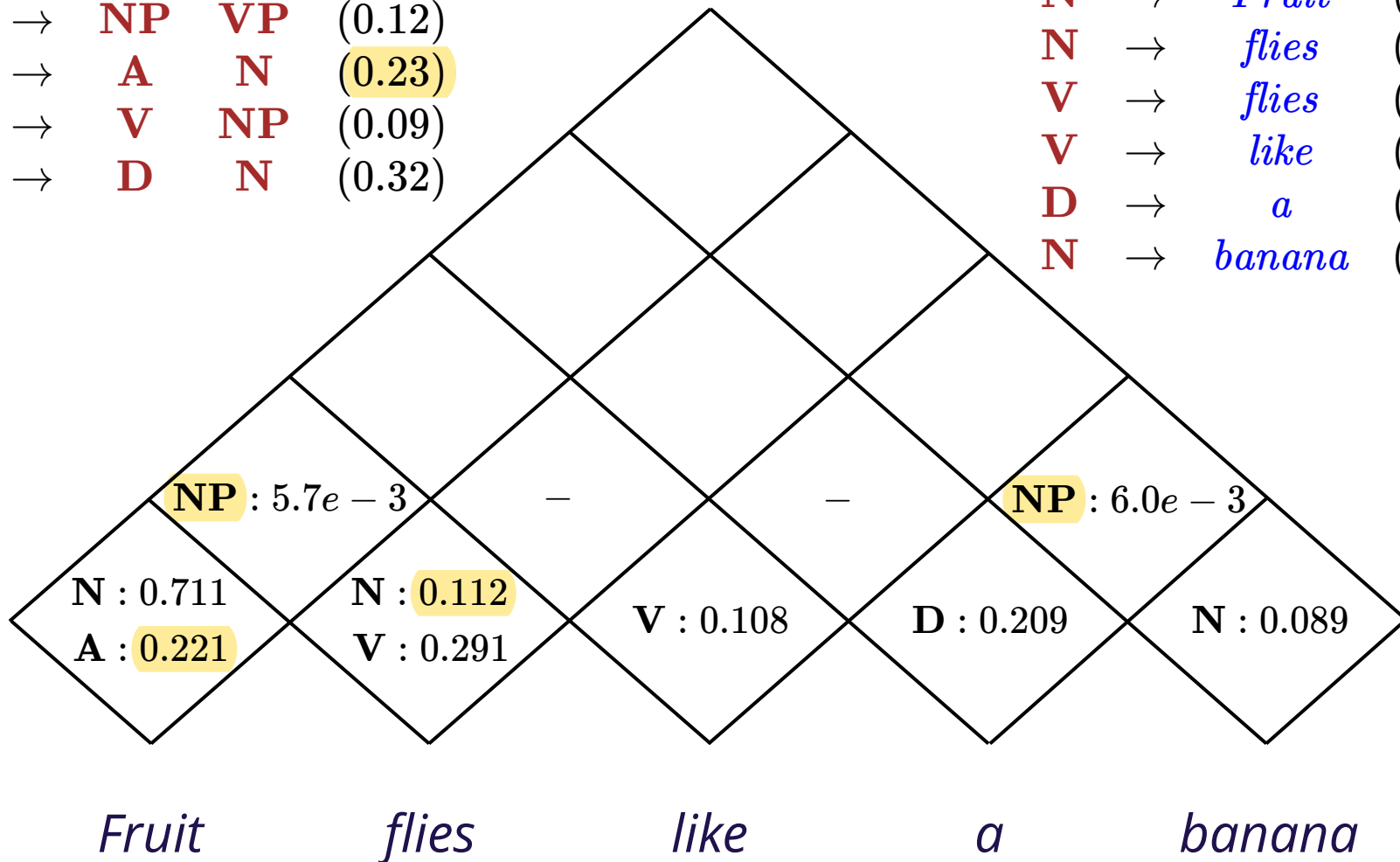
A → *Fruit* (0.221)
N → *Fruit* (0.711)
N → *flies* (0.112)
V → *flies* (0.291)
V → *like* (0.108)
D → *a* (0.209)
N → *banana* (0.089)



CKY Algorithm

S → **NP** **VP** (0.12)
NP → **A** **N** (0.23)
VP → **V** **NP** (0.09)
NP → **D** **N** (0.32)

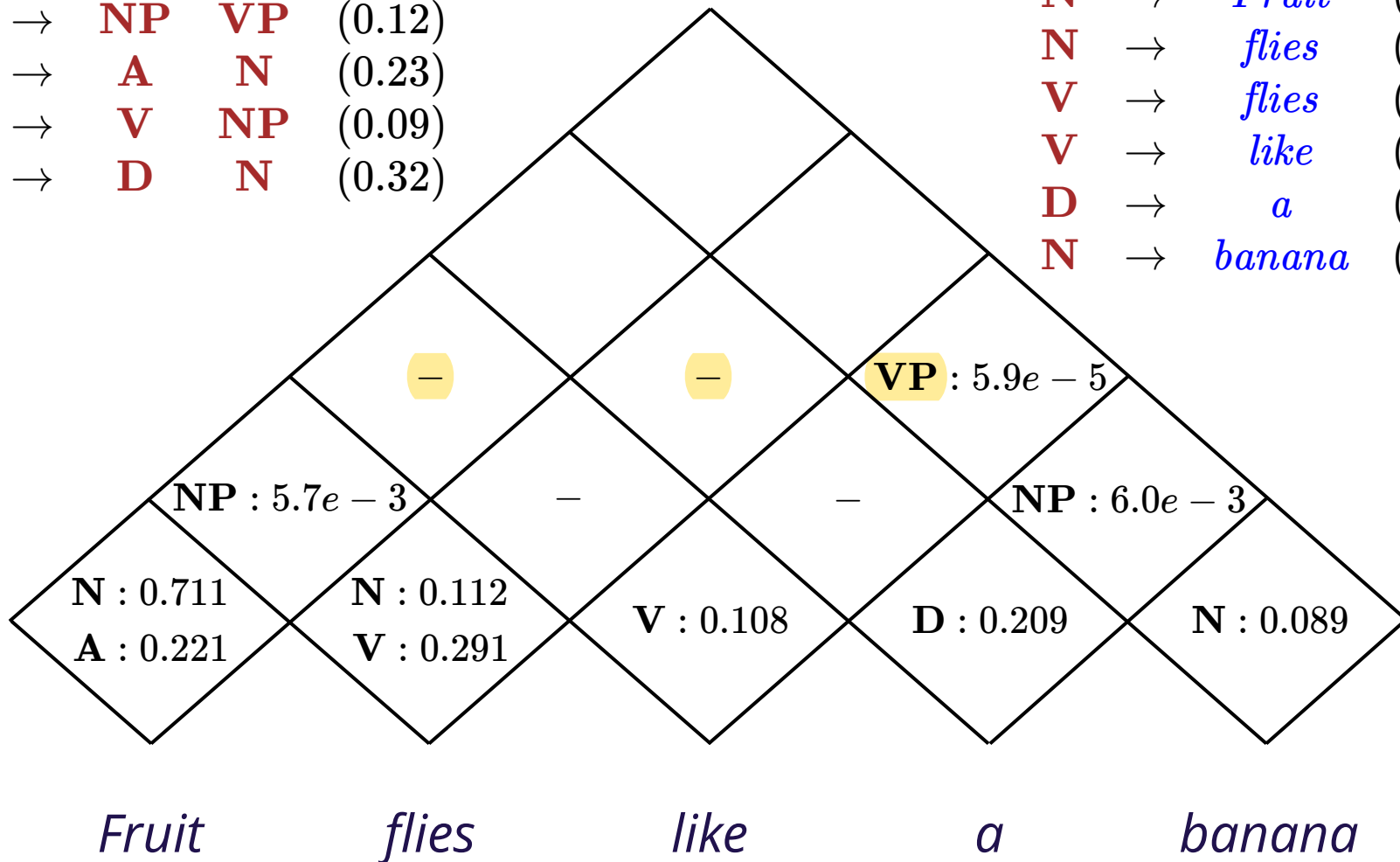
A → *Fruit* (0.221)
N → *Fruit* (0.711)
N → *flies* (0.112)
V → *flies* (0.291)
V → *like* (0.108)
D → *a* (0.209)
N → *banana* (0.089)



CKY Algorithm

S → **NP** **VP** (0.12)
NP → **A** **N** (0.23)
VP → **V** **NP** (0.09)
NP → **D** **N** (0.32)

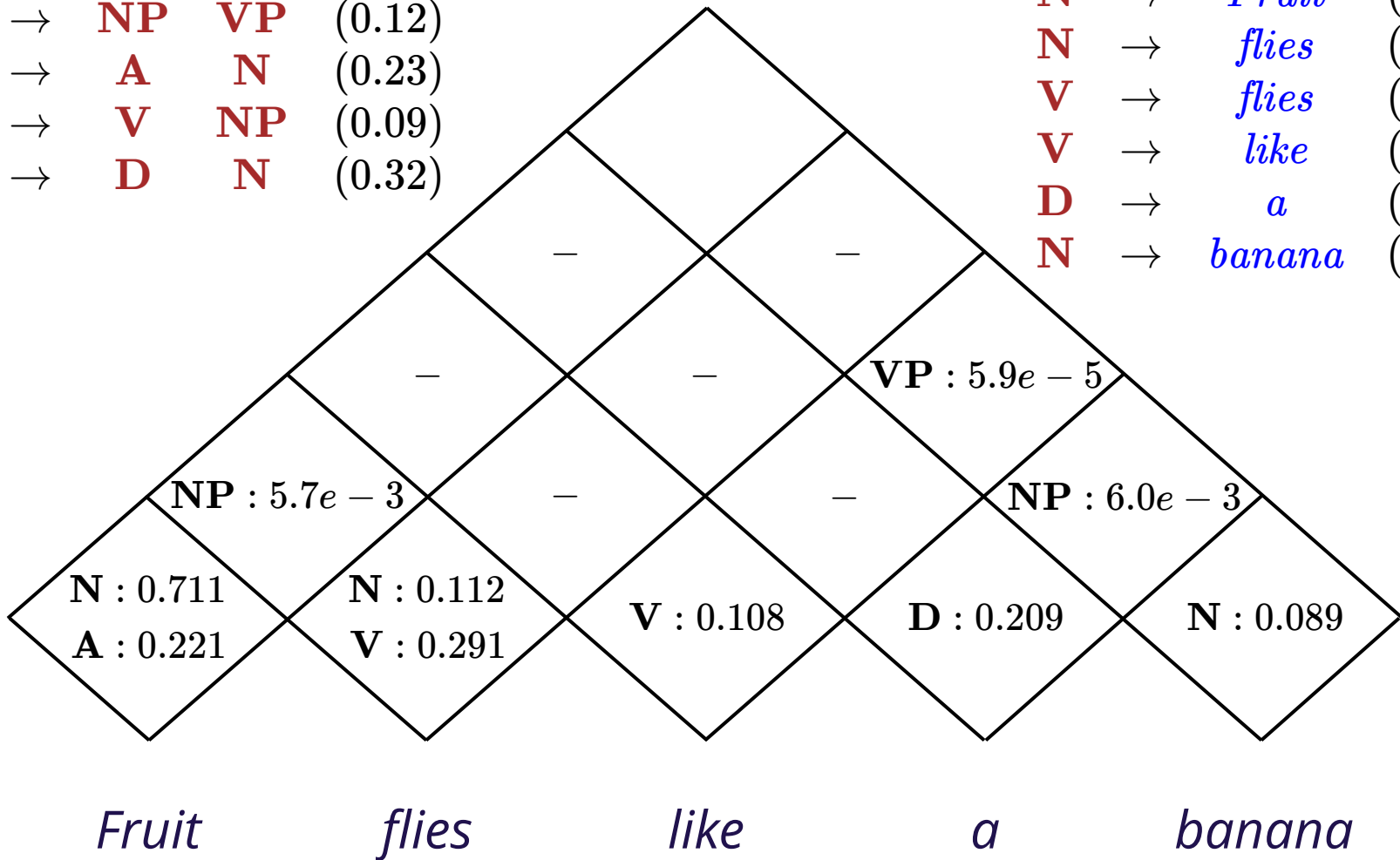
A → *Fruit* (0.221)
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N → *flies* (0.112)
V → *flies* (0.291)
V → *like* (0.108)
D → *a* (0.209)
N → *banana* (0.089)



CKY Algorithm

A	→	<i>Fruit</i>	(0.221)
N	→	<i>Fruit</i>	(0.711)
N	→	<i>flies</i>	(0.112)
V	→	<i>flies</i>	(0.291)
V	→	<i>like</i>	(0.108)
D	→	<i>a</i>	(0.209)
N	→	<i>banana</i>	(0.089)

S	\rightarrow	NP	VP	(0.12)
NP	\rightarrow	A	N	(0.23)
VP	\rightarrow	V	NP	(0.09)
NP	\rightarrow	D	N	(0.32)

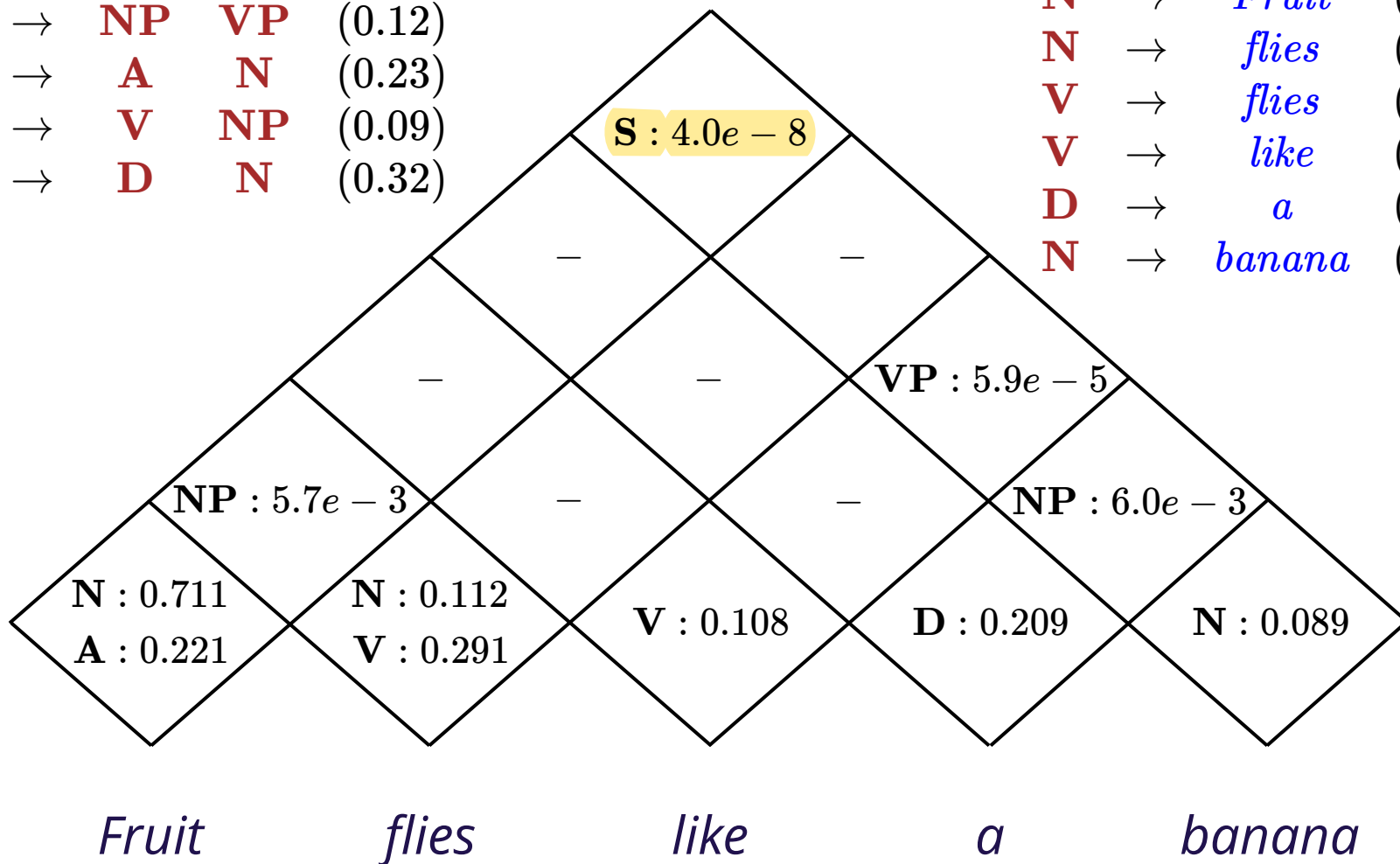


CKY Algorithm



S → **NP** **VP** (0.12)
NP → **A** **N** (0.23)
VP → **V** **NP** (0.09)
NP → **D** **N** (0.32)

A → *Fruit* (0.221)
N → *Fruit* (0.711)
N → *flies* (0.112)
V → *flies* (0.291)
V → *like* (0.108)
D → *a* (0.209)
N → *banana* (0.089)



Question

What is the time complexity of CKY?



Time complexity: $O(n^3|R|)$

n : length of parsed string

$|R|$: size of grammar rules

We have n^2 entries in the table. But for each entry, we have to consider all the possible split points.

Each rule is in CNF, you have to consider the possibility of each rule to be applied to every span. Within each span, you have to find the split point. Essentially, for each entry, you have to consider all possible rules at worst case.

Probabilistic CFG Summary

Learning

$$p(\mathbf{A} \rightarrow \mathbf{exp}) = \frac{\text{count}(\mathbf{A} \rightarrow \mathbf{exp})}{\text{count}(\mathbf{A})}$$

Decoding

CKY Algorithm
(Dynamic Programming)

There are limitations with the probabilistic CFG as it is a generative approach...

We will learn some
improved models next time!!

Structured Prediction

