# Trees!

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# Admin

All grades are now Pass / No Record.
II / TQE status is not affected.

Midterm has been turned into a homework assignment,
and no peer grading on future assignments.
Deadlines are flexible.

Let us know if you’re having trouble accessing videos.

Stay safe!

# Recap: labels and sequences

# Predicting labels

$$s = W_2^\top f(W_1^\top x)$$

$x$

$f(W_1^\top x) = h_1$

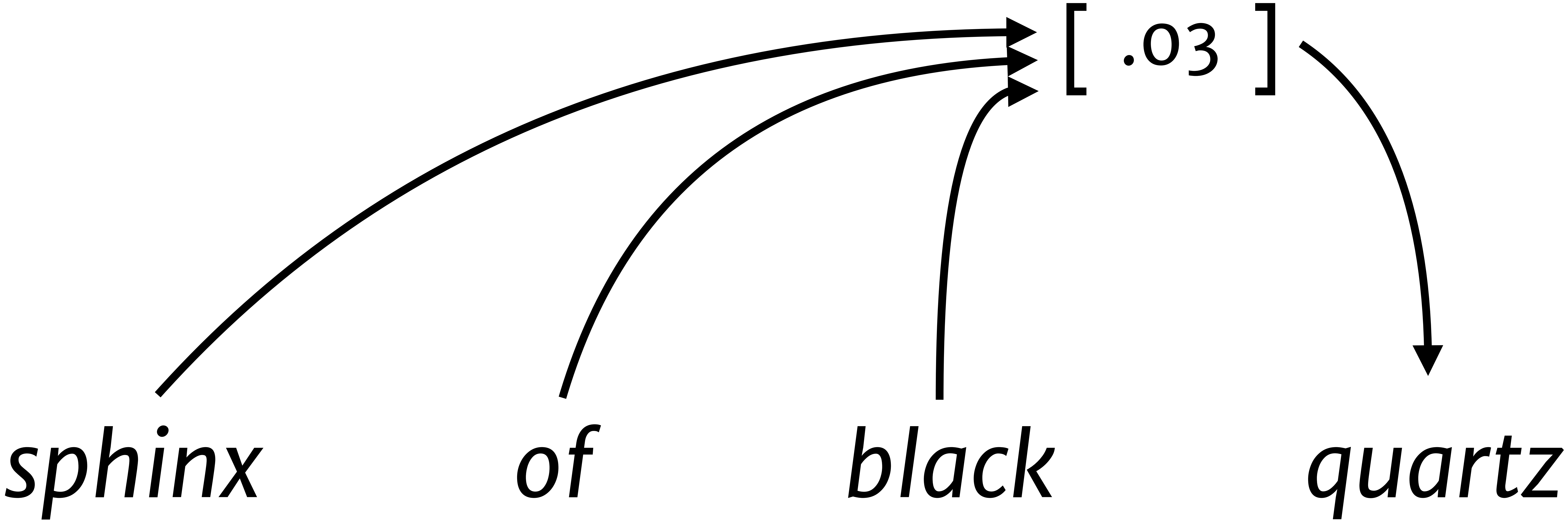
$W_2^\top h_1 = s$

$\begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$ input

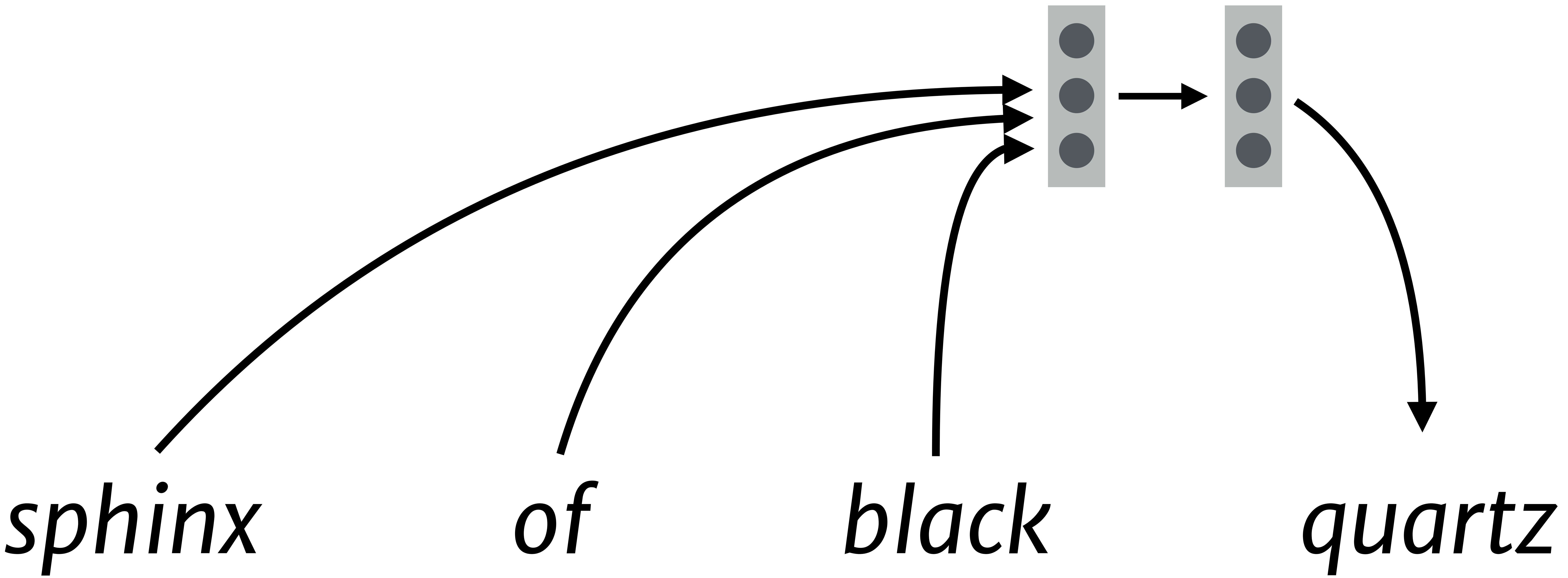
$\begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$ “hidden layer”

$\begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$ output

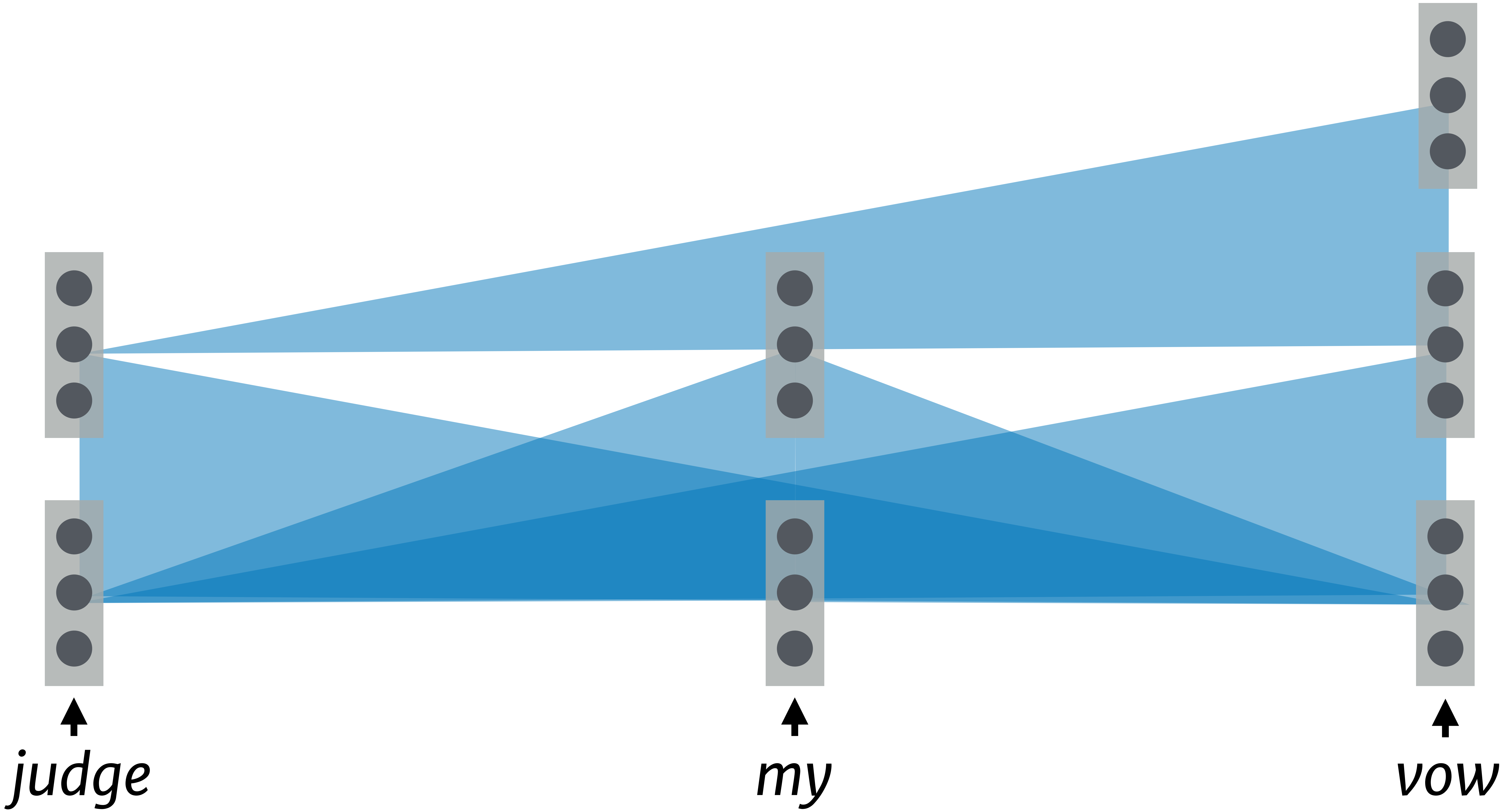
# Predicting sequences: n-gram models



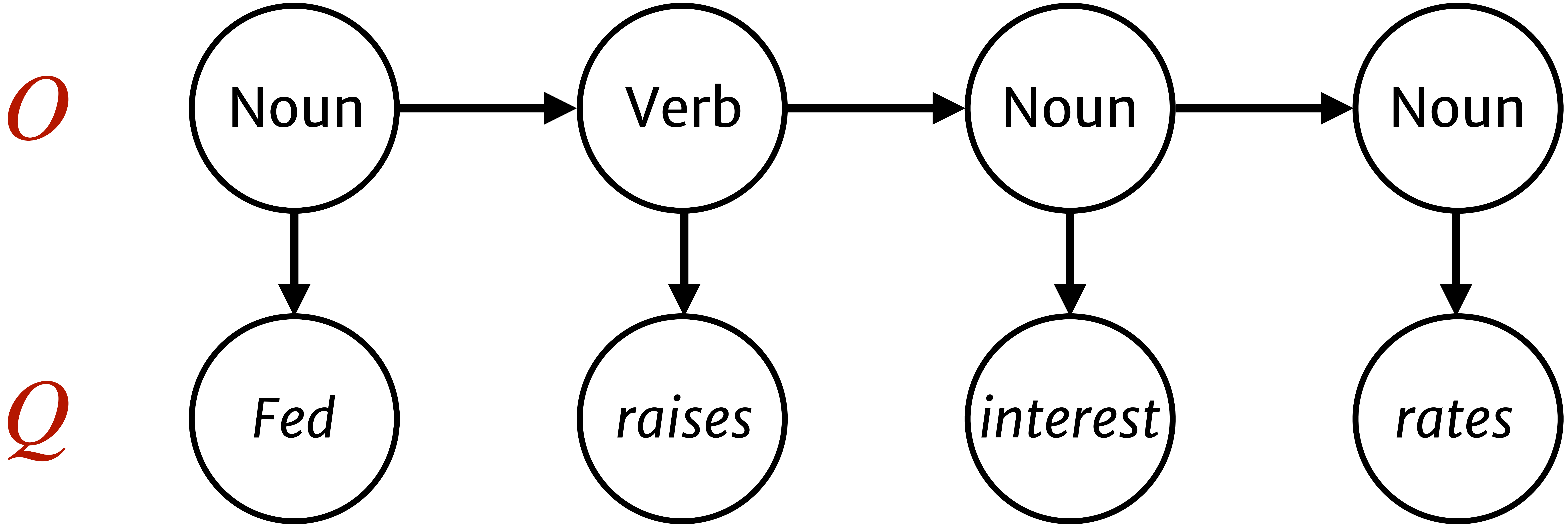
# Predicting sequences: n-gram models



# Predicting sequences: neural networks

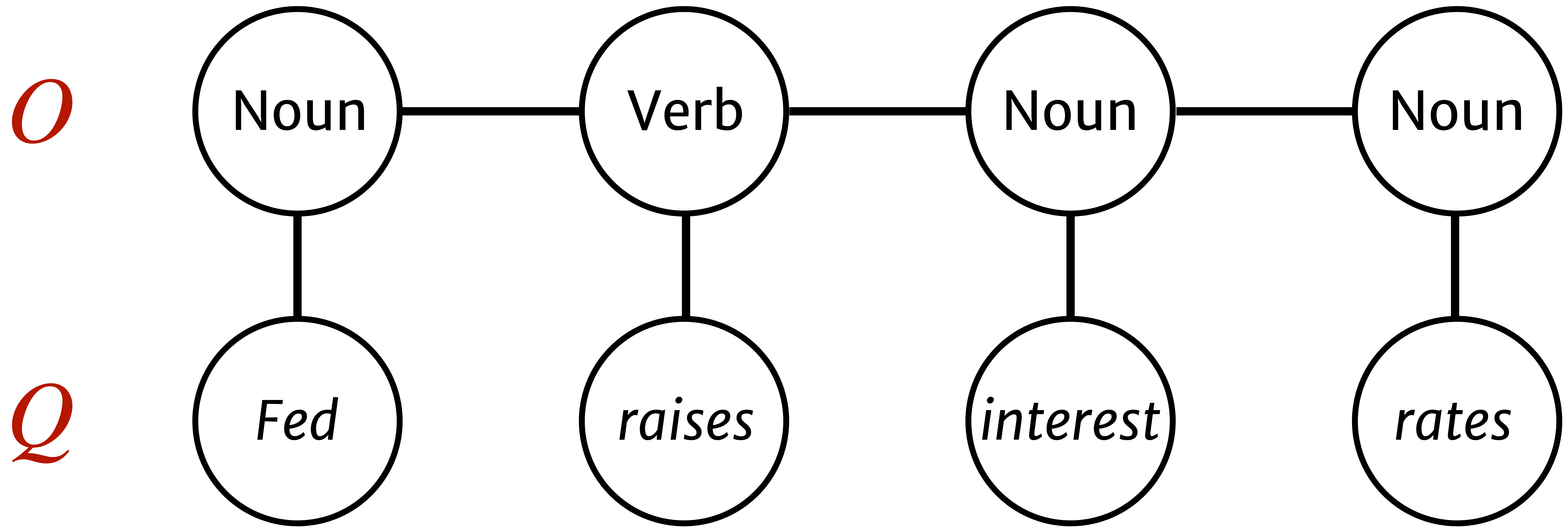


# Labeling sequences: HMMs & CRFs



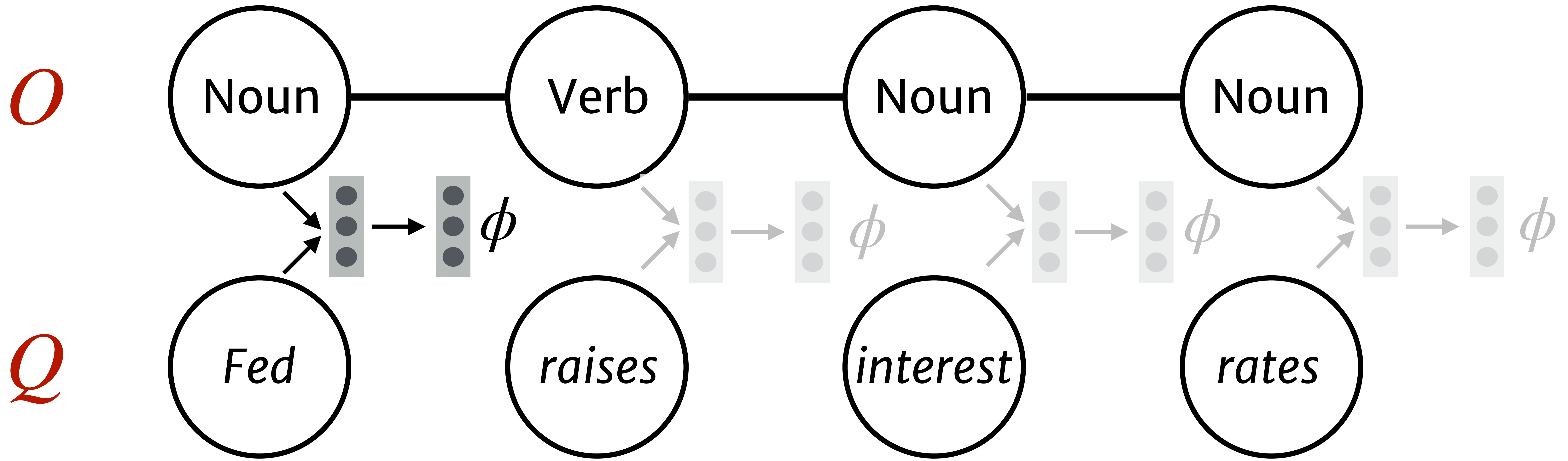

**HMM:** $p(O, Q) = \prod_t p(q_t \mid q_{:t-1})\, p(o_t \mid q_t)$

# Labeling sequences: HMMs & CRFs



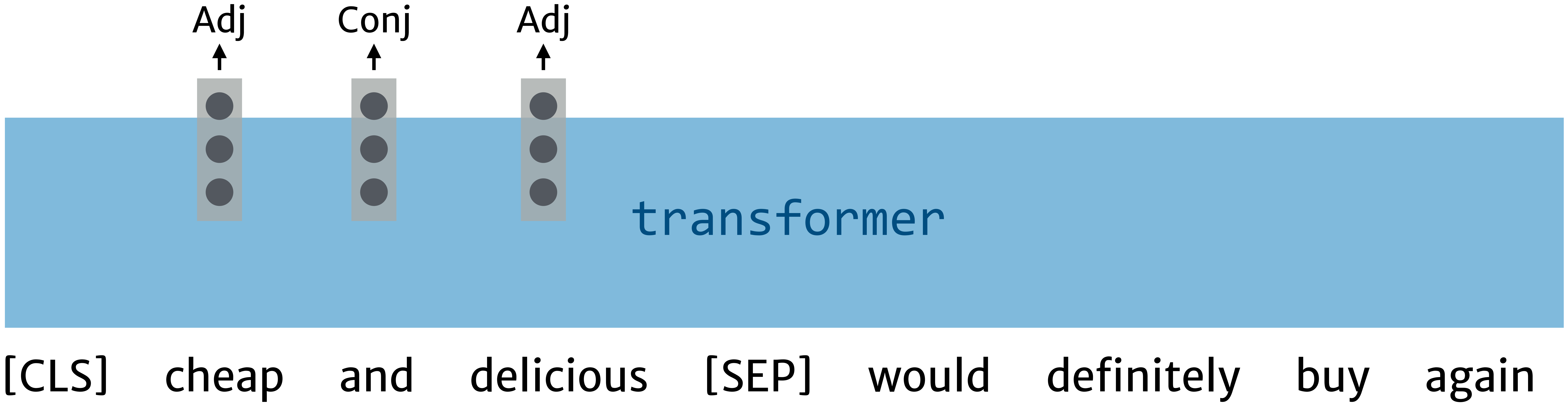

**CRF:** $p(O,Q) = \frac{1}{Z}\exp\{\sum_t a^\top \phi(q_t, q_{:t-1}) + b^\top \phi(o_t \mid q_t)\}$

# Labeling sequences: HMMs & CRFs

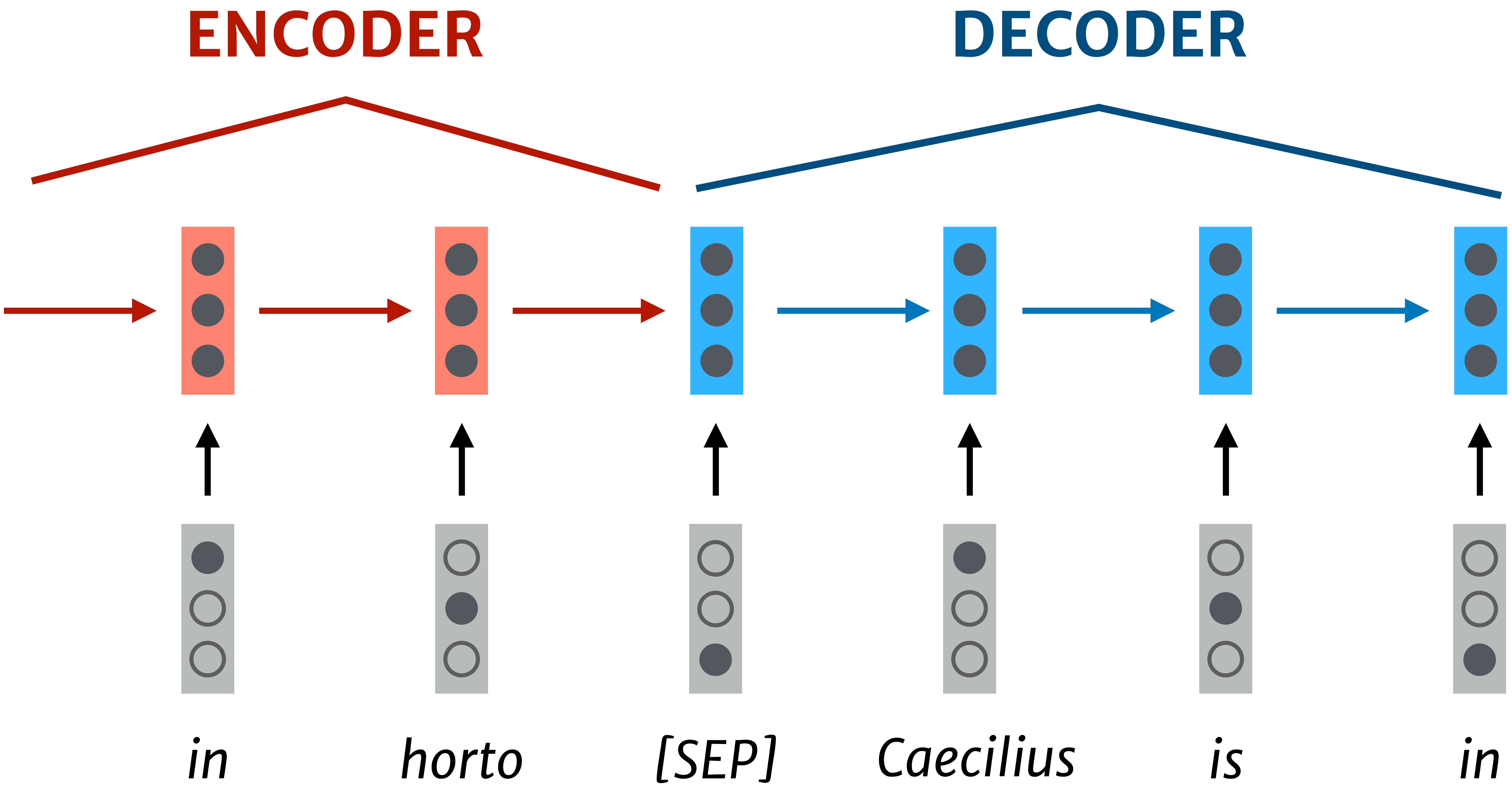



**CRF:** $$p(O, Q) = \frac{1}{Z} \exp\{ \sum_t a^\top \phi(q_t, q_{:t-1}) + b^\top \phi(o_t \mid q_t) \}$$

# Labeling sequences: neural networks

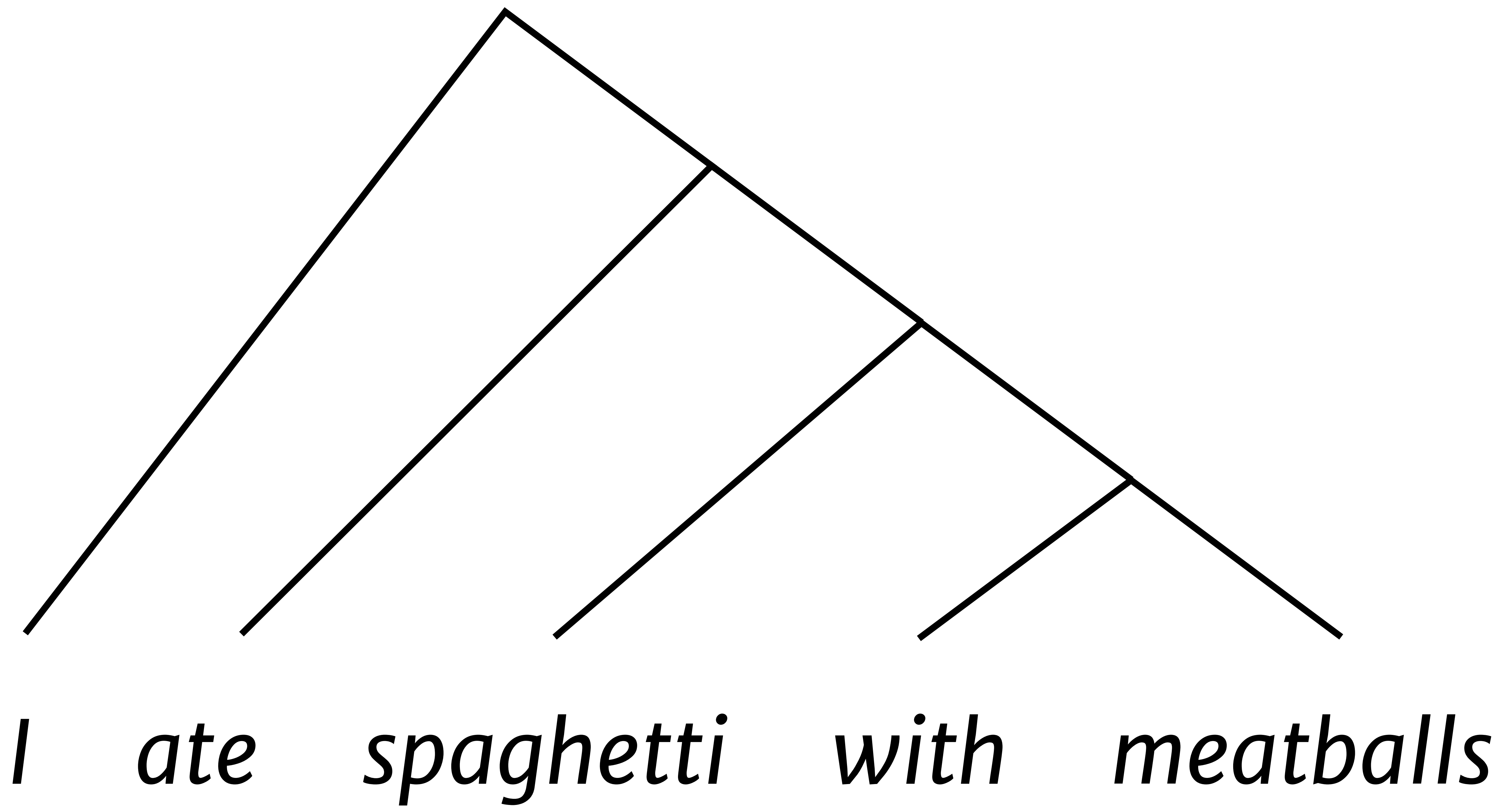


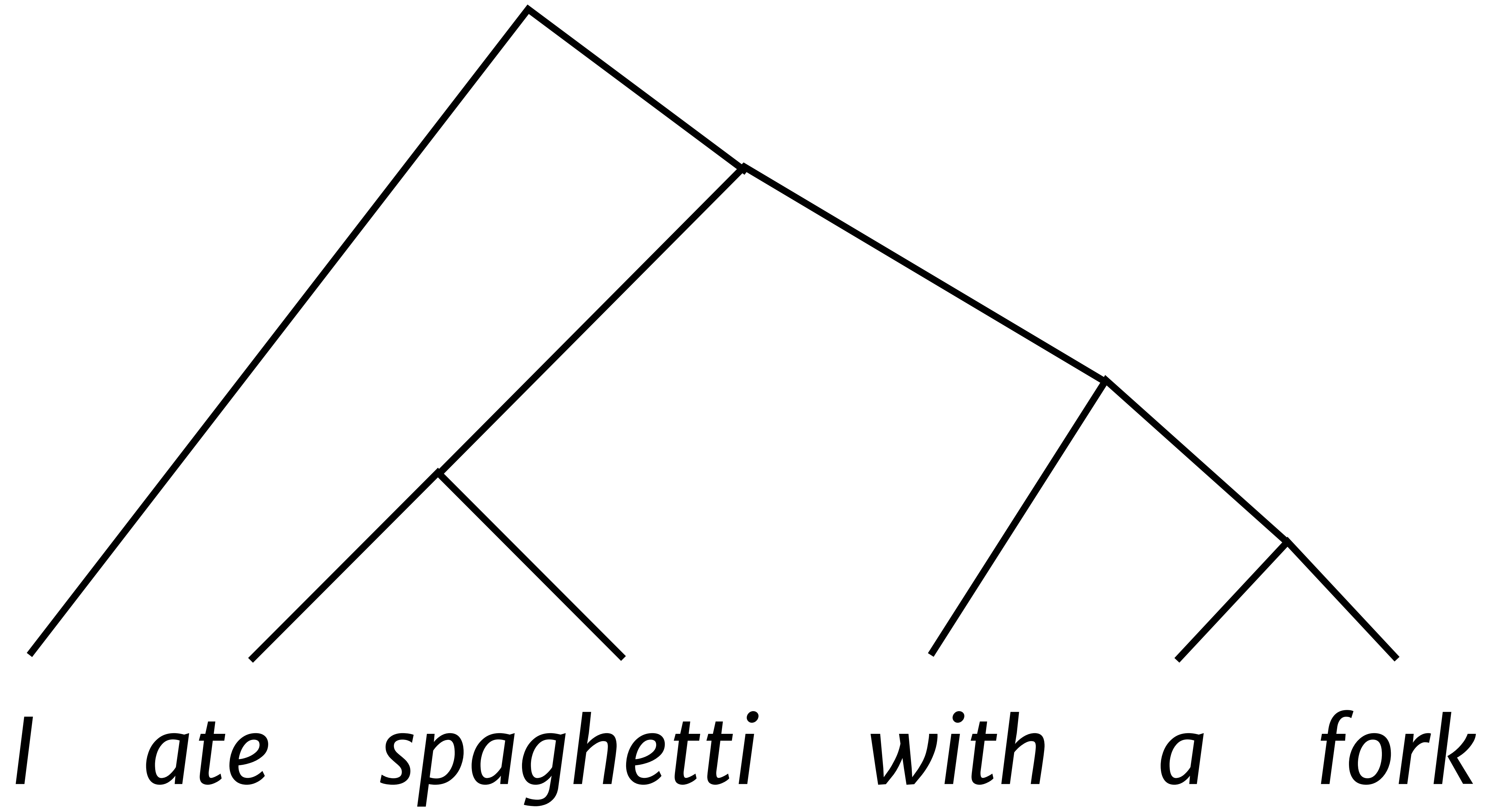
# Sequence-to-sequence models



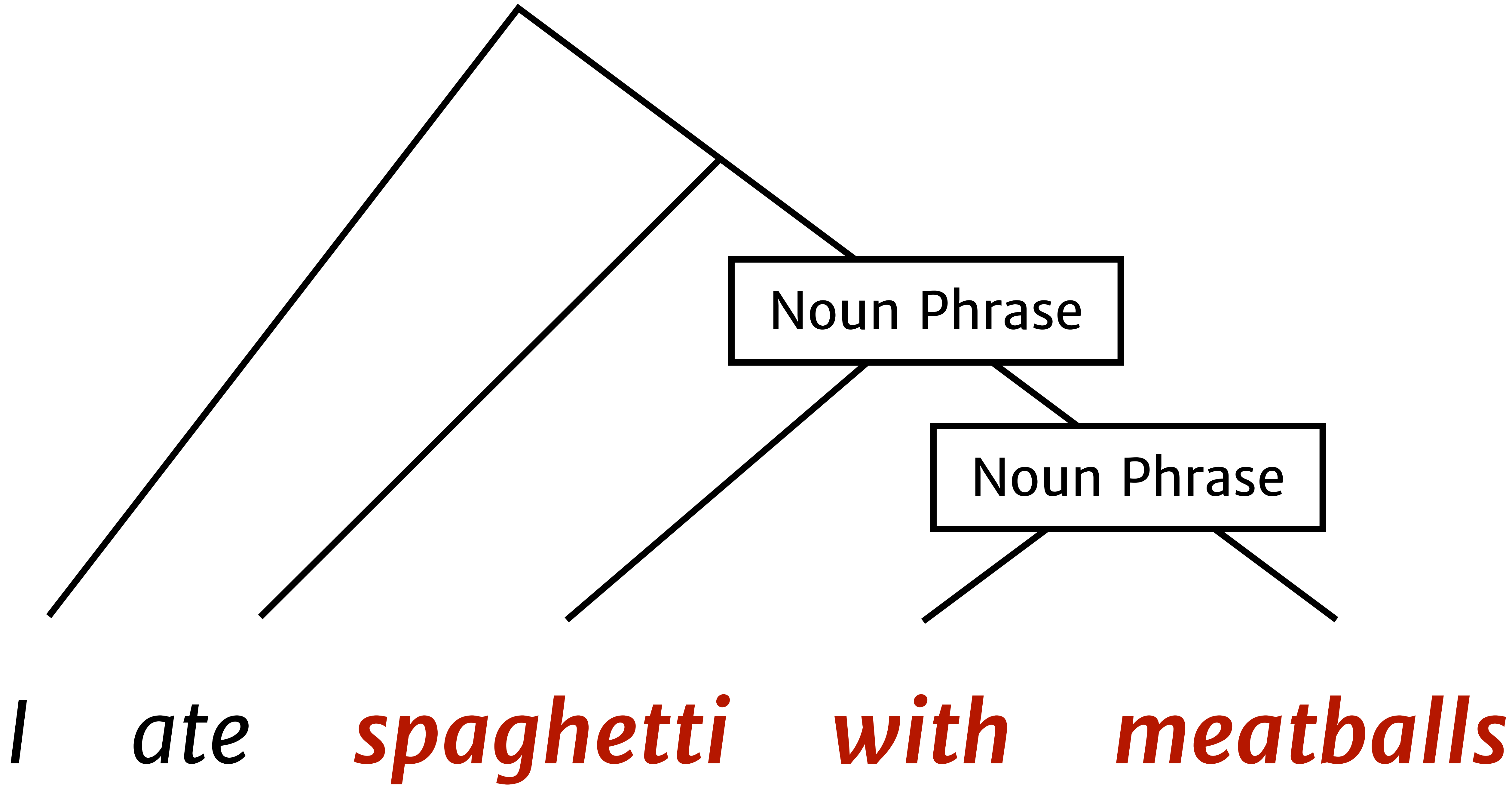
# Other structures

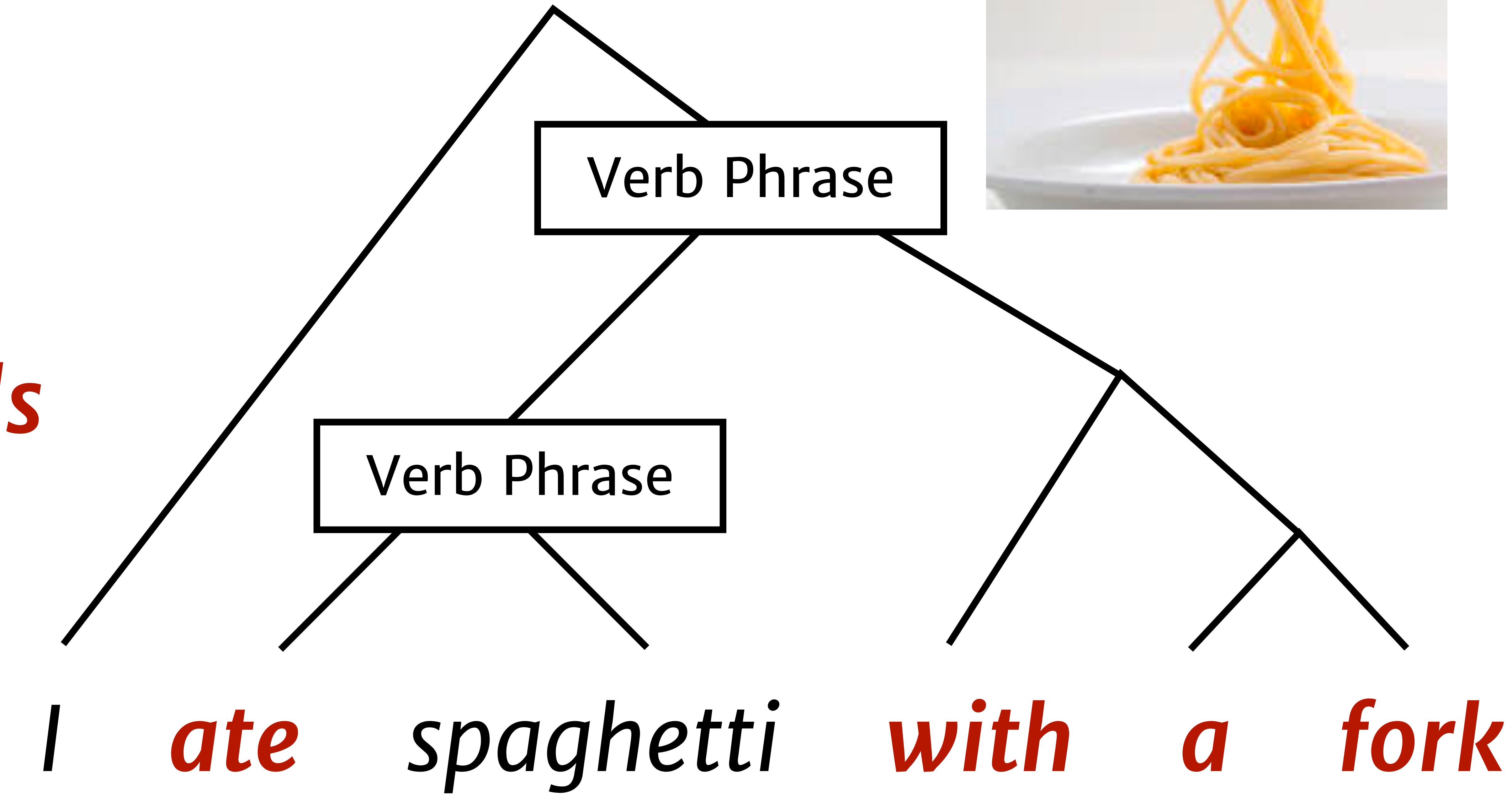
# Syntax



# Syntax

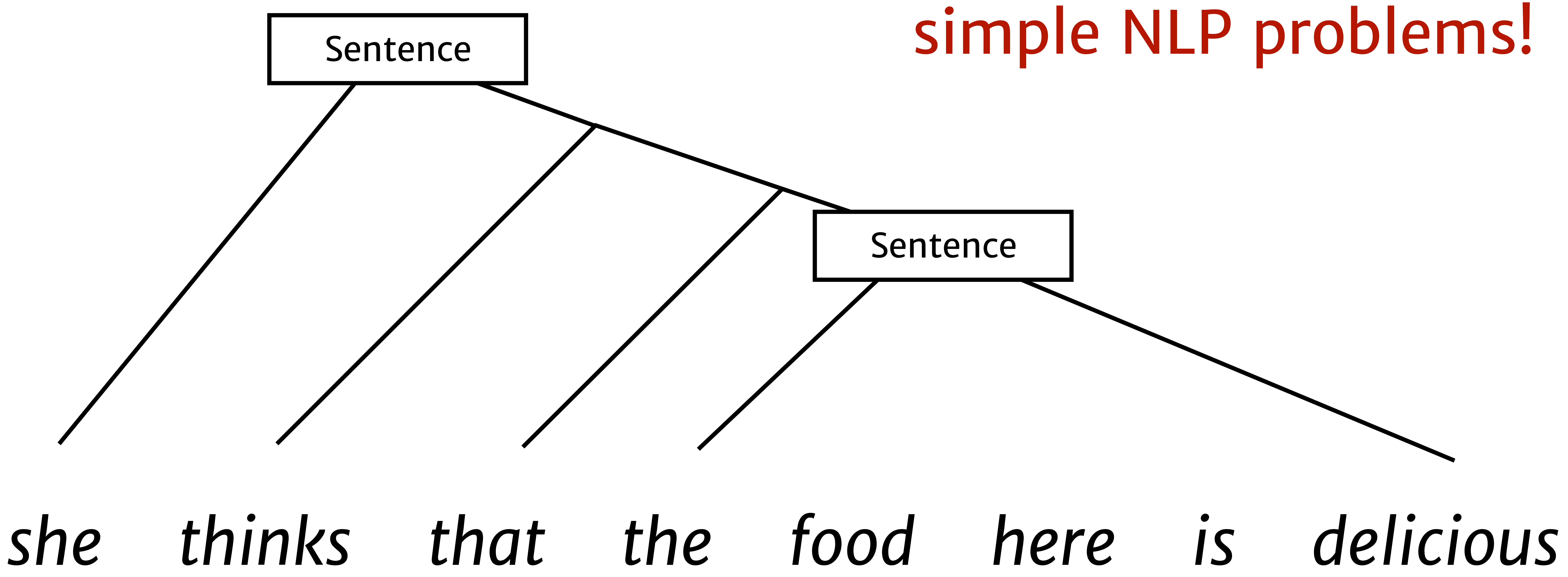



[Images: thespruceeats.com, freepik.com]

# Syntax

Useful to distinguish between statements and beliefs, even in simple NLP problems!



# Semantics

```
forbid(send(find(type=email), find(keyword=dean))
```

*don’t send the email to the dean*

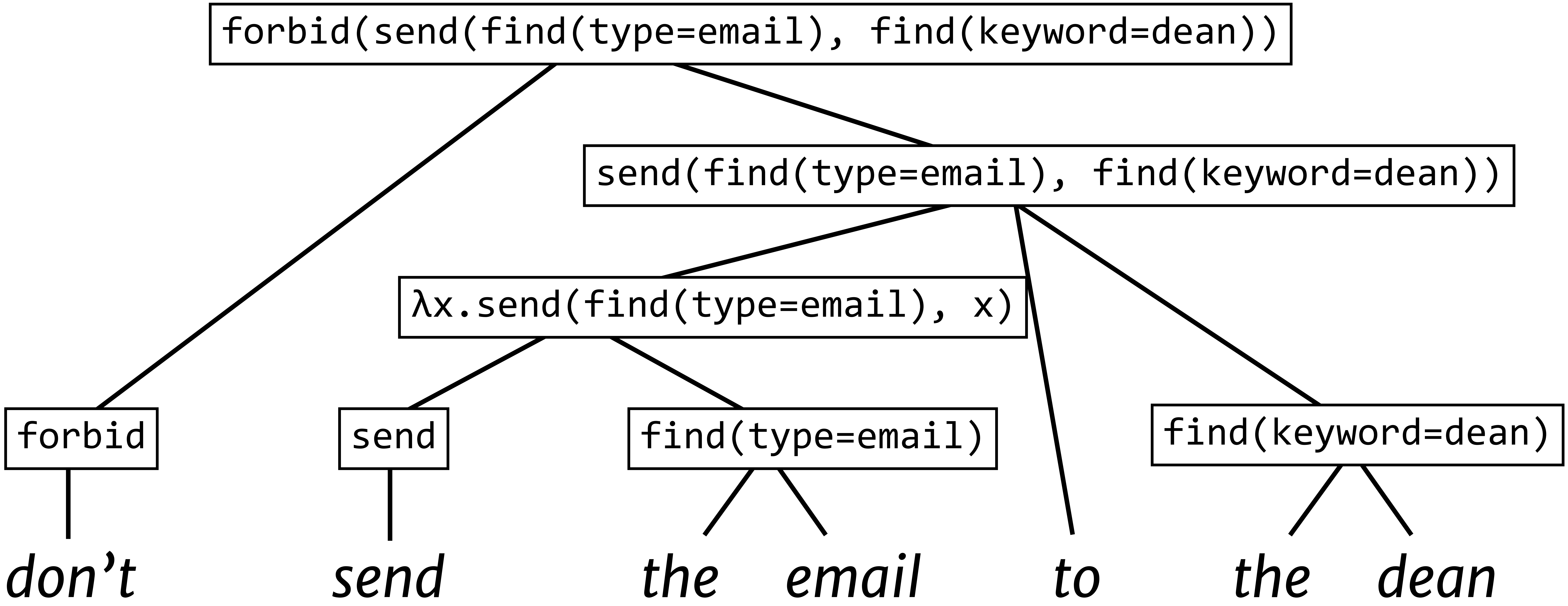
# Semantics

`forbid(send(find(type=email), find(keyword=dean))`

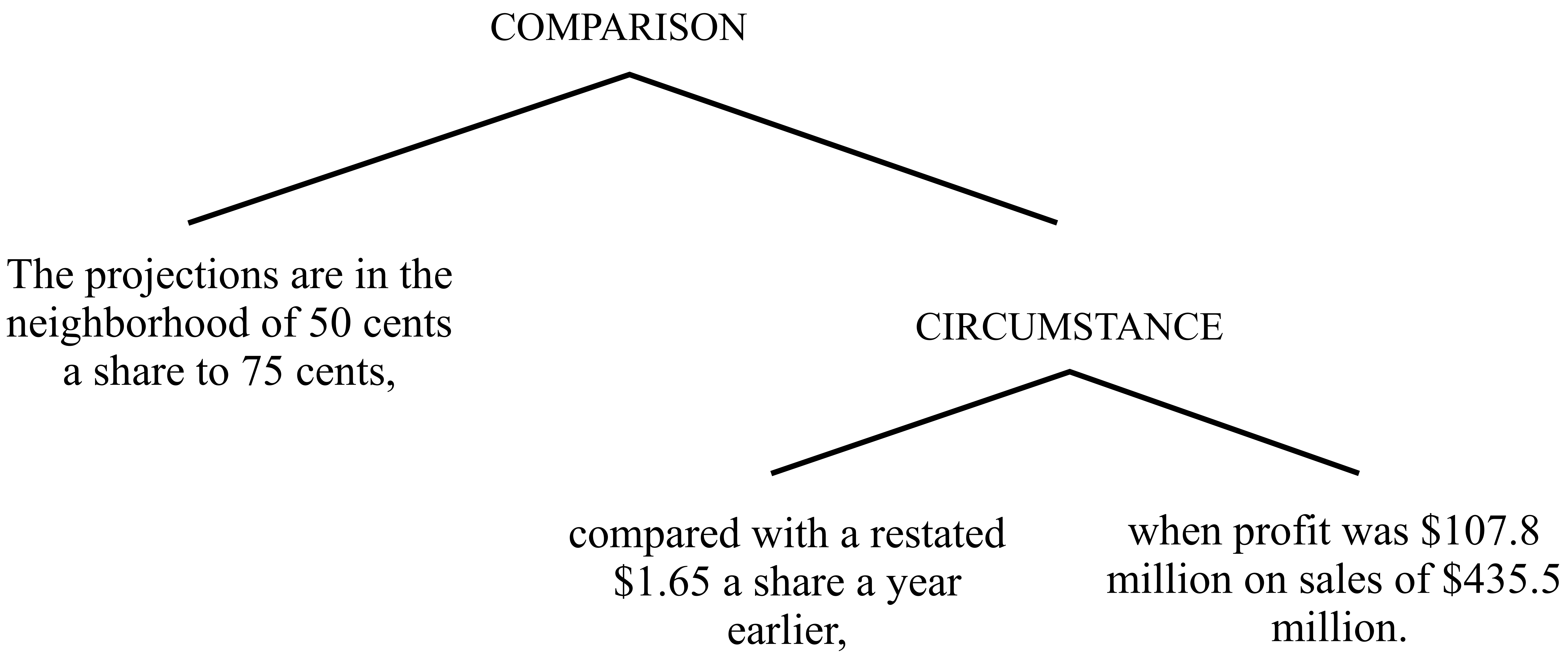
`forbid` `send` `find(type=email)` `find(keyword=dean)`

*don't* *send* *the* *email* *to* *the* *dean*

# Semantics


forbid(send(find(type=email), find(keyword=dean))
send(find(type=email), find(keyword=dean))
λx.send(find(type=email), x)
forbid
send
find(type=email)
find(keyword=dean)
don't
send
the
email
to
the
dean

# Discourse




[Ji and Eisenstein 2014]

# Why trees?

"Simplest" formal generative process that provides **hierarchical relationships** and **long-distance dependencies**:

*My <u>aunt</u> <u>gave</u> me a <u>microscope</u>.*

*My aunt's <u>sister</u> <u>gave</u> me a <u>microscope</u>.*

*My aunt's <u>sister</u>, who works at the NIH, <u>gave</u> me a microscope.*

*My aunt's <u>sister</u>, who works at a little-known constituent institute of th*

# Syntax in ten minutes

# Constituents

Key idea from previous examples: some sentence fragments "stick together"—can be moved around, replaced, and modified without affecting meaning / grammaticality:

*I ate* ***spaghetti with meatballs***

*I ate*

*I ate* ***it***

*It was* ***spaghetti with meatballs*** *that I ate*

# Constituents

Some fragments are harder to manipulate:

*I* ***ate*** ***spaghetti*** ***with*** *meatballs*

*I* ***ate*** *meatballs* ✘ (meaning changed)

*It was* ***ate spaghetti with*** *that I meatballs* ✘ (not grammatical)

# Constituents

Not just things:

*I ate spaghetti* ***with a fork***

*I ate spaghetti*

*It was* ***with a fork*** *that I ate spaghetti*

# Constituents & Types

event

action

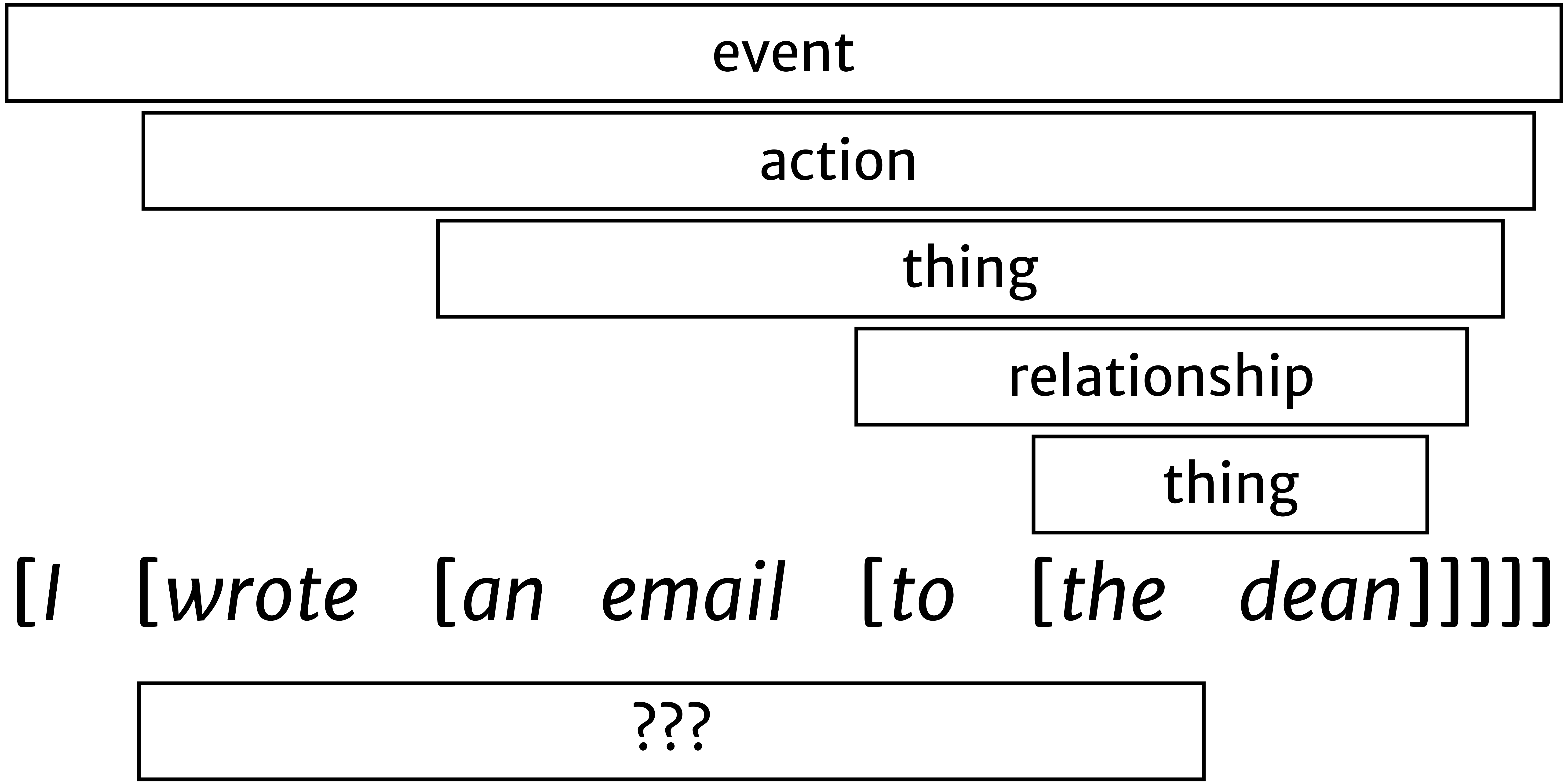
thing

relationship

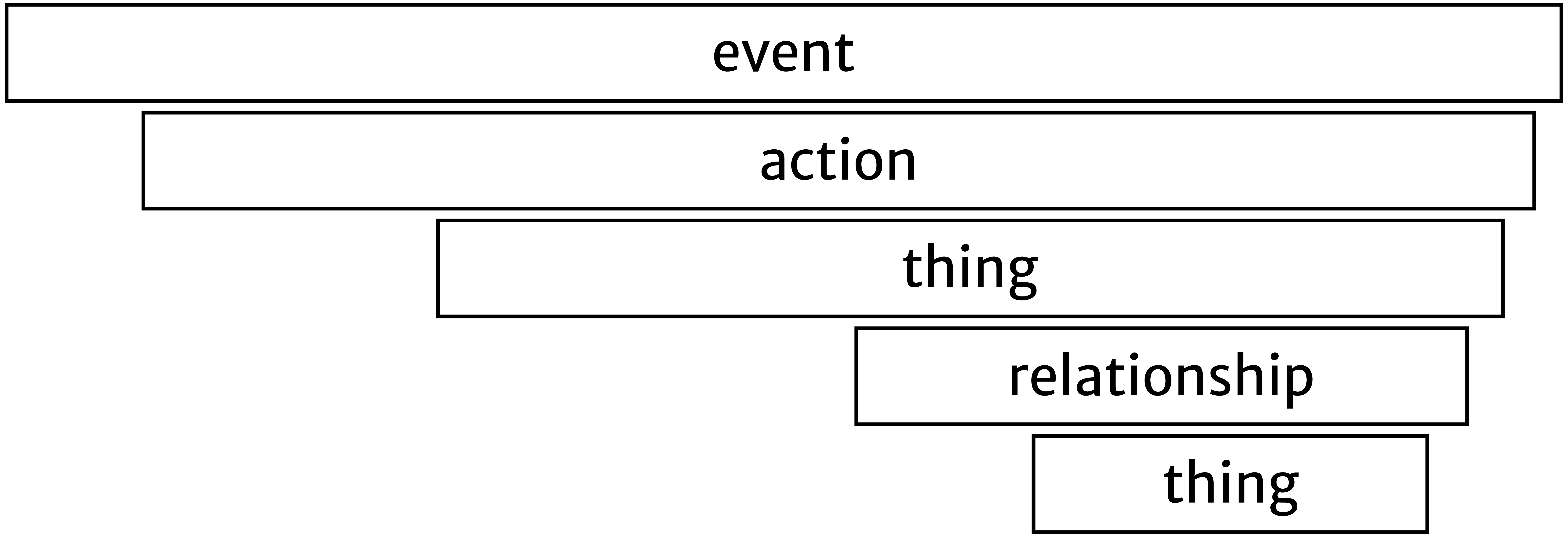
thing

[*I* [*wrote* [*an email* [*to* [*the dean*]]]]]

# Constituents & Types



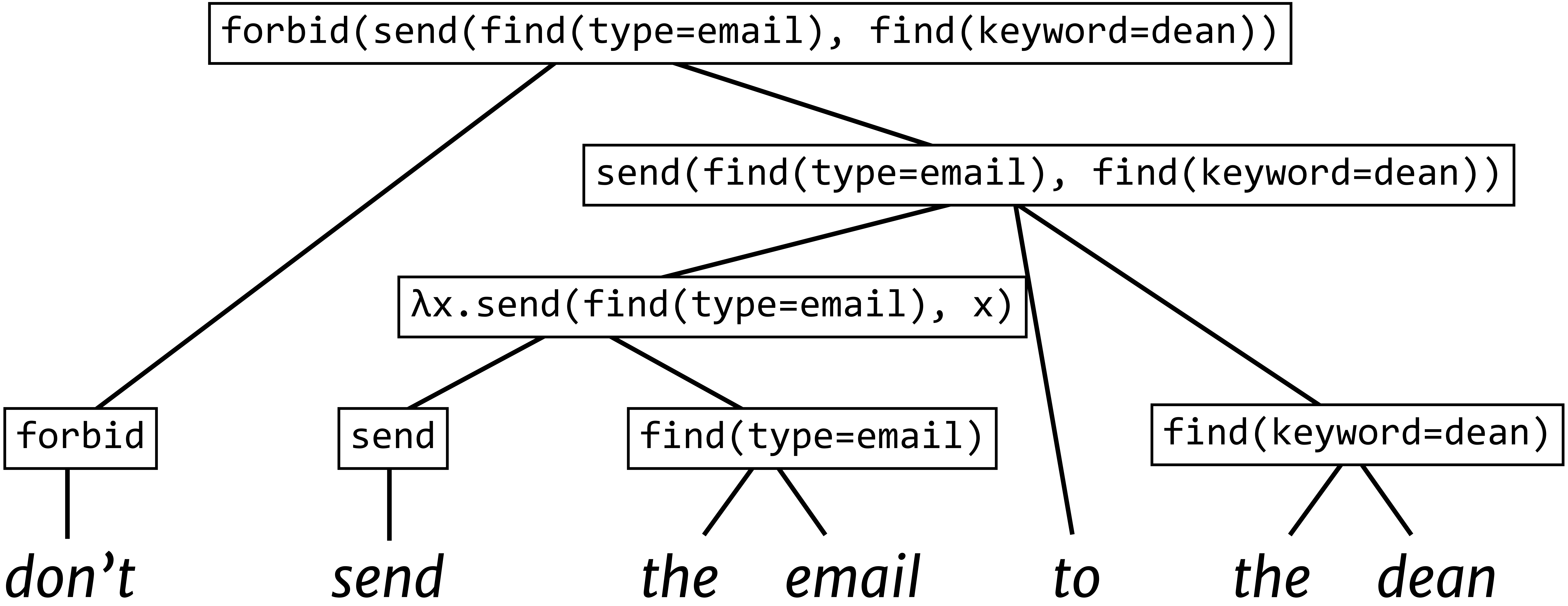
# Constituents & Types



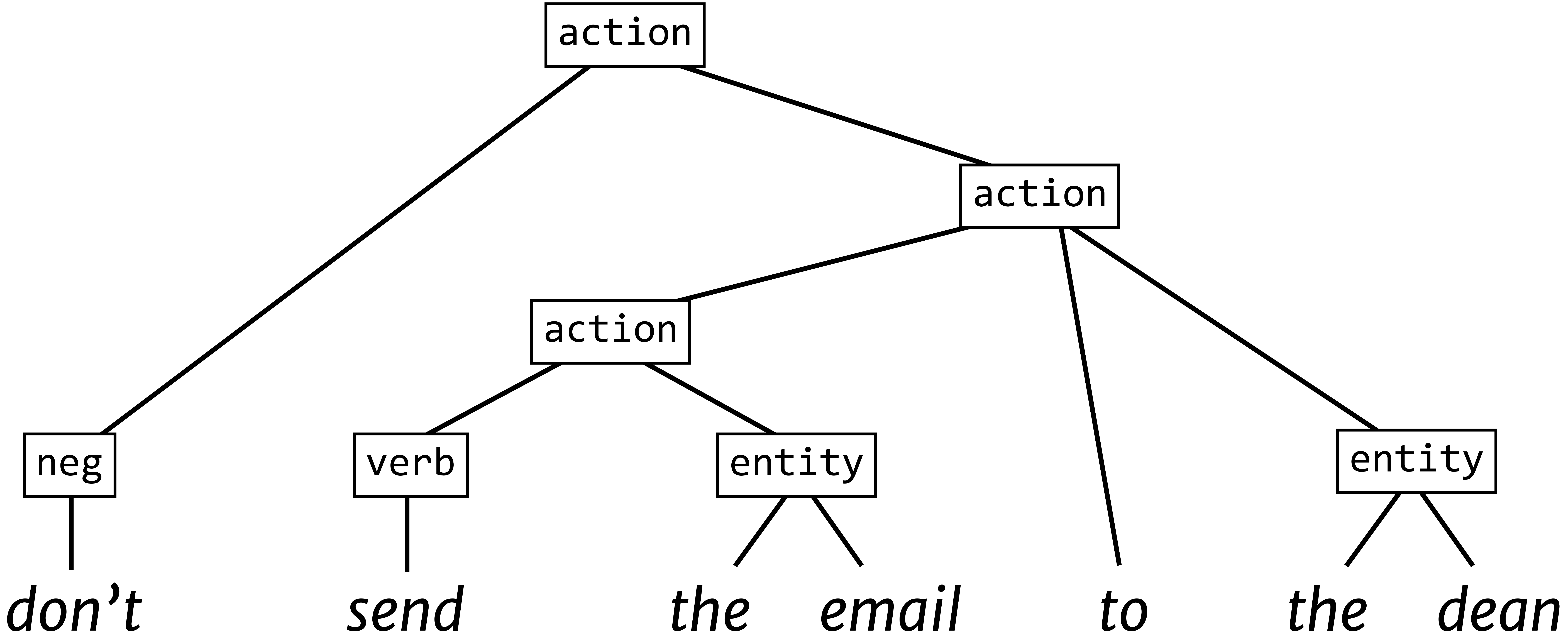

*[I [wrote [an email [to [the dean]]]]]*

Lots of research on the exact form of this hierarchy.
For most NLP applications: **entities, events, relations.**

# Types & semantics



# Types & semantics



# Context free grammars

Just like in HMMs, we'd like to define some joint distribution over sentences and underlying structures, and reason about marginals and conditionals.

What's the right distribution over trees and sentences?

# Context free grammars

A **sentence** might consist of an entity and an action.

[*I*] [*swallowed the spider*]

# Context free grammars

A **sentence** might consist of an entity and an action.

[*I*] [*swallowed the spider*]

S → NP VP    a Noun Phrase followed by a Verb Phrase make a Sentence

A **sentence** might just consist of an action.

[*eat the spider*]

S → VP    a Verb Phrase makes a Sentence

# Context free grammars

S → NP VP | VP

"or"

*the* followed by a noun makes an entity

NP → *the* N

N → *cat* | *dog* | *spider* | *cheesecake* | *democracy*

a verb and an optional entity make an action

VP → V | V NP

V → eat | eats | run | differentiate | …

# A sample from our CFG

| | | |
|---|---|---|
| S | → | NP VP \| VP |
| NP | → | *the* N |
| N | → | *cat* \| *dog* \| *spider* \| *cheesecake* \| *democracy* |
| VP | → | V \| V NP |
| V | → | eat \| eats \| run \| differentiate \| … |

# A sample from our CFG

S → NP VP | VP
NP → *the* N
N → *cat* | *dog* | *spider* | *cheesecake* | *democracy*
VP → V | V NP
V → eat | eats | run | differentiate | …

S

NP VP

*the* N VP

*the cat* VP

*the cat* V NP

*the cat eat* NP

*the cat eat the* N

***the cat eat the democracy***

# A sample from our CFG

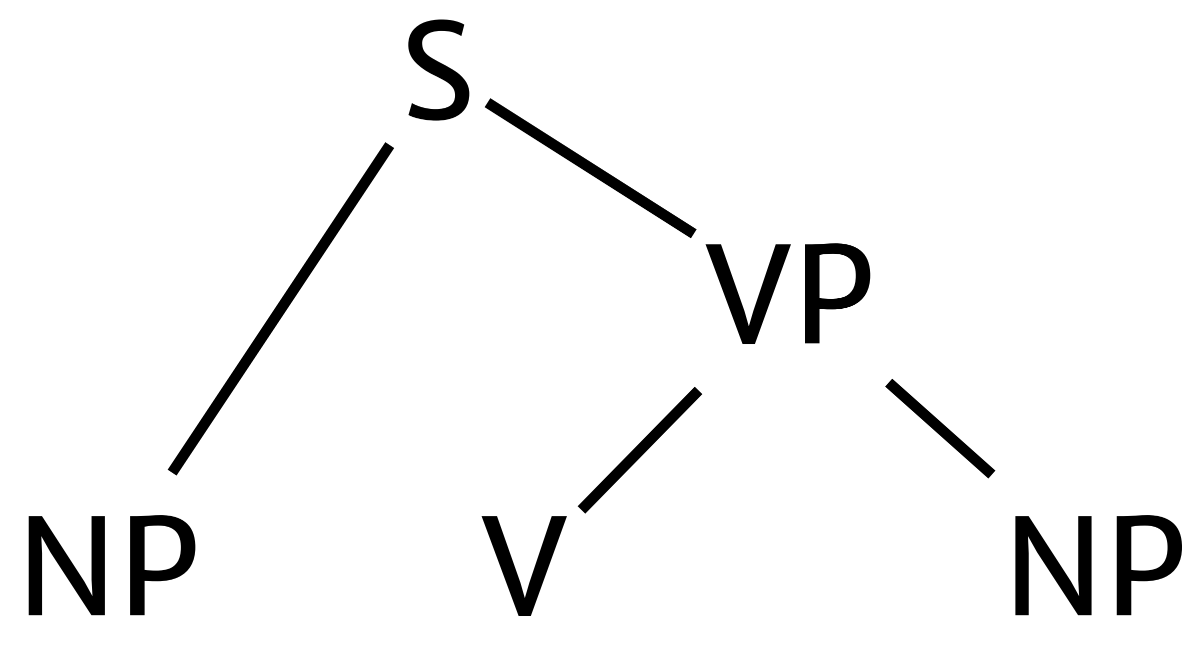
S → NP VP | VP

NP → *the* N

N → *cat* | *dog* | *spider* | *cheesecake* | *democracy*

VP → V | V NP

V → eat | eats | run | differentiate | ...




***the cat eat the democracy***

# What about other languages?

| | | | | | | |
|---|---|---|---|---|---|---|
| *a* | *taky* | *na* | *to* | *většinou* | *nemá* | *peníze* |
| and | also | for | it | generally | hasn't | money |

*and in most cases he has no money for it either*

[McDonald et al 2005]

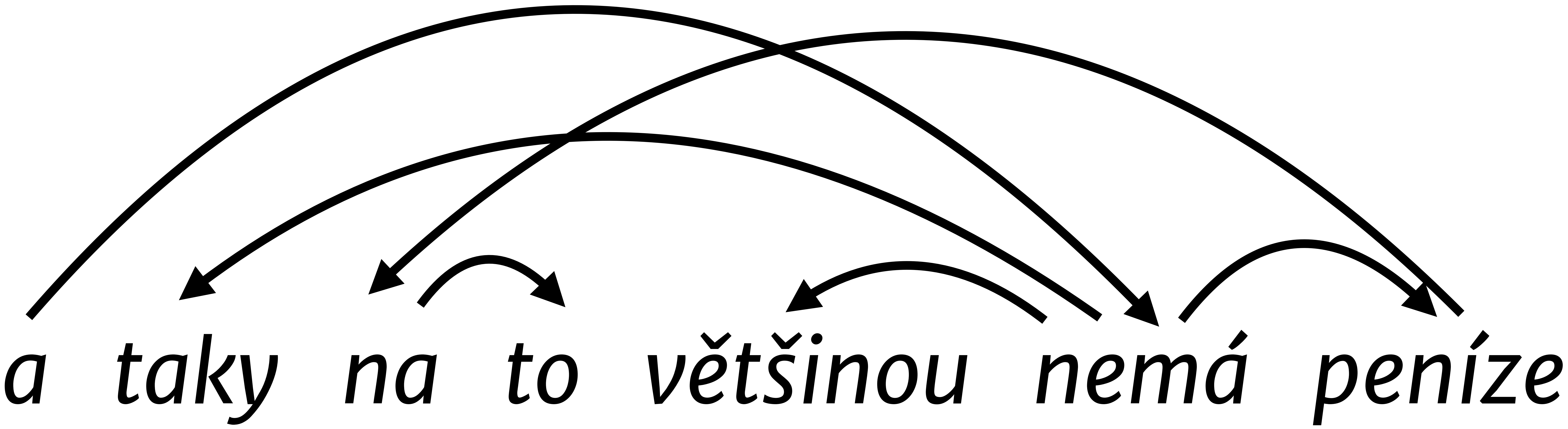
# What about other languages?

| | | | | | | |
|---|---|---|---|---|---|---|
| *a* | *taky* | *na* | *to* | *většinou* | *nemá* | *peníze* |
| and | also | for | it | generally | hasn't | money |

*and in most cases he has no money for it either*

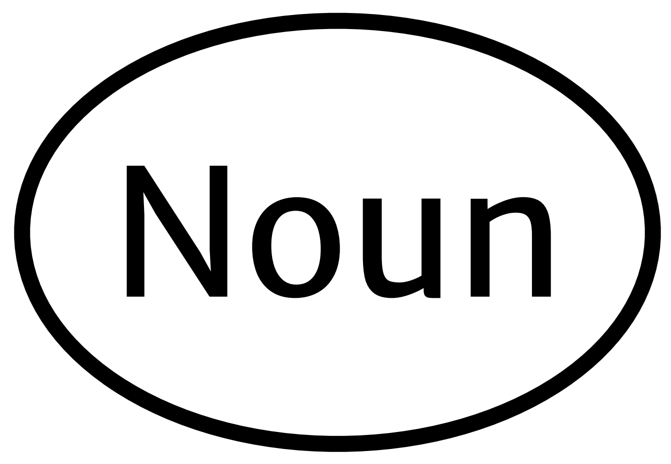
can't draw a constituency tree!

# Dependency grammar

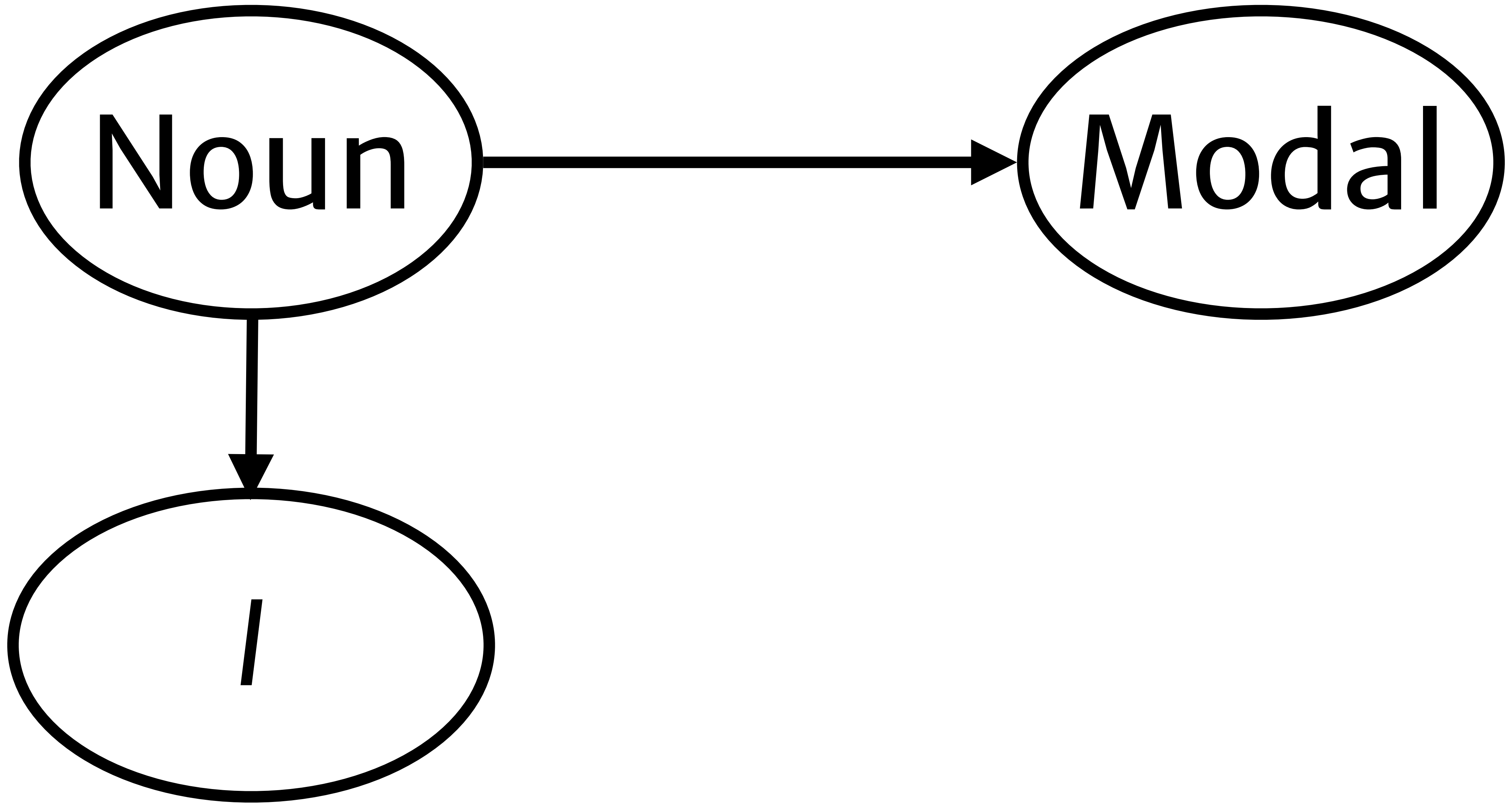


# Probabilistic grammars

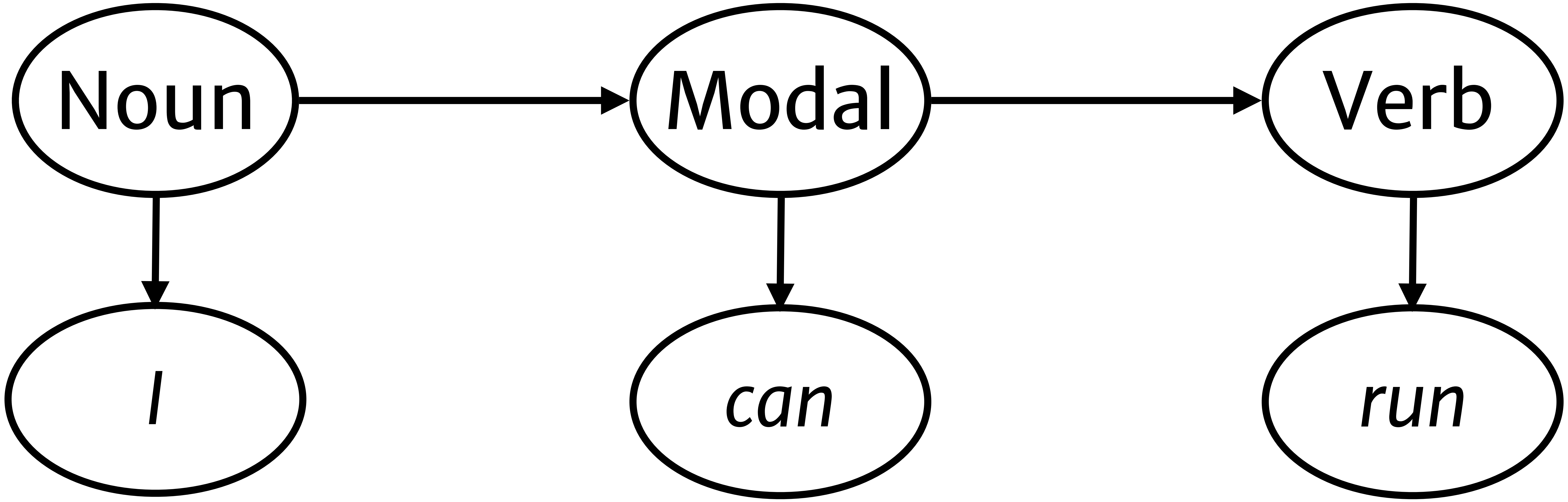
# CFGs as generative models



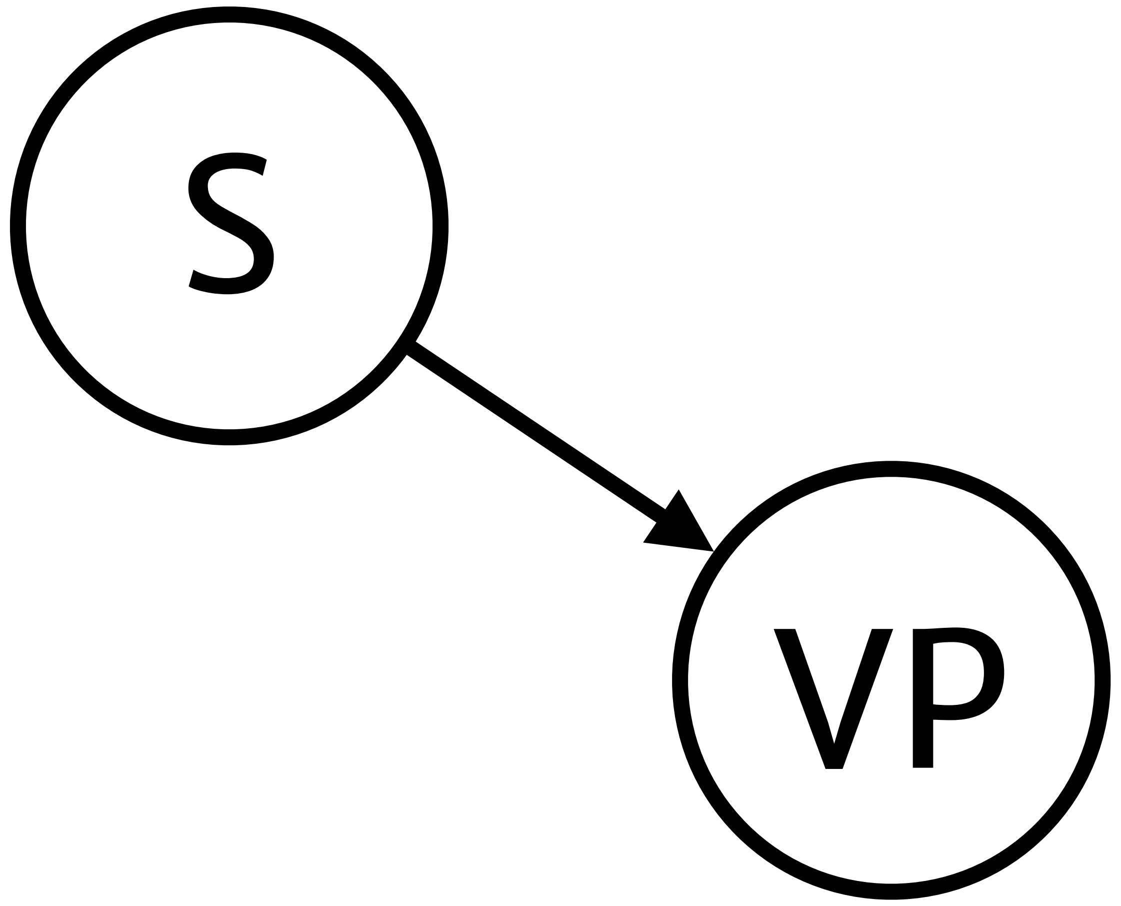
# CFGs as generative models



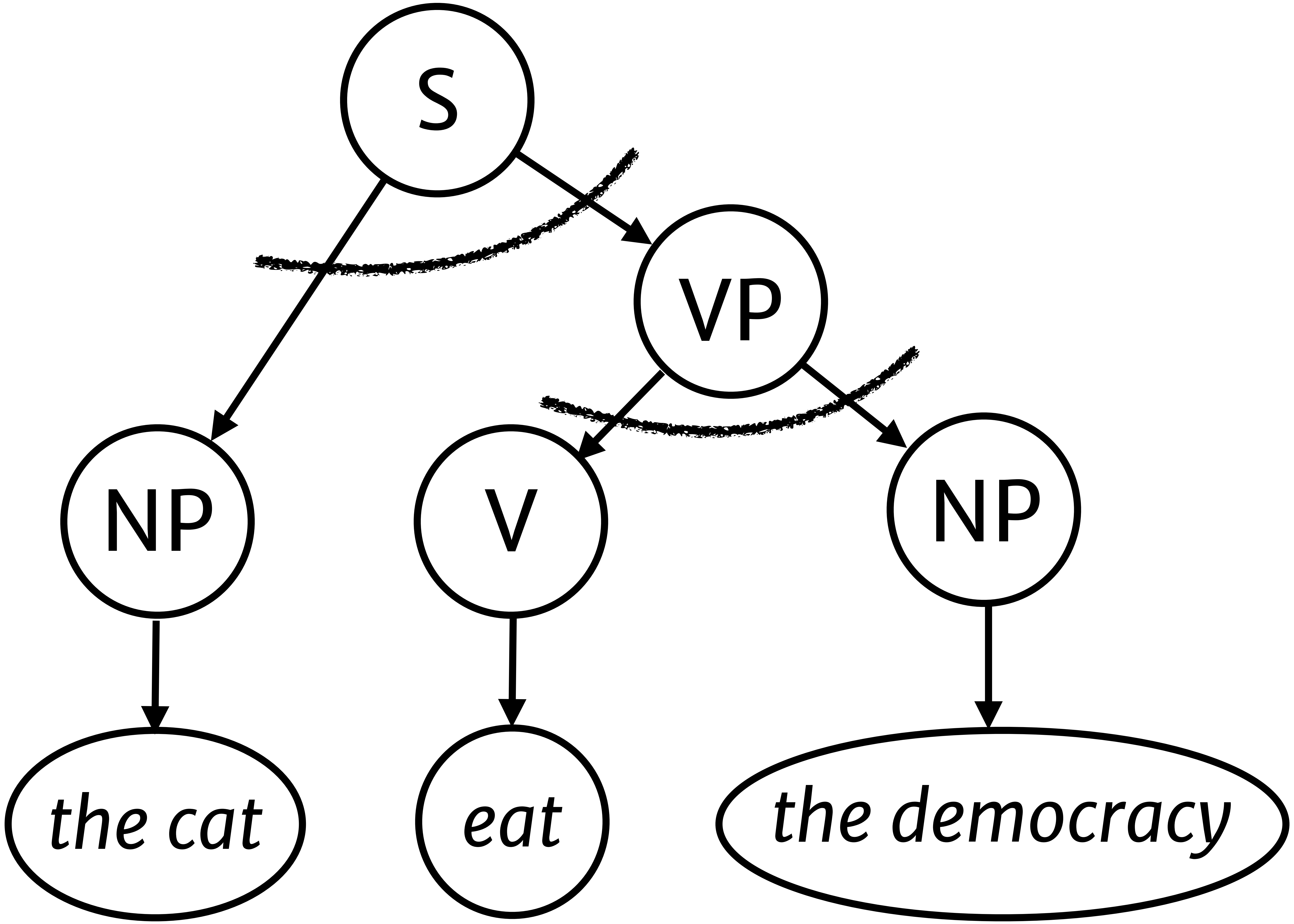
# CFGs as generative models



# CFGs as generative models



# CFGs as generative models



# Probabilistic CFGs

A probabilistic context free grammar (PCFG) consists of

1. A set of nonterminal symbols $N$
2. A set of terminal symbols $T$
3. A set of rules $R$
4. A set of rule probabilities $p(r \in R \mid n \in N)$

# Probabilistic CFGs

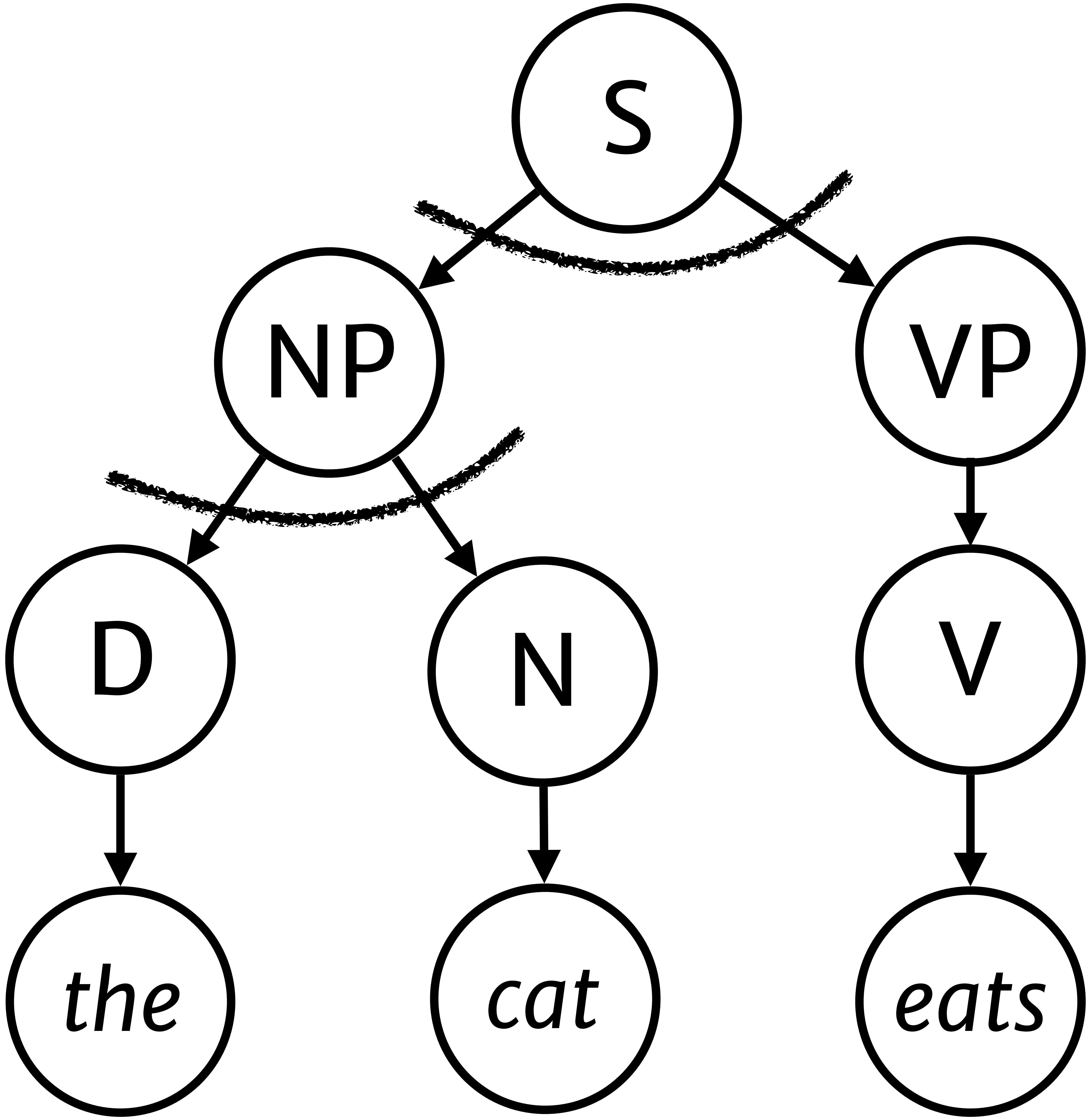
A rule consists of

1. A left hand symbol
2. A sequence of right-hand symbols

| LHS | | RHS | prob |
|---|---|---|---|
| S | $\rightarrow$ | NP VP | 0.75 |

such that $\sum_{\text{rules with LHS symbol A}} p(\text{rule} \mid \text{LHS}) = 1$

# Queries: joint probability

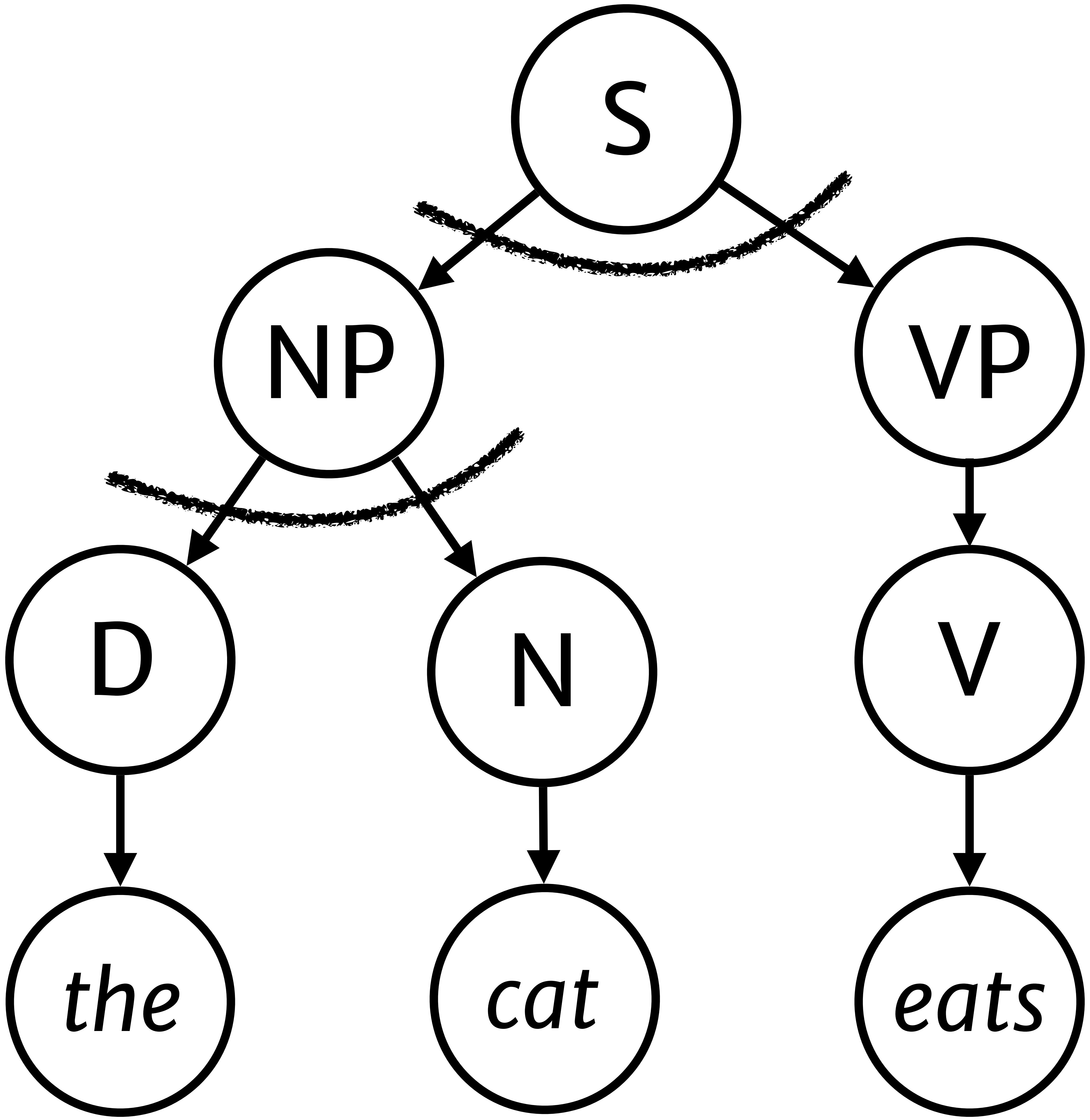



$$p(T, S)$$

joint prob. of tree and sentence

$$p(\text{S} \rightarrow \text{NP VP}) \cdot p(\text{NP} \rightarrow \text{D N})$$
$$p(\text{D} \rightarrow \text{the}) \cdot p(\text{N} \rightarrow \text{cat}) \;\; \cdots$$

# Queries: best tree

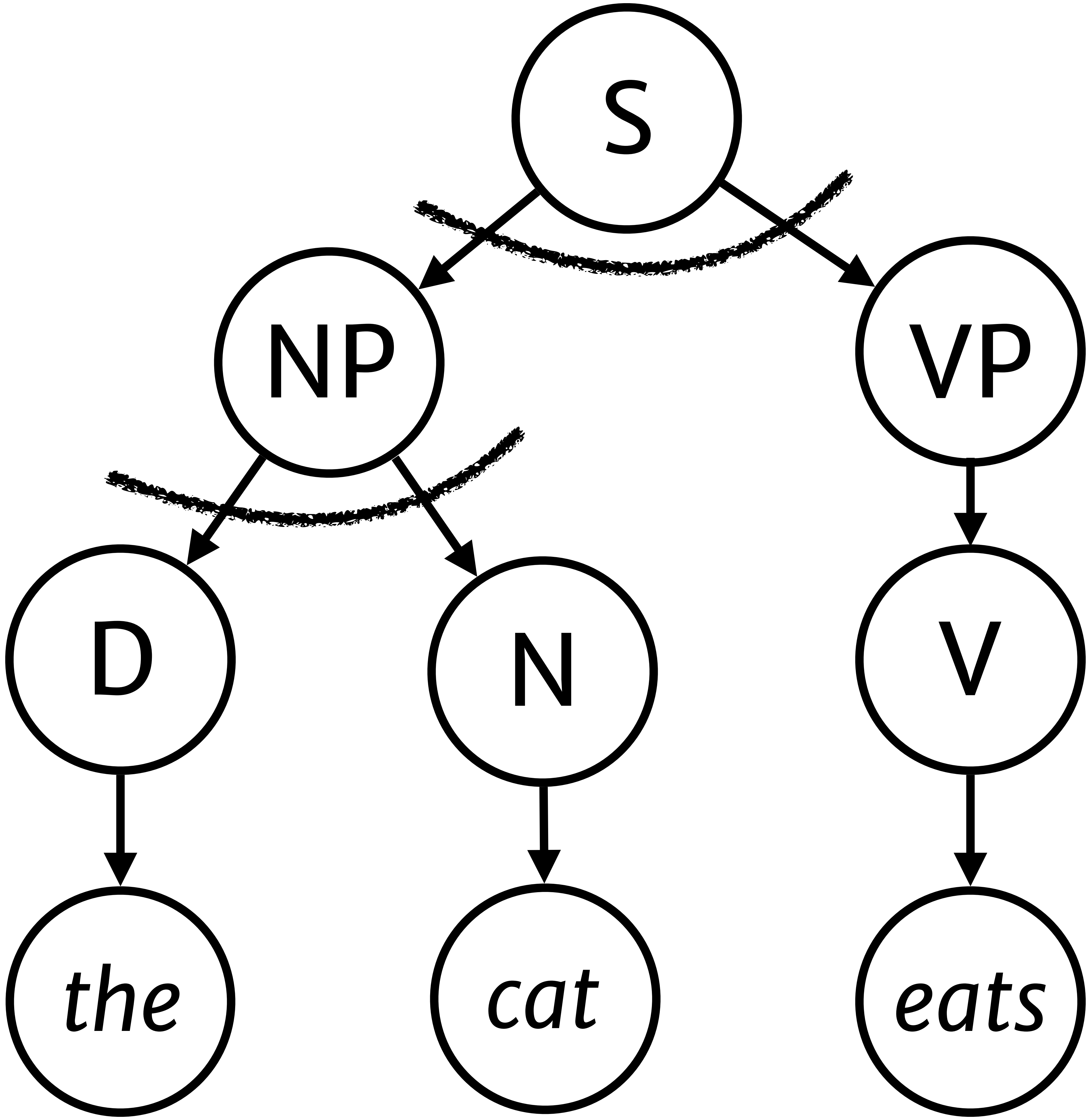



$$\text{argmax}_T \; p(T \mid S)$$

most probable tree given sent.

$$p(\text{S} \rightarrow \text{NP VP}) \cdot p(\text{NP} \rightarrow \text{D N})$$
$$p(\text{D} \rightarrow \textbf{the}) \cdot p(\text{N} \rightarrow \textbf{cat}) \;\; \cdots$$

# Queries: sentence marginal




$$p(S)$$

prob. of sentence under **any** tree

(there are $\frac{(2n)!}{(n+1)!n!}$ *unlabeled* binary trees over $n$ words...)

# Parsing

# Chomsky normal form

Notational convenience: only binary trees.

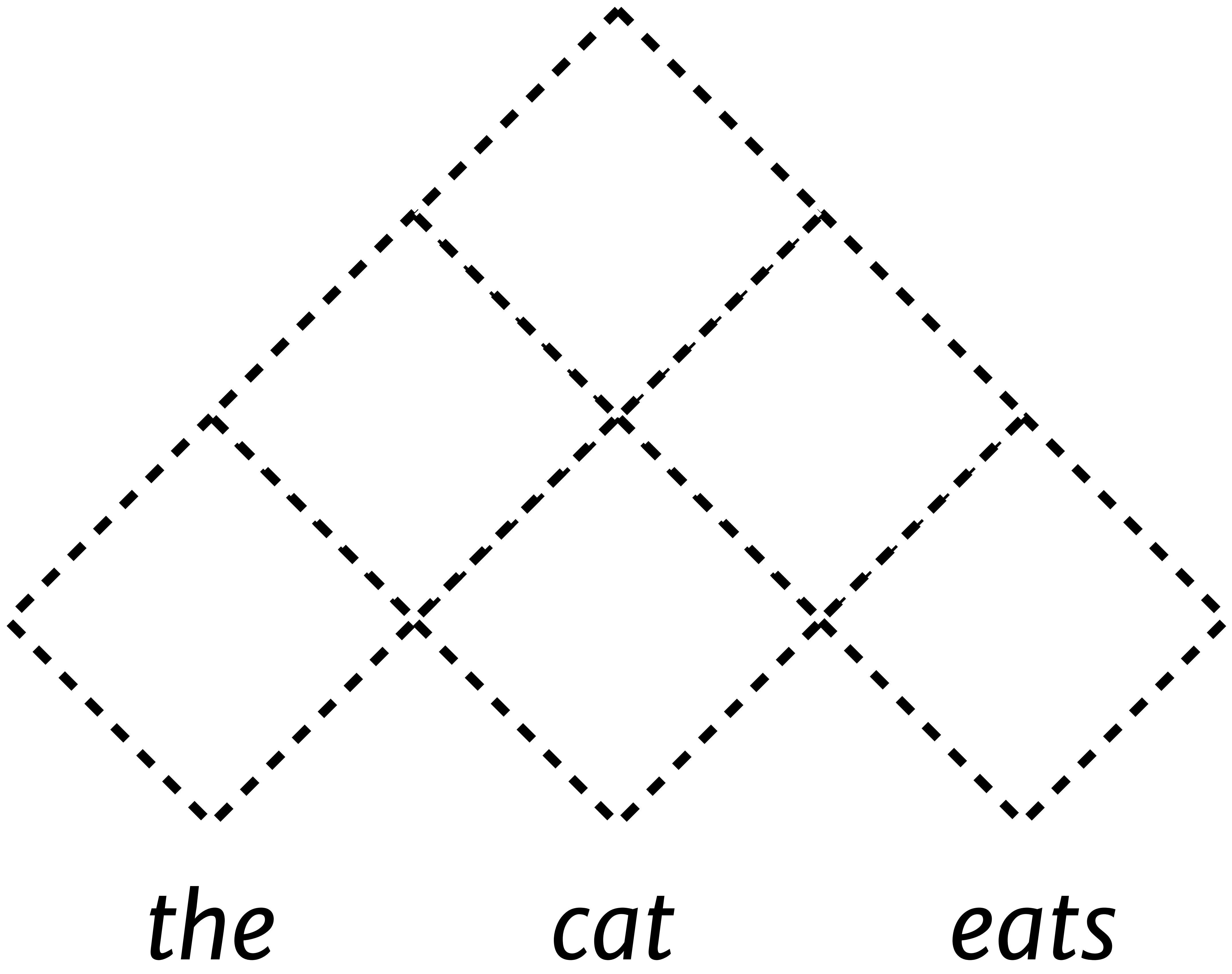
Every rule has one of these forms:

Nonterminal → Terminal
Nonterminal → Nonterminal  Nonterminal

(Can always get rules into this form by introducing new NTs)

# Warmup: the CKY algorithm

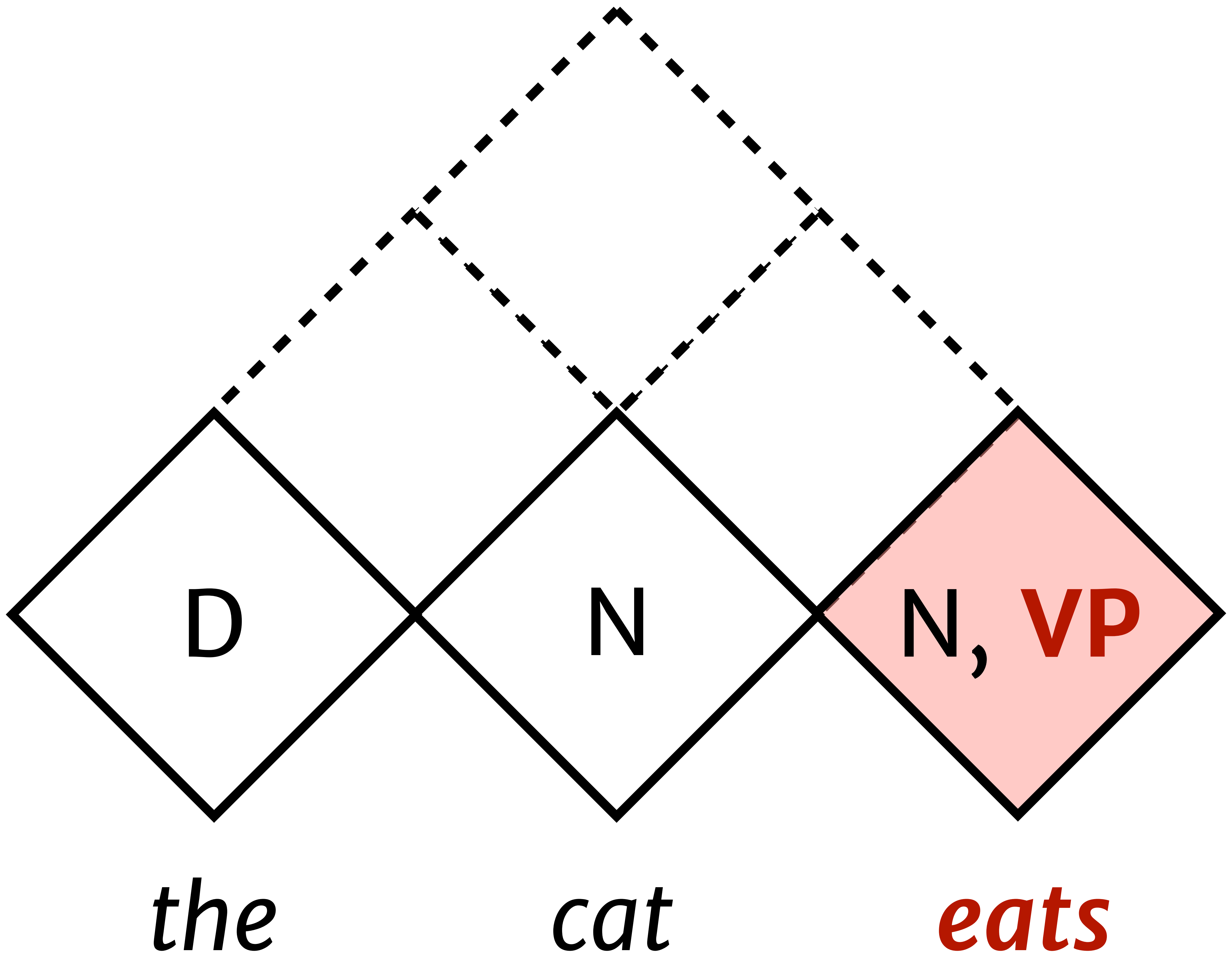
Is the string S generated by CFG G?




| | | |
|---|---|---|
| S | → | NP VP |
| NP | → | D N |
| N | → | cat \| eats |
| VP | → | eats \| sings |
| D | → | the \| a |

# Warmup: the CKY algorithm

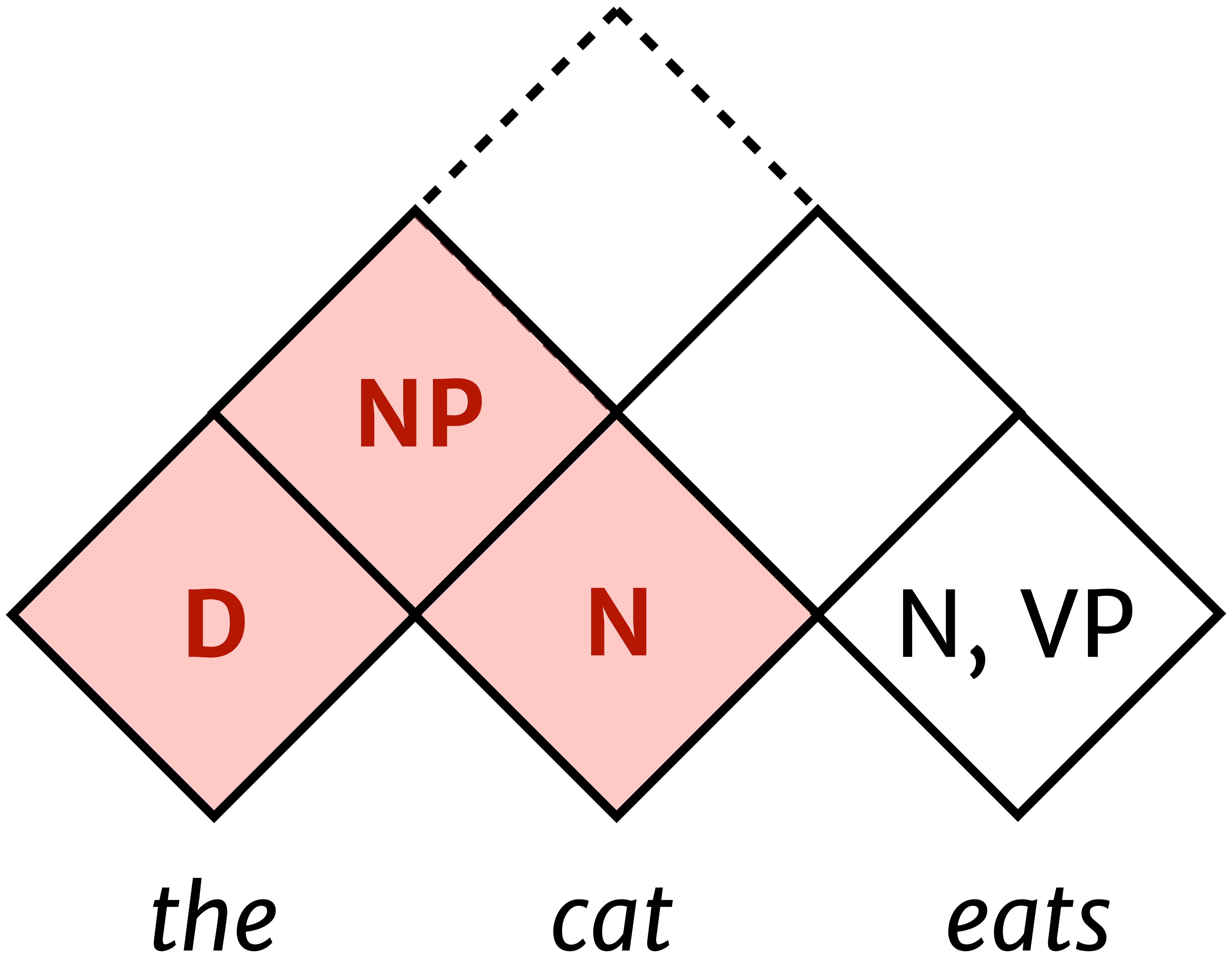
## 1. Fill in bottom row with NTs that can generate observed words




S → NP VP
NP → D N
N → cat | eats
**VP → eats | sings**
D → the | a

# Warmup: the CKY algorithm

## 2. Fill in second row with NTs that generate a symbol in **each** child




S → NP VP

**NP → D N**

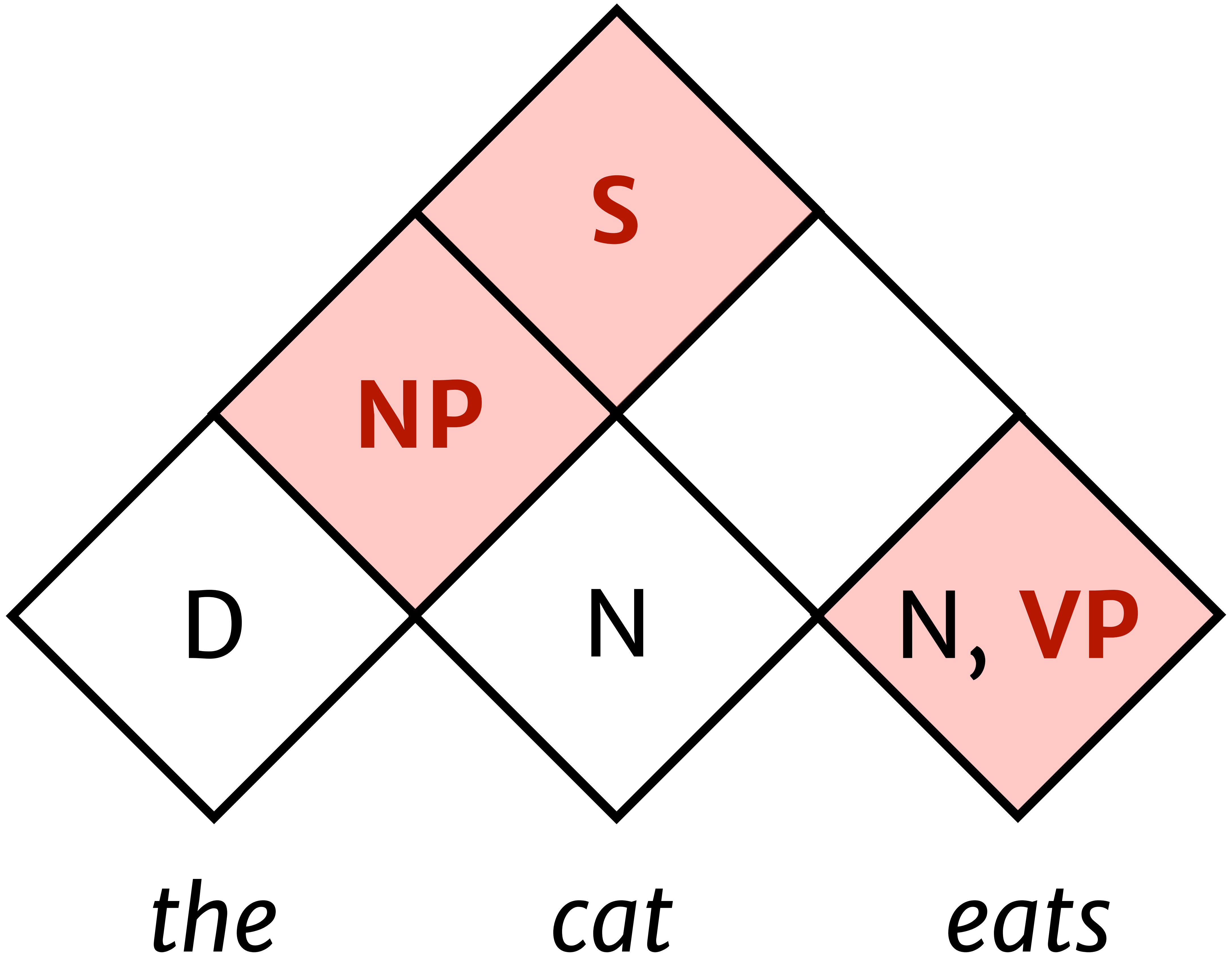
N → cat | eats

VP → eats | sings

D → the | a

# Warmup: the CKY algorithm

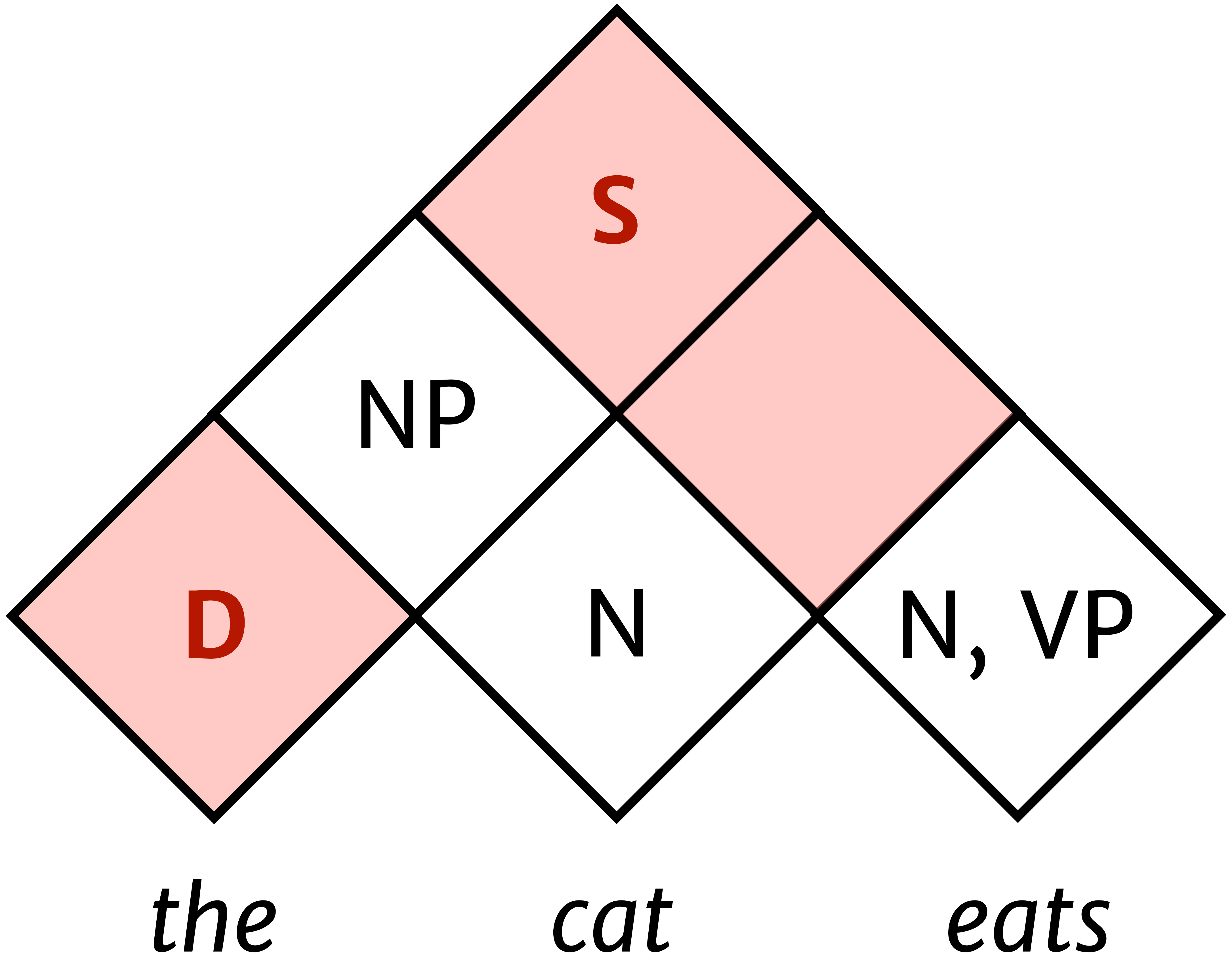
3. Fill in higher rows with NTs that generate a symbol **any pair of non-overlapping** children




**S → NP VP**
NP → D N
N → cat | eats
VP → eats | sings
D → the | a

# Warmup: the CKY algorithm

3. Fill in higher cells with NTs that generate symbols in **any pair of non-overlapping** children




**S → NP VP**

NP → D N

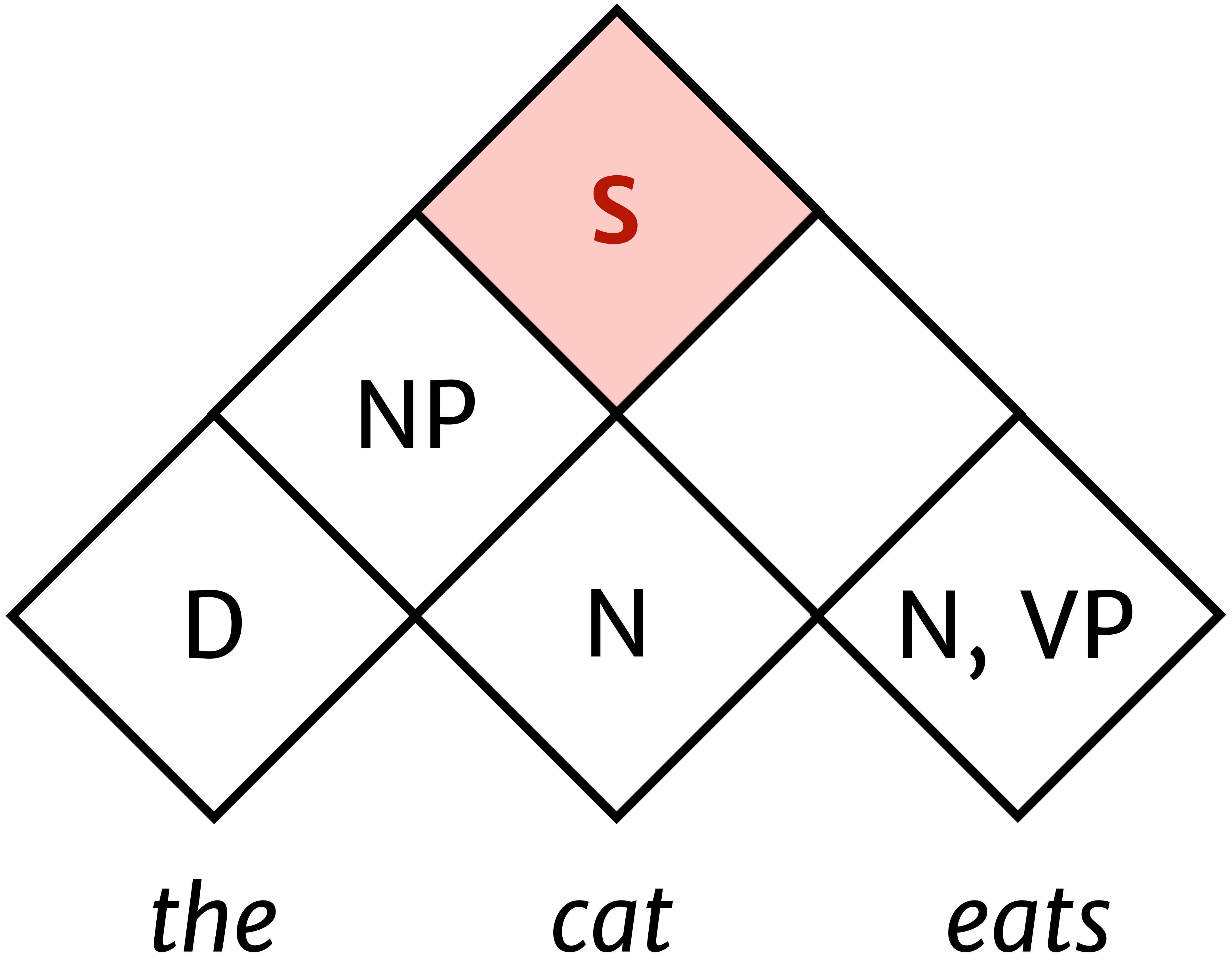
N → cat | eats

VP → eats | sings

D → the | a

# Warmup: the CKY algorithm

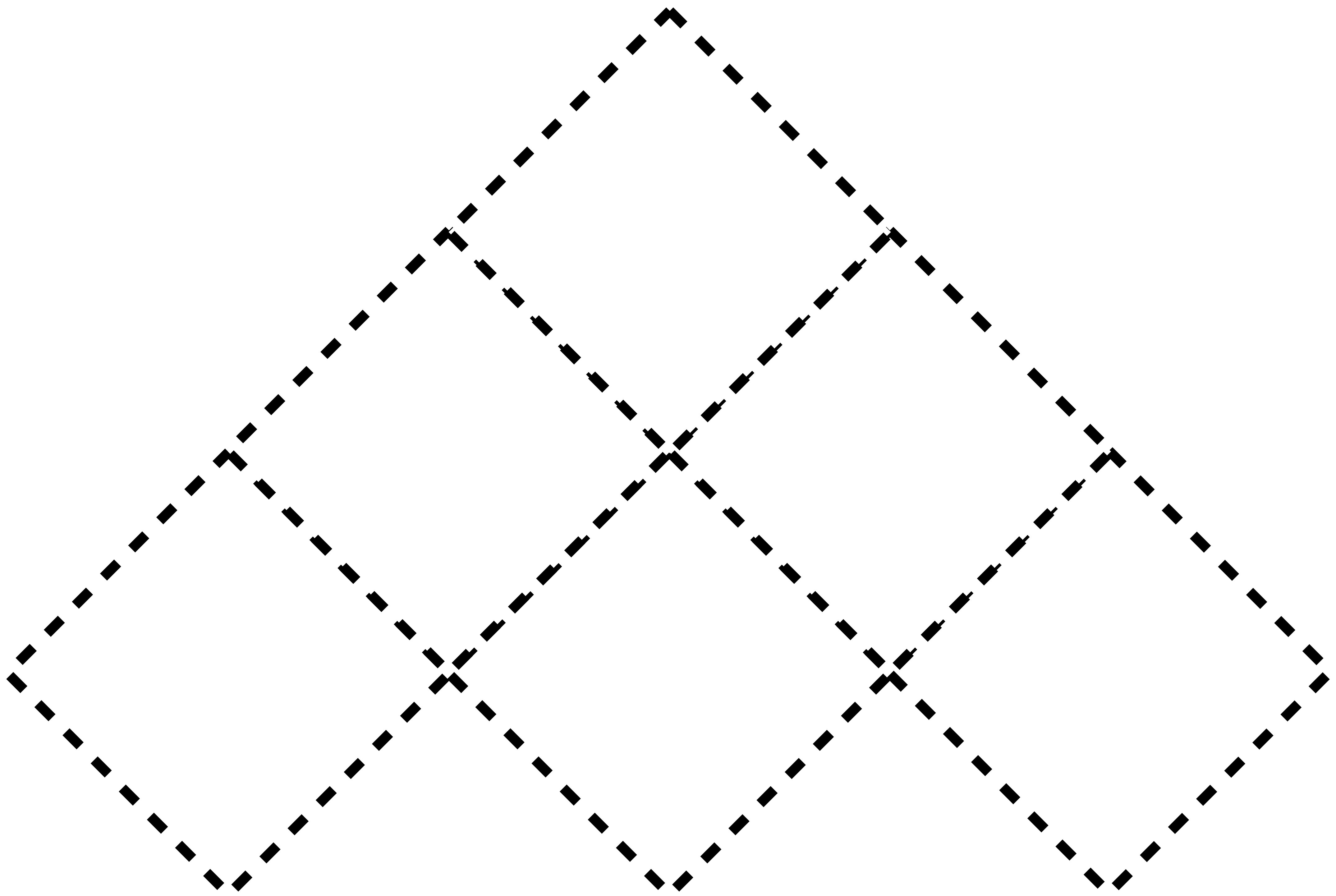
4. If the top cell contains the start symbol, the string is generated.




| | | |
|---|---|---|
| S | → | NP VP |
| NP | → | D N |
| N | → | cat \| eats |
| VP | → | eats \| sings |
| D | → | the \| a |

# Highest-scoring parse

## What parse assigns highest prob. to S under the PCFG G?



*the* *cat* *eats*

$$S \rightarrow \overset{0.9}{NP\ VP} \mid \overset{0.1}{NP\ N}$$

$$NP \rightarrow \overset{1}{D\ N}$$

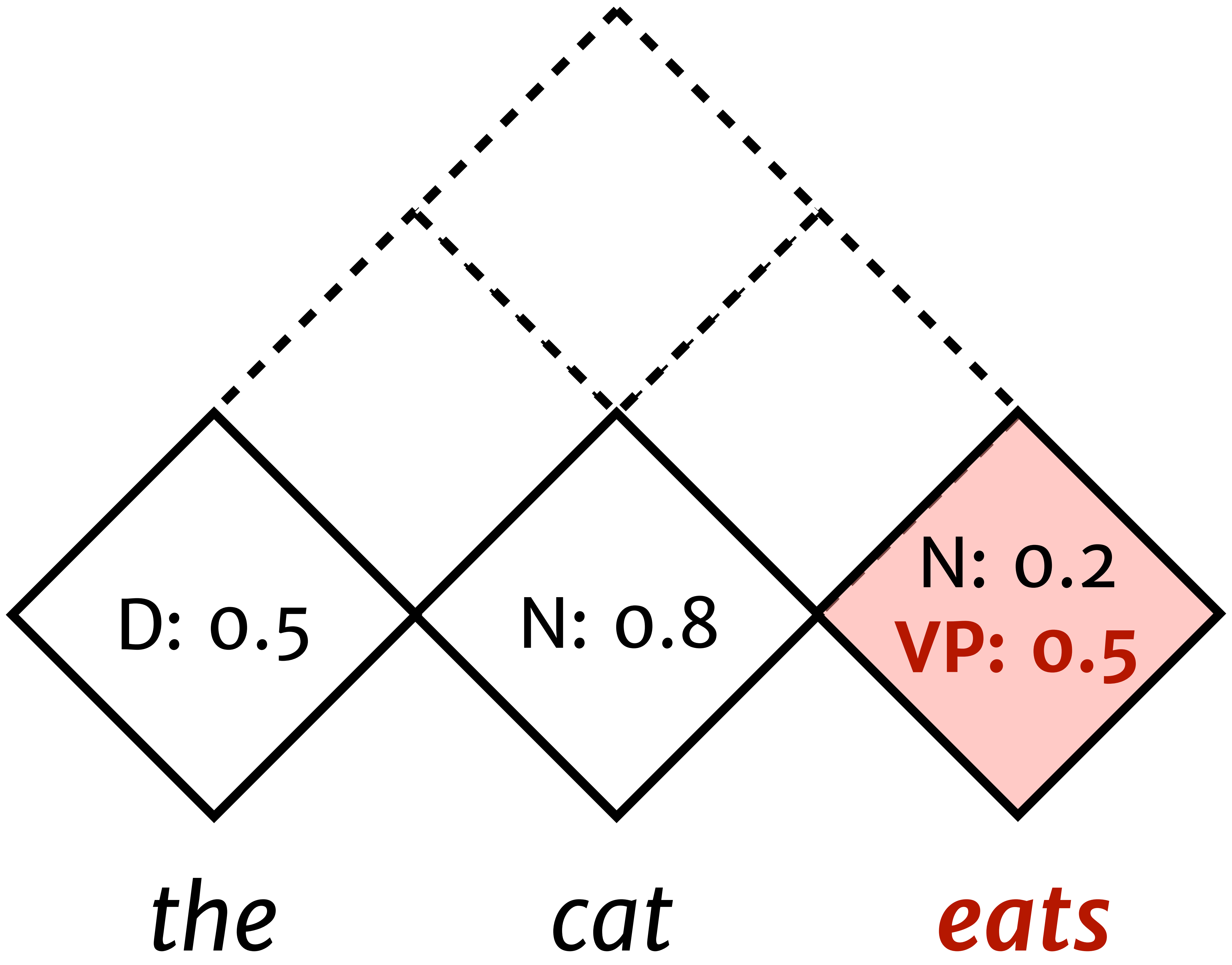
$$N \rightarrow \overset{0.8}{cat} \mid \overset{0.2}{eats}$$

$$VP \rightarrow \overset{0.5}{eats} \mid \overset{0.5}{sings}$$

$$D \rightarrow \overset{0.5}{the} \mid \overset{0.5}{a}$$

# Highest-scoring parse

**1. Fill in bottom row with prob. that each NT generates word**




$$\mathrm{S} \rightarrow \overset{0.9}{\mathrm{NP\ VP}} \mid \overset{0.1}{\mathrm{NP\ N}}$$

$$\mathrm{NP} \rightarrow \overset{1}{\mathrm{D\ N}}$$

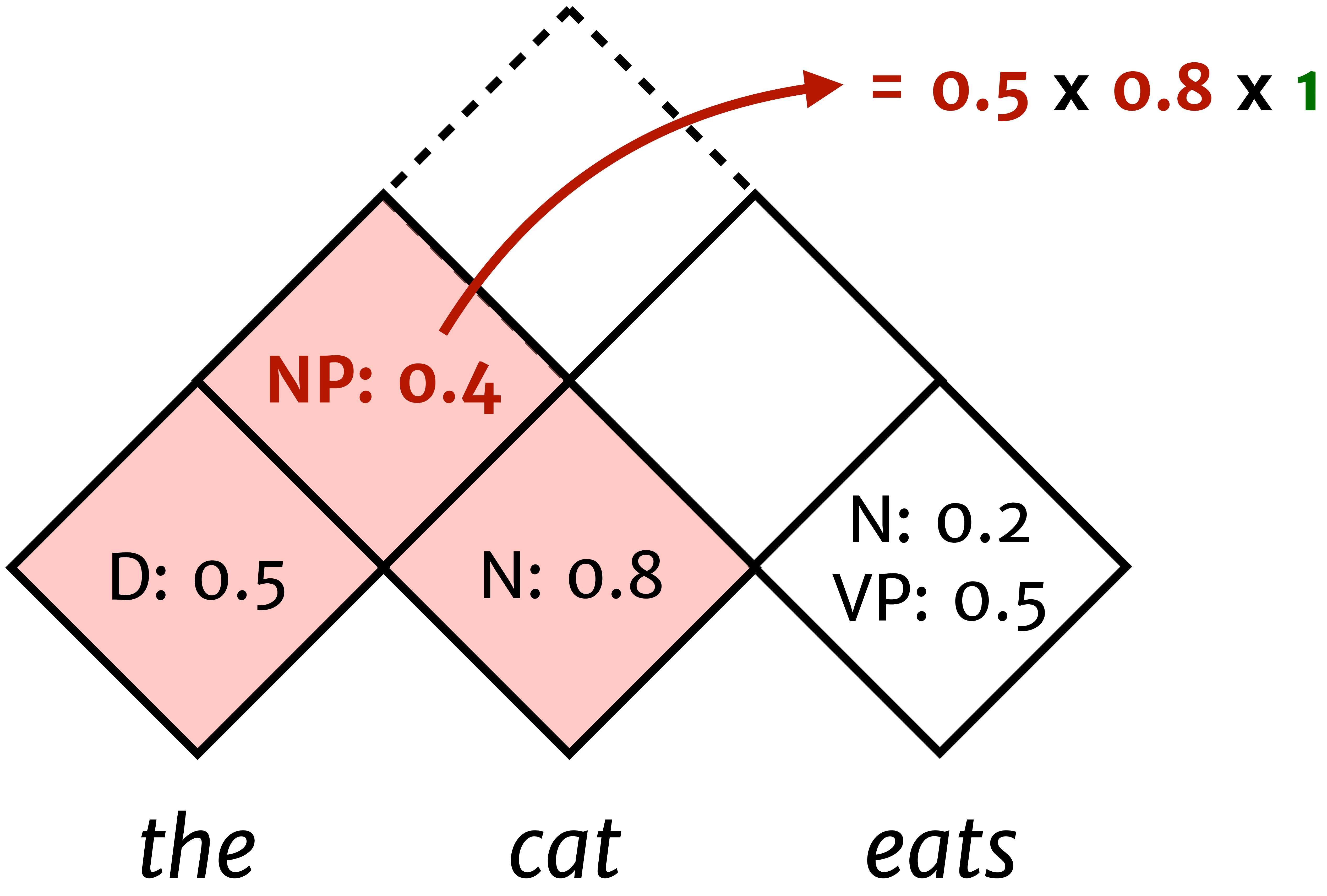
$$\mathrm{N} \rightarrow \overset{0.8}{\mathrm{cat}} \mid \overset{0.2}{\mathrm{eats}}$$

$$\mathbf{VP} \rightarrow \overset{0.5}{\mathbf{eats}} \mid \overset{0.5}{\mathbf{sings}}$$

$$\mathrm{D} \rightarrow \overset{0.5}{\mathrm{the}} \mid \overset{0.5}{\mathrm{a}}$$

# Highest-scoring parse

2. Fill in higher rows with highest-scoring product of child probs. times rule prob.




0.9 0.1
S → NP VP | NP N

1
**NP → D N**

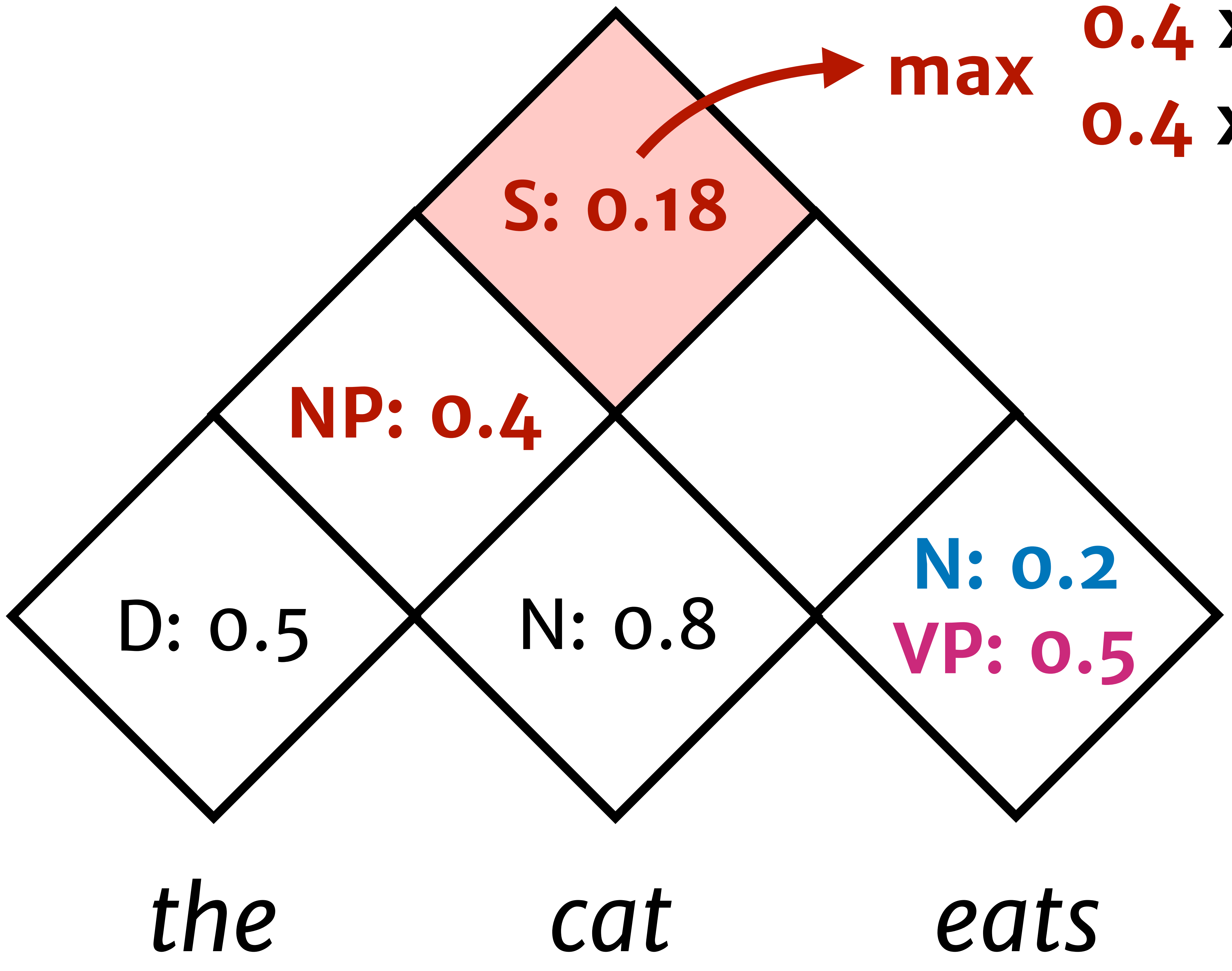
0.8 0.2
N → cat | eats

0.5 0.5
VP → eats | sings

0.5 0.5
D → the | a

# Highest-scoring parse

2. Fill in higher rows with highest-scoring product of child probs. times rule prob.




max $0.4 \times 0.5 \times 0.9,\ 0.4 \times 0.2 \times 0.1$

$S \rightarrow \overset{0.9}{NP\ VP} \mid \overset{0.1}{NP\ N}$

$NP \rightarrow \overset{1}{D\ N}$

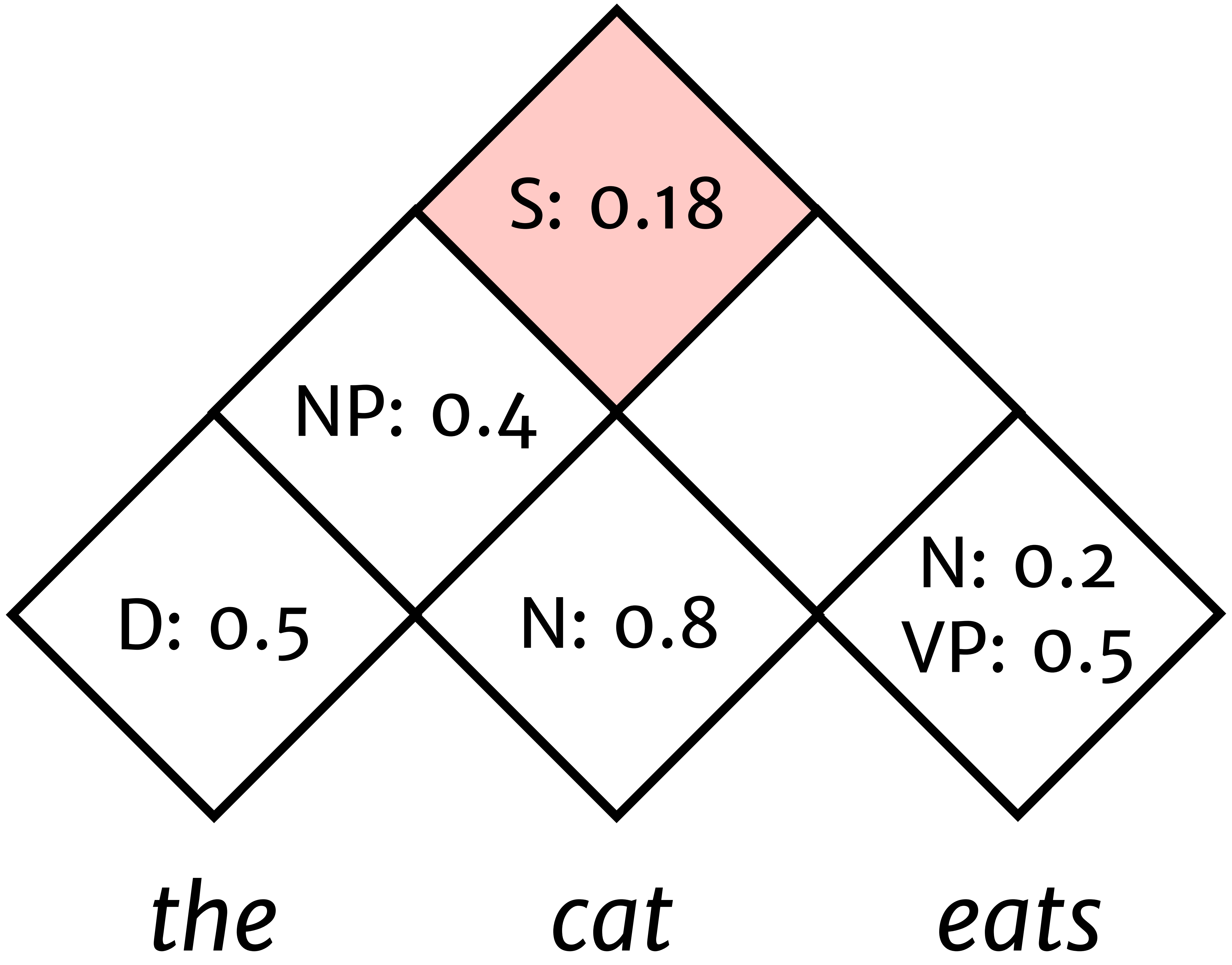
$N \rightarrow \overset{0.8}{\text{cat}} \mid \overset{0.2}{\text{eats}}$

$VP \rightarrow \overset{0.5}{\text{eats}} \mid \overset{0.5}{\text{sings}}$

$D \rightarrow \overset{0.5}{\text{the}} \mid \overset{0.5}{\text{a}}$

# Highest-scoring parse

## 3. The score for S in the top cell is the score of the best parse.




$$S \rightarrow \overset{0.9}{\text{NP VP}} \mid \overset{0.1}{\text{NP N}}$$

$$NP \rightarrow \overset{1}{\text{D N}}$$

$$N \rightarrow \overset{0.8}{\text{cat}} \mid \overset{0.2}{\text{eats}}$$

$$VP \rightarrow \overset{0.5}{\text{eats}} \mid \overset{0.5}{\text{sings}}$$

$$D \rightarrow \overset{0.5}{\text{the}} \mid \overset{0.5}{\text{a}}$$

# The Viterbi algorithm for CFGs

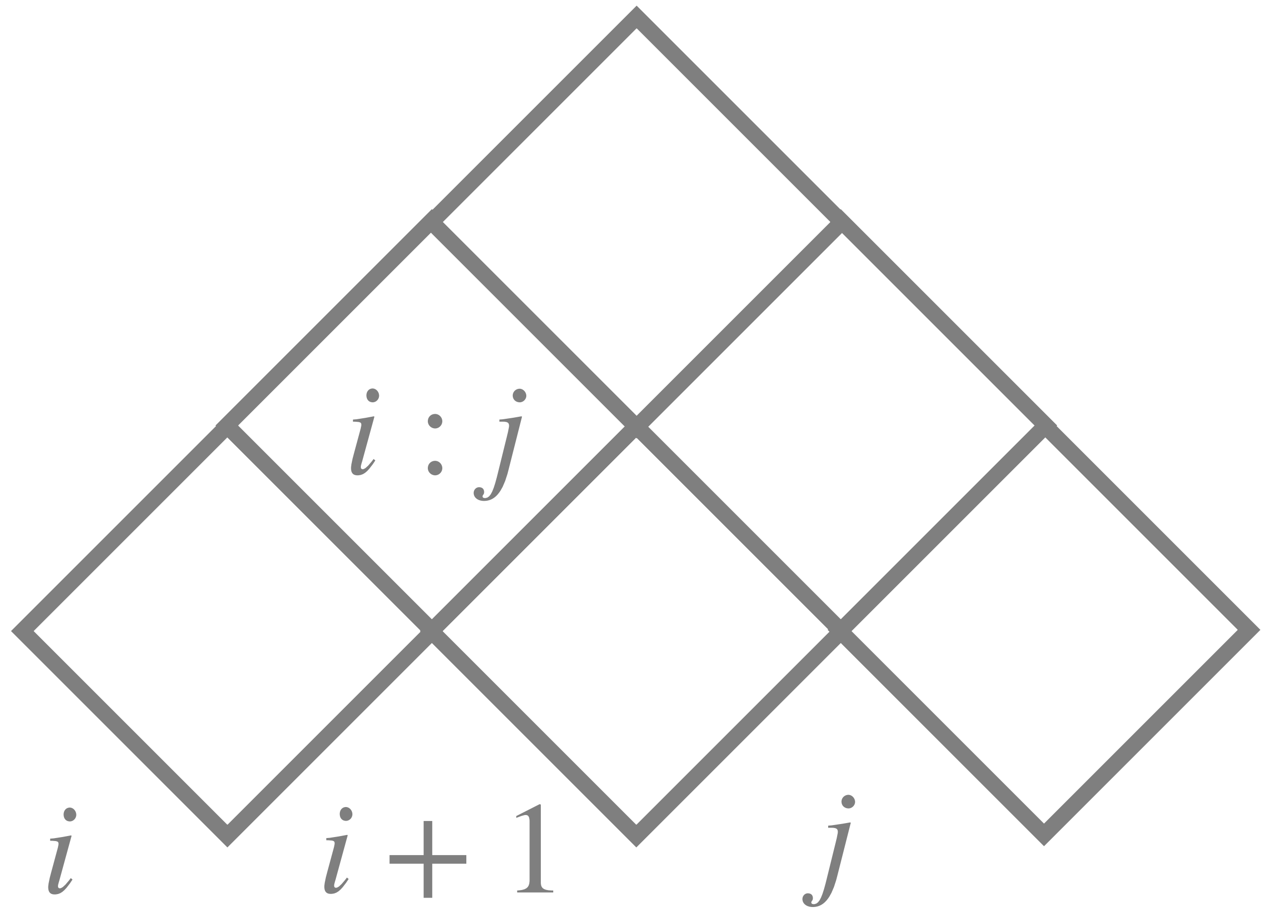
Q: what is the **most probable** tree for a given sentence?

$$\max_T \; p(T, S)$$

$\delta(s, i, j)$ highest-scoring tree with root s covering words i:j

base case:

$$\delta(s, i, i+1) = p(s \to w_i)$$




inductive case:

$$\delta(s, i, j) = \max_{k \in [i+1, j-1]} \; \max_{s', s''} p(s \to s' s'') \; \delta(s', i, k) \; \delta(s'', k, j)$$

# The Viterbi algorithm for CRFs

Q: what is the **most probable** assignment of tags to observations?

$$\text{argmax}_Q \; p(Q \mid O)$$

$$\boxed{\delta(t,j) = \max_i \delta(t-1,i)\; a_{ij}\; b_j(o_t) \qquad \delta(1,j) = \pi(j)\; b_j(o_1)}$$

# The inside algorithm for CFGs

Q: what is the marginal probability of a sentence given a tree?

$$\sum_T p(T, S)$$

$\beta(s, i, j)$ probability of all parses with root s covering words i:j

base case:

$$\beta(s, i, i+1) = p(s \rightarrow w_i)$$

inductive case:

$$\beta(s, i, j) = \sum_{k \in [i+1, j-1]} \sum_{s', s''} p(s \rightarrow s's'')\ \beta(s', i, k)\ \beta(s'', k, j)$$

# Tree-structured CRFs

Instead of scores $p(A \to B\ C)$, use an arbitrary scorer

$$w^\top \phi(A, B, C, i, j)$$

(can be different in each cell & look at full sentence sentence)

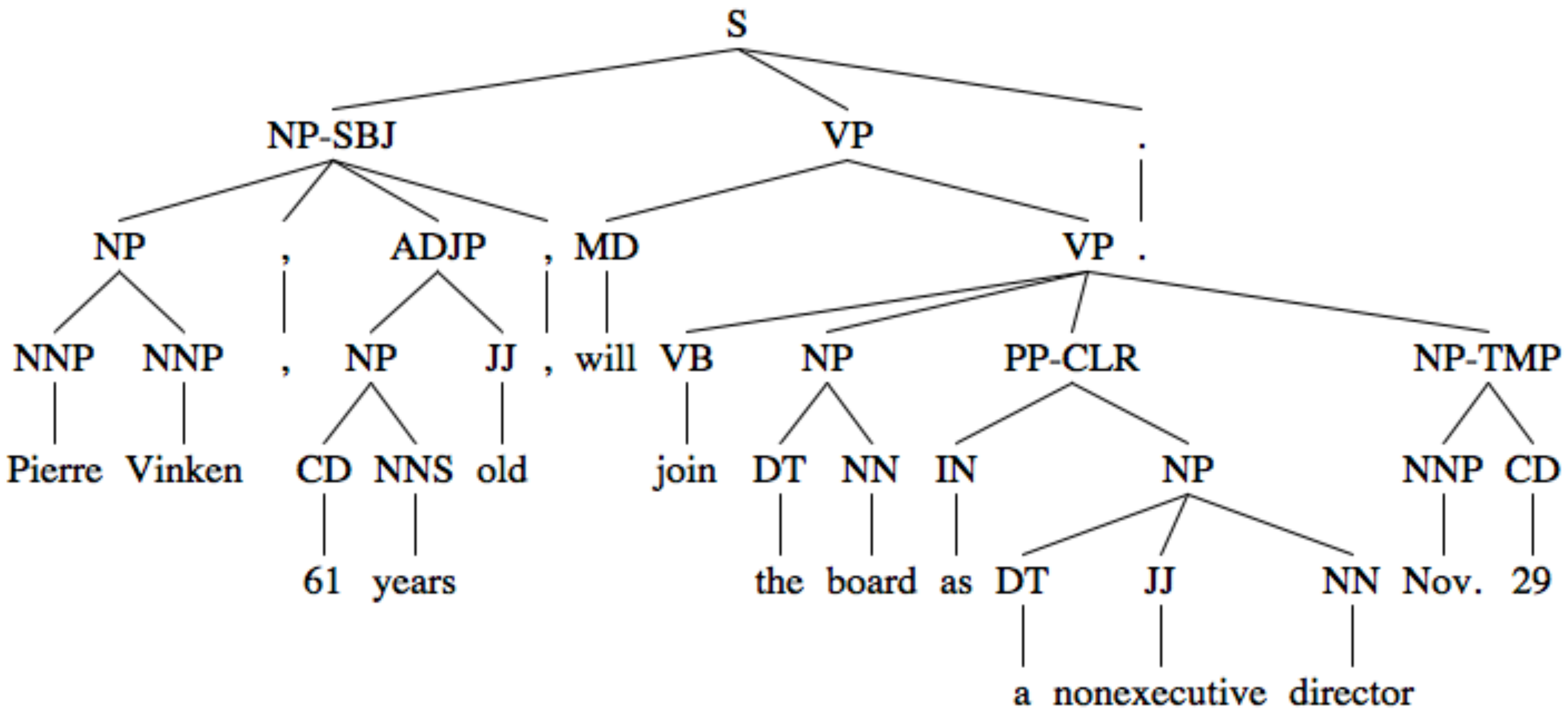
Works just like the HMM version!

$\beta(\text{S}, 0, |S|)$ is the partition function

# Learning

# Supervised learning

For PCFGs—given a **treebank,** estimate by counting:

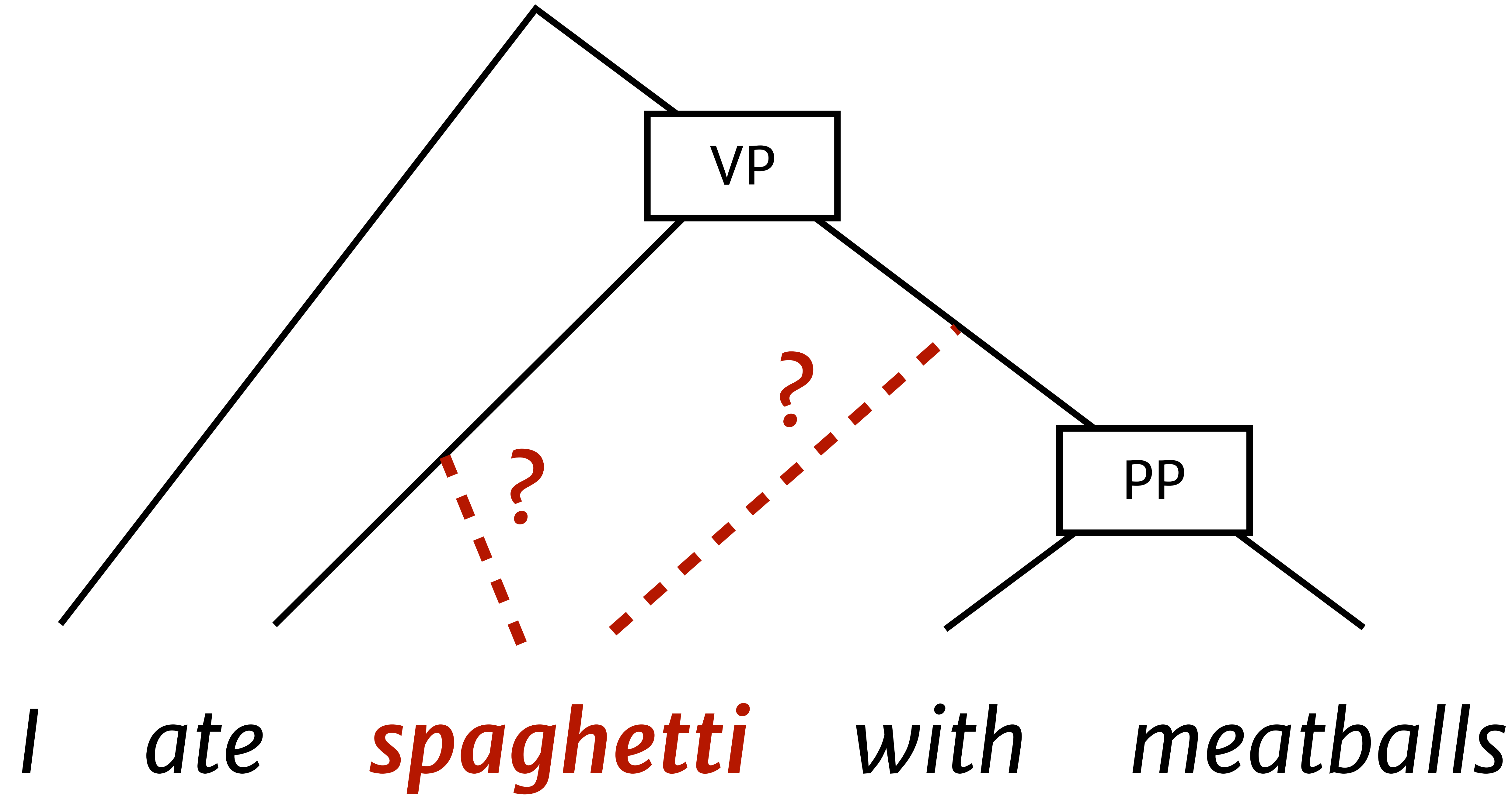



$$p(\mathsf{S} \rightarrow \mathsf{NP}\ \mathsf{VP})$$

$$= \frac{\#(\mathsf{S} \rightarrow \mathsf{NP}\ \mathsf{VP})}{\#(\mathsf{S})}$$

# Supervised learning

For PCFGs—given a **treebank,**



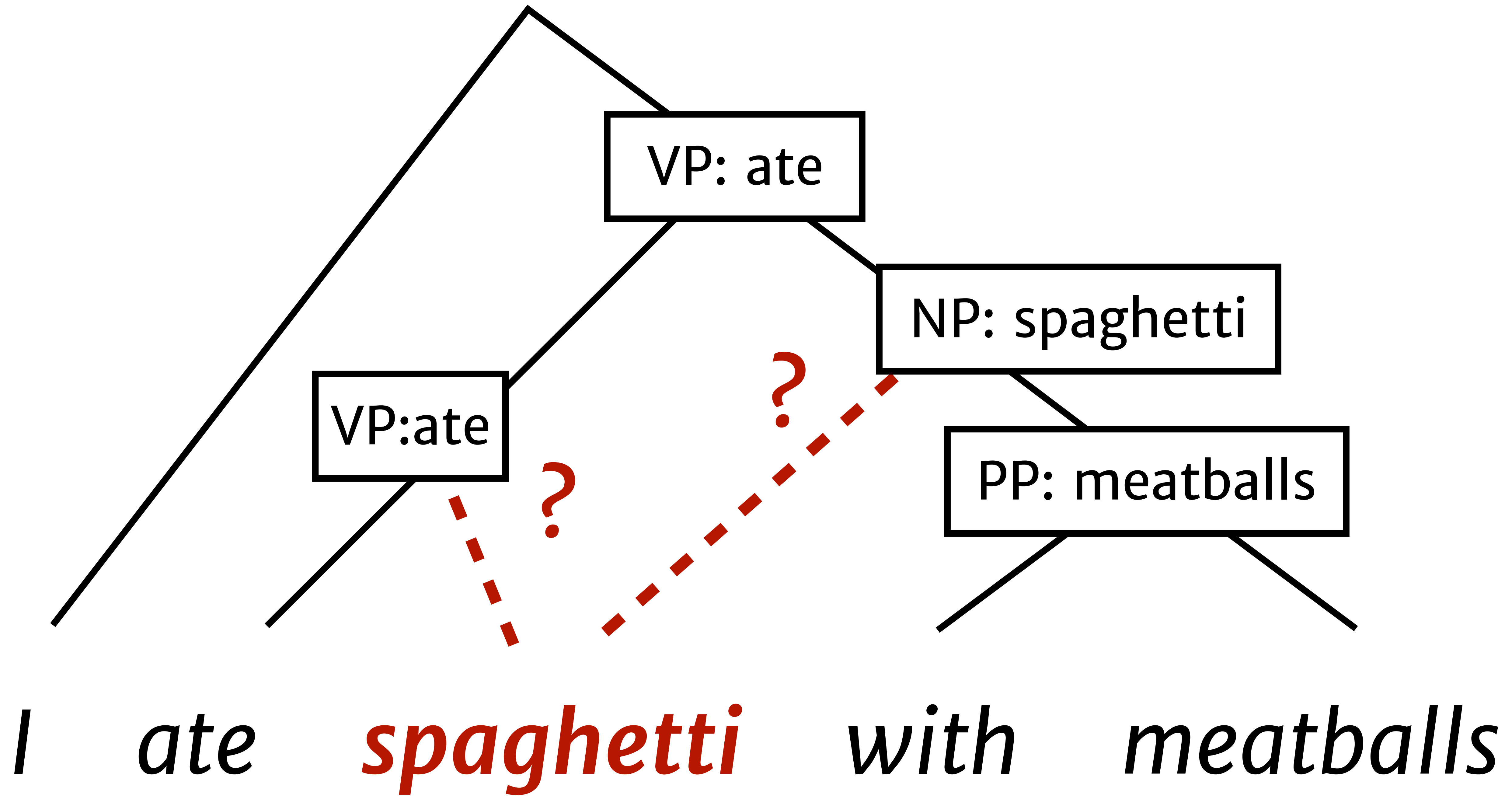

estimate by counting:

$$p(\mathsf{S} \rightarrow \mathsf{NP}\ \mathsf{VP}) = \frac{\#(\mathsf{S} \rightarrow \mathsf{NP}\ \mathsf{VP})}{\#(\mathsf{S})}$$

This doesn't work very well: basic syntactic categories are too coarse.

# Supervised learning: lexicalization

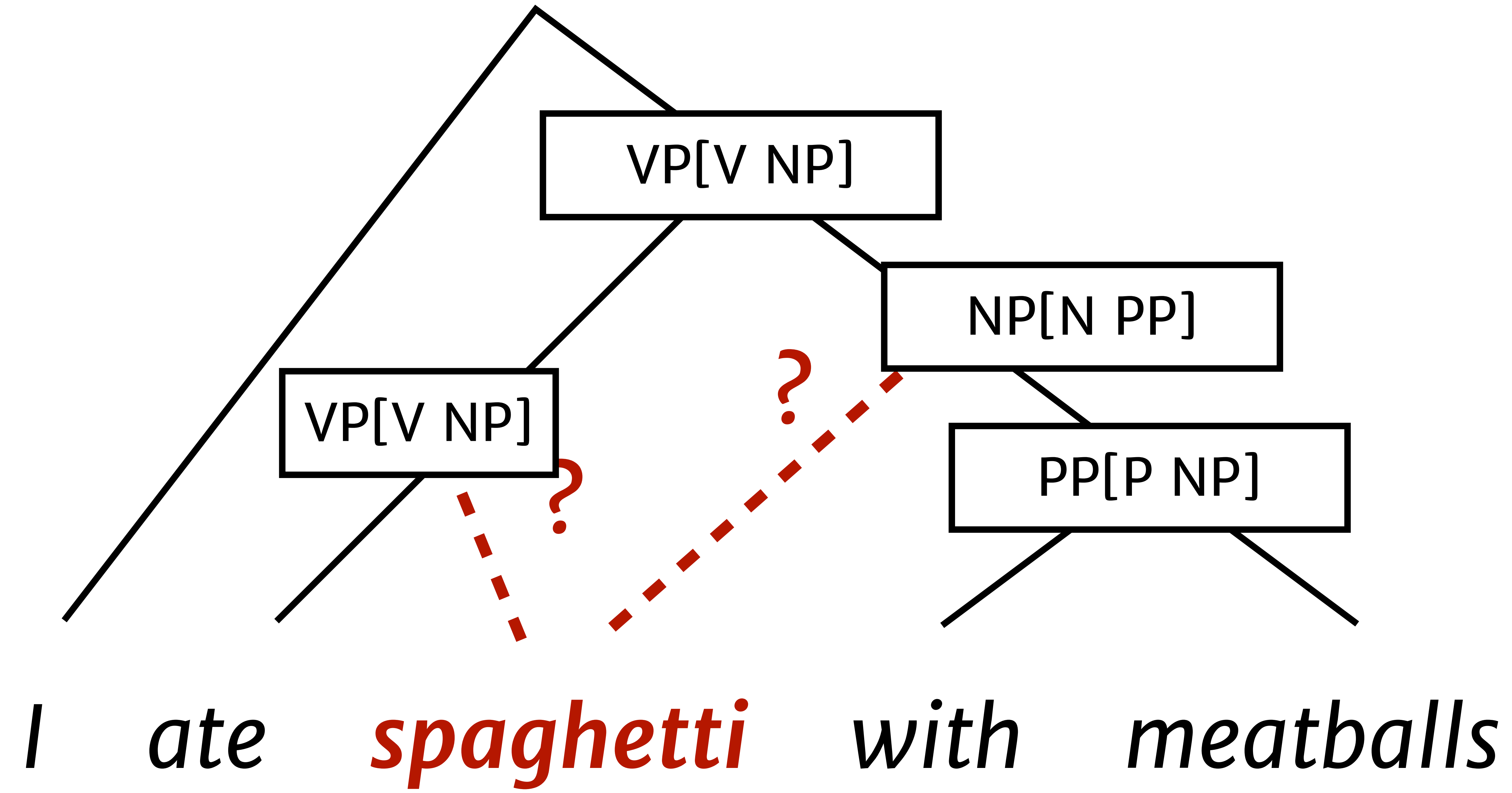
Idea: enrich nonterminal alphabet with information about the most important **word** underneath:




[e.g. Collins 97]

# Supervised learning: Markovization

Idea: enrich nonterminal alphabet with more information about the local tree structure:




[e.g. Klein 03]

# Supervised learning: features & NNs

Idea: Use the CRF version

$$P(T) \propto \exp\left\{ \sum_{(A\to B\ C,i,k,j)} w^\top \phi(A,B,C,i,k,j) \right\}$$

and give $\phi$ features like "A = NP and *j:k* contains *fork*"
(or make it a neural network)

# Supervised parsing: what's still hard?

| Error Type | Occurrences | Nodes Involved | Ratio |
|---|---|---|---|
| PP Attachment | 846 | 1455 | 1.7 |
| Single Word Phrase | 490 | 490 | 1.0 |
| Clause Attachment | 385 | 913 | 2.4 |
| Adverb and Adjective Modifier Attachment | 383 | 599 | 1.6 |
| Different Label | 377 | 754 | 2.0 |
| Unary | 347 | 349 | 1.0 |
| NP Attachment | 321 | 597 | 1.9 |
| NP Internal Structure | 299 | 352 | 1.2 |
| Coordination | 209 | 557 | 2.7 |
| Unary Clause Label | 185 | 200 | 1.1 |
| VP Attachment | 64 | 159 | 2.5 |
| Parenthetical Attachment | 31 | 74 | 2.4 |
| Missing Parenthetical | 12 | 17 | 1.4 |
| Unclassified | 655 | 734 | 1.1 |

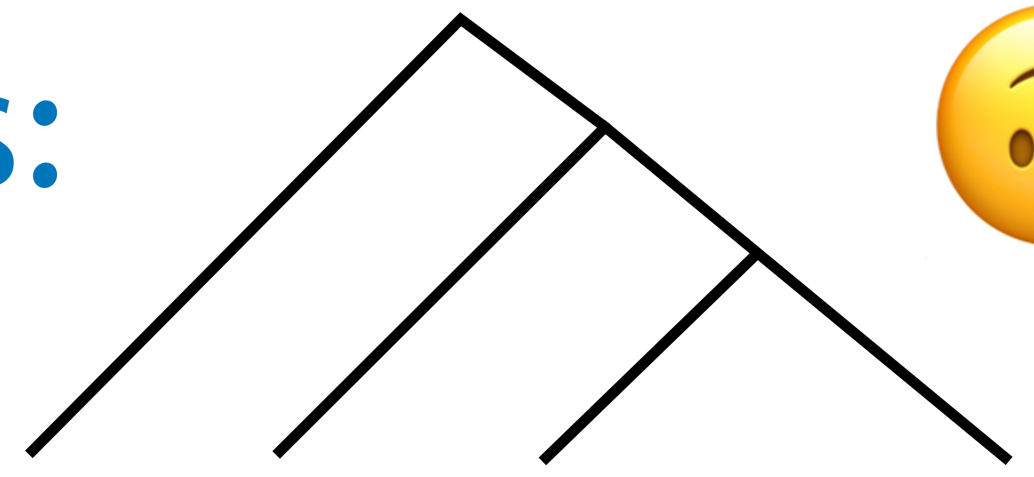
→ *spaghetti with a fork*

→ *[[world oil] prices]*

[Kummerfeld, 2016]

# Unsupervised learning

| Model | $F_1$ | Training/Test PPL |
|---|---|---|
| Random Trees | 19.5 | – |
| Right Branching | 39.5 | – |
| Scalar PCFG (unsupervised) | $< 35.0$ | $> 350$ |

worse than assuming every tree looks like this:  🙃

[Kim et al. 2018]

# Unsupervised learning: embeddings

| Model | $F_1$ | Training/Test PPL |
|---|---|---|
| Random Trees | 19.5 | – |
| Right Branching | 39.5 | – |
| Scalar PCFG | $< 35.0$ | $> 350$ |
| Neural PCFG | 52.6 | $\approx 250$ |

"Grammar embeddings": $p(A \rightarrow B\ C) \propto \exp\{v_A^\top f(v_B, v_C)\}$

[Kim et al. 2018]

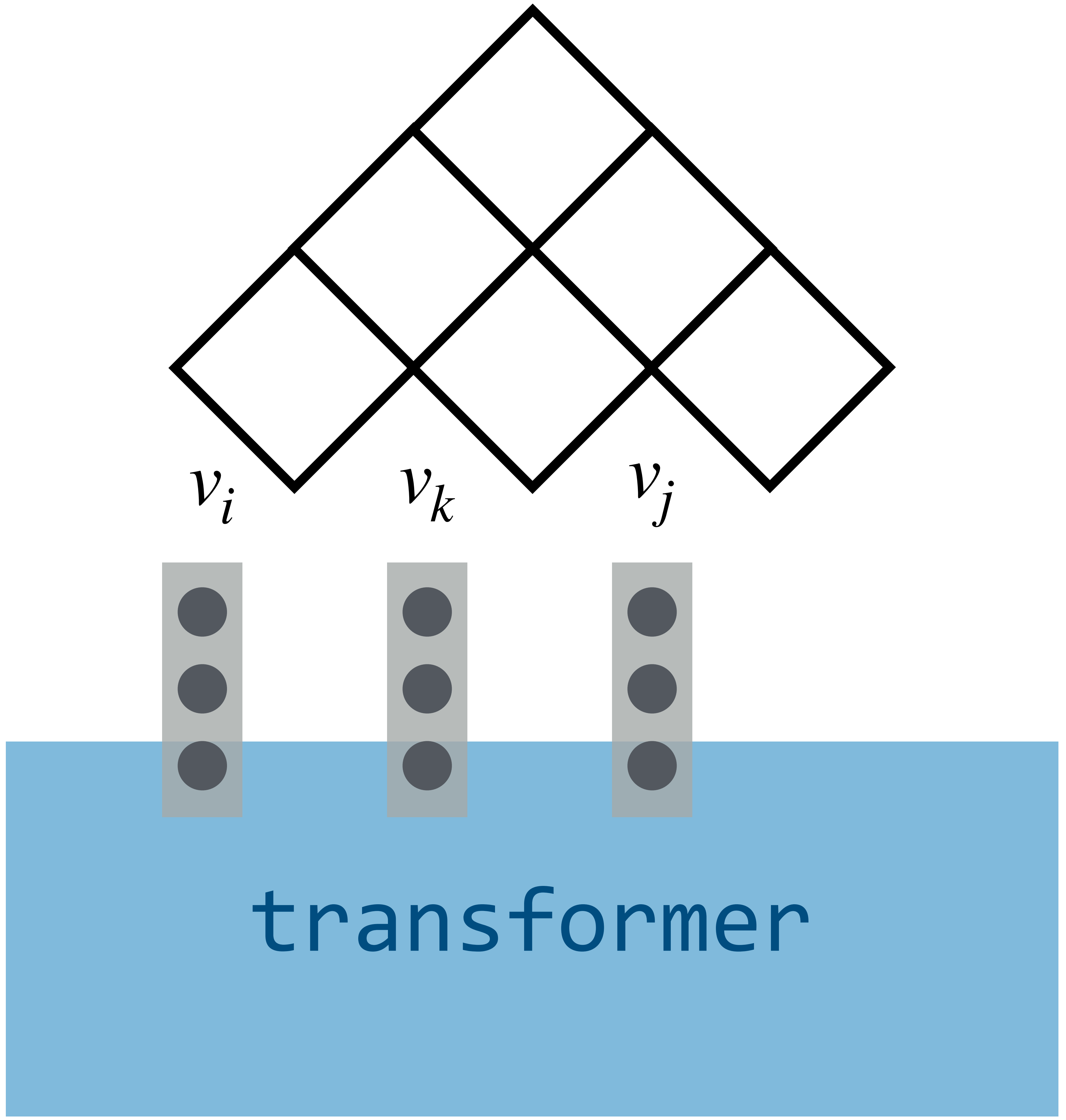
# What about neural nets?

**best:**

$$\exp\left\{ \sum_{(A \to B\ C, i, k, j)} w^\top \phi(A, B, C, v_i, v_k, v_j) \right\} \Big/ Z$$

**almost as good:**

train an independent cell classifier
that takes $v_{i,j,k}$ as input



# Next class: advanced language modeling