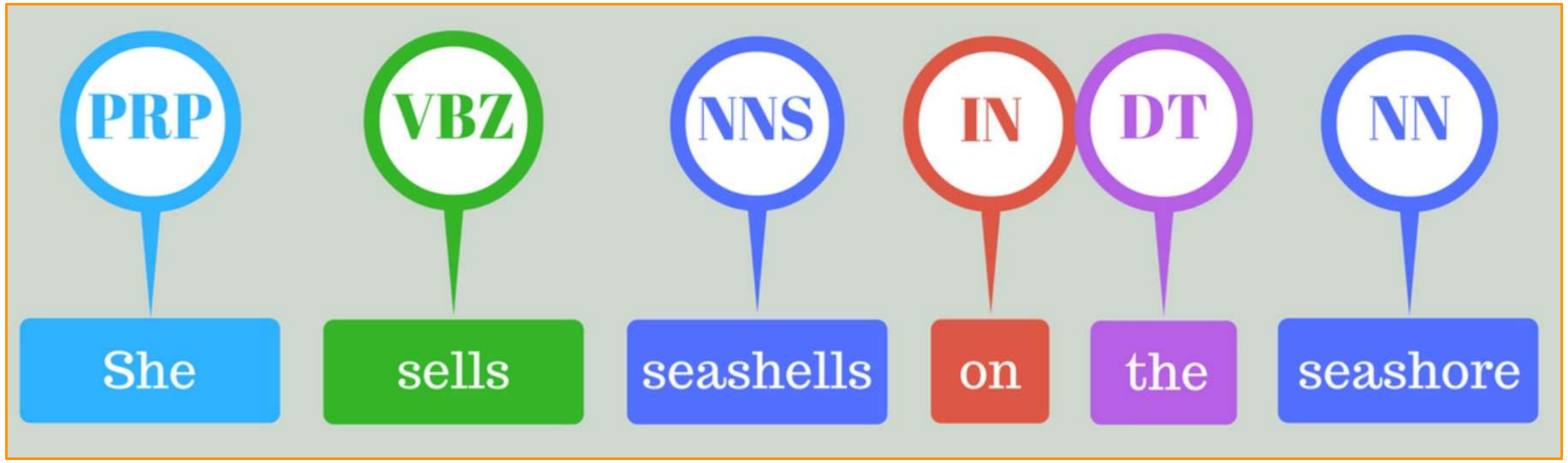
AIE1007: Natural Language Processing

L6: Sequence Models

Autumn 2024

Why model sequences?



Part-of-speech (POS) tagging

PRP: Personal pronoun

VBZ: Verb, 3rd person singular present

NN: singular noun
NNS: plural noun

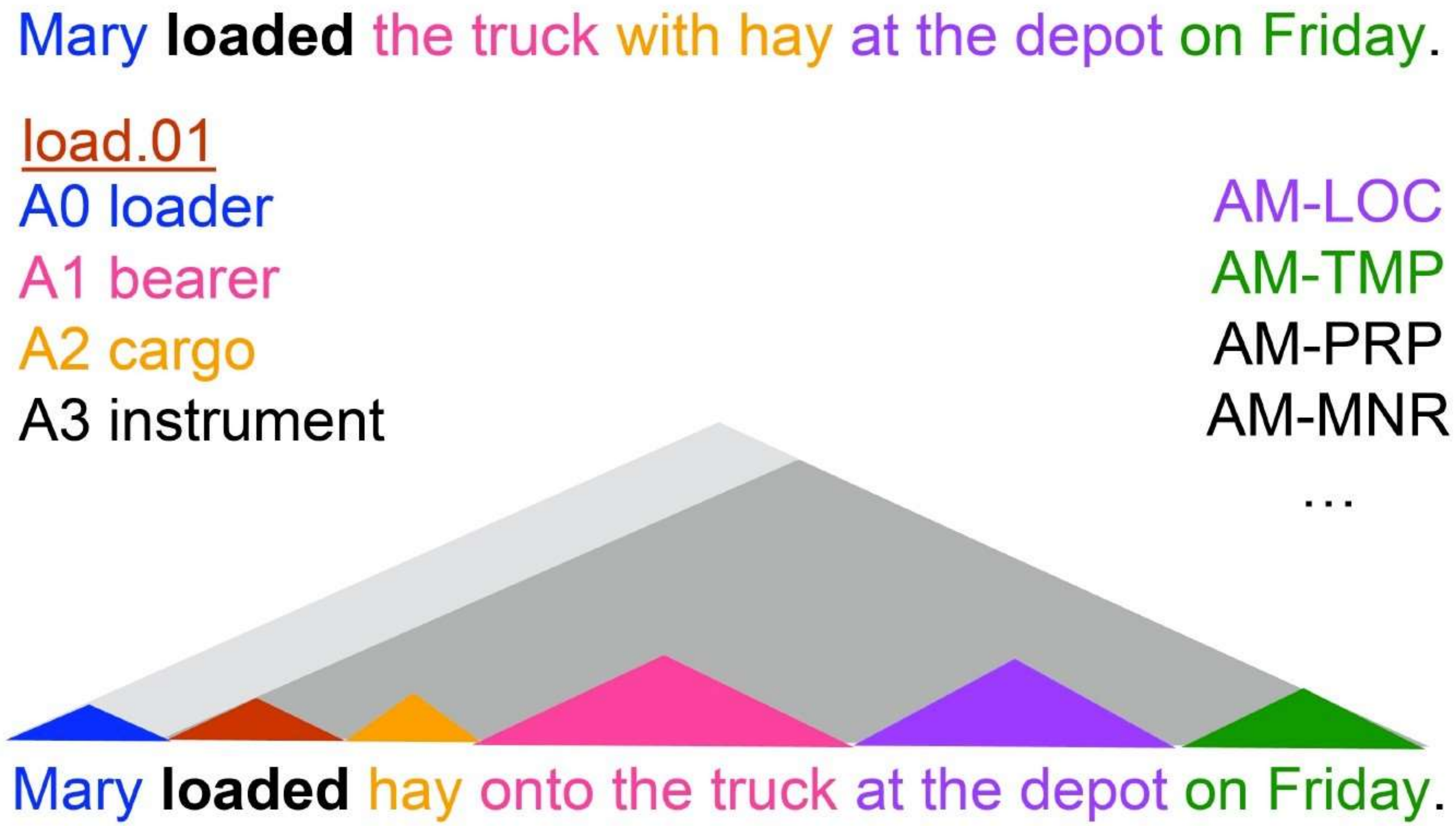
IN: preposition or subordinating conjunction
DT: determiner

Why model sequences?

Named Entity recognition

Image: https://www.analyticsvidhya.com/blog/2021/11/a-beginners-introduction-to-ner-named-entity-recognition/

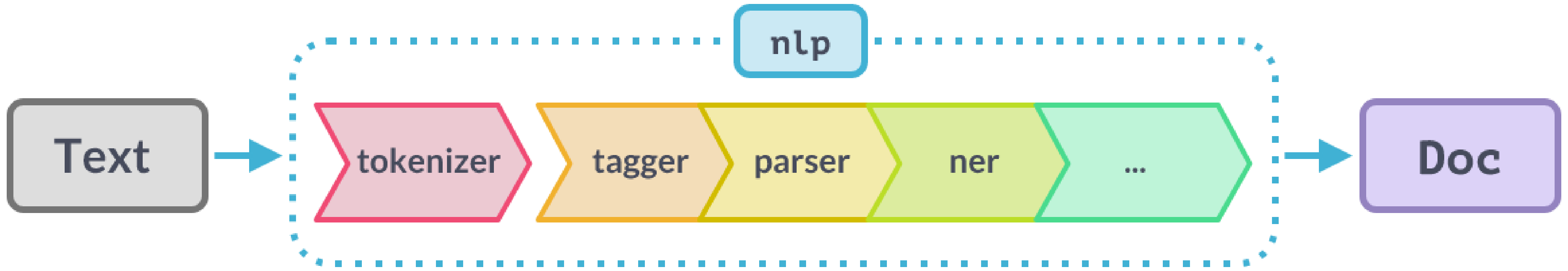
Why model sequences?



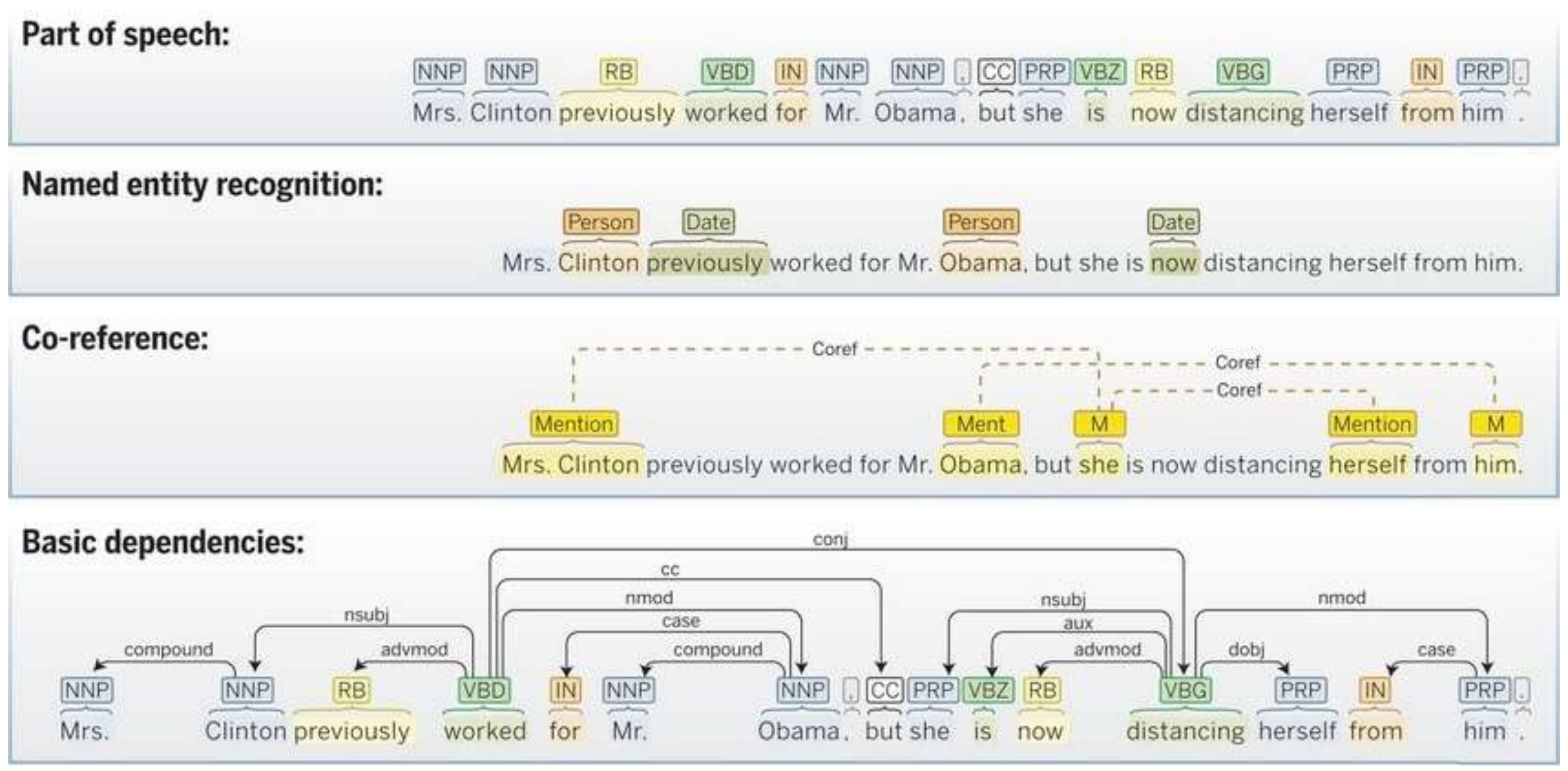
Semantic role labeling

https://devopedia.org/semantic-role-labelling

NLP pipelines



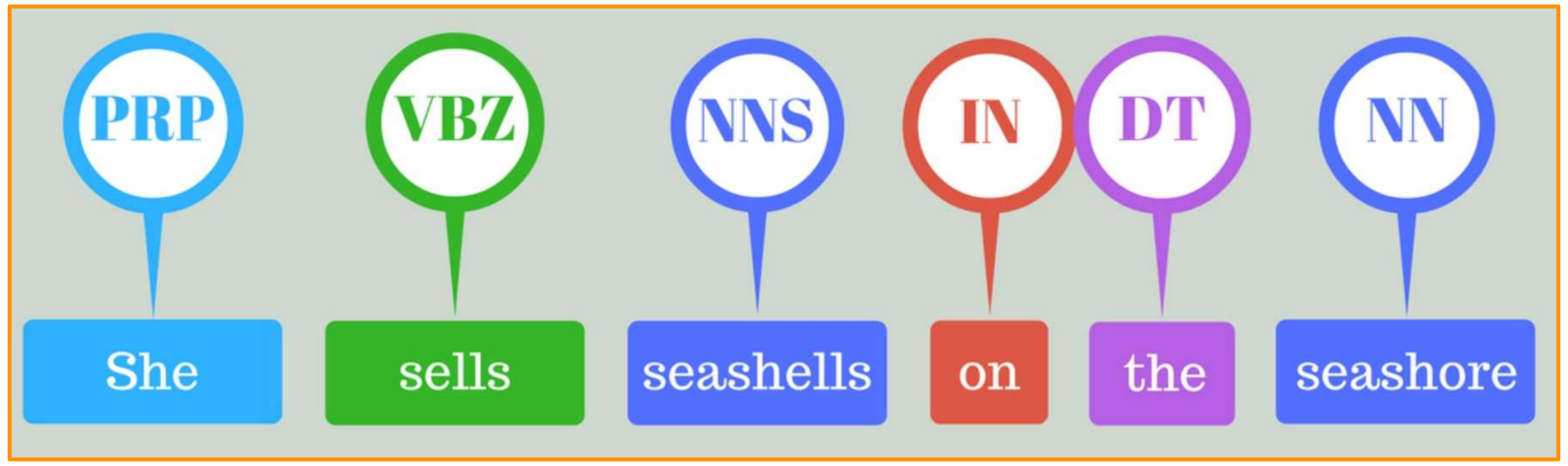
NAME	COMPONENT	CREATES	DESCRIPTION
tokenizer	`Tokenizer`	`Doc`	Segment text into tokens.
PROCESSING PIPELINE tagger	`Tagger`	`Token.tag`	Assign part-of-speech tags.
parser	`DependencyParser`	`Token.head`, `Token.dep`, `Doc.sents`, `Doc.noun_chunks`	Assign dependency labels.
ner	`EntityRecognizer`	`Doc.ents`, `Token.ent_iob`, `Token.ent_type`	Detect and label named entities.



https://spacy.io/usage/processing-pipelines

https://stanfordnlp.github.io/CoreNLP/pipeline.html

What are part of speech tags?



- Word classes or syntactic categories
  - Reveal useful information about a word (and its neighbors!)

1. The/DT cat/NN sat/VBD on/IN the/DT mat/NN
2. Princeton/NNP is/VBZ in/IN New/NNP Jersey/NNP
3. The/DT old/NN man/VBP the/DT boat/NN

Parts of Speech

- Different words have different functions
- Can be roughly divided into two classes
- **Closed class**: fixed membership, **function words**
  - e.g. prepositions (*in, on, of*), determiners (*the, a*)
- **Open class**: New words get added frequently
  - e.g. nouns (Twitter, Facebook), verbs (google), adjectives, adverbs

Parts of Speech

How many part of speech tags do you think English has?

A) < 10

B) 10 - 20

C) 20 - 40

D) > 40

The answer is (D) - well, depends on definitions!

Penn treebank part-of-speech tagset

Tag	Description	Example	Tag	Description	Example	Tag	Description	Example
CC	coordinating conjunction	*and, but, or*	PDT	predeterminer	*all, both*	VBP	verb non-3sg present	*eat*
CD	cardinal number	*one, two*	POS	possessive ending	*'s*	VBZ	verb 3sg pres	*eats*
DT	determiner	*a, the*	PRP	personal pronoun	*I, you, he*	WDT	wh-determ.	*which, that*
EX	existential ‘there’	*there*	PRP$	possess. pronoun	*your, one's*	WP	wh-pronoun	*what, who*
FW	foreign word	*mea culpa*	RB	adverb	*quickly*	WP$	wh-possess.	*whose*
IN	preposition/ subordin-conj	*of, in, by*	RBR	comparative adverb	*faster*	WRB	wh-adverb	*how, where*
JJ	adjective	*yellow*	RBS	superlatv. adverb	*fastest*	$	dollar sign	*$*
JJR	comparative adj	*bigger*	RP	particle	*up, off*	#	pound sign	*#*
JJS	superlative adj	*wildest*	SYM	symbol	+,%, &	“	left quote	‘ or “
LS	list item marker	*1, 2, One*	TO	“to”	*to*	”	right quote	’ or ”
MD	modal	*can, should*	UH	interjection	*ah, oops*	(	left paren	[, (, {, <
NN	sing or mass noun	*llama*	VB	verb base form	*eat*	)	right paren	],), }, >
NNS	noun, plural	*llamas*	VBD	verb past tense	*ate*	,	comma	,
NNP	proper noun, sing.	*IBM*	VBG	verb gerund	*eating*	.	sent-end punc	. ! ?
NNPS	proper noun, plu.	*Carolinas*	VBN	verb past part.	*eaten*	:	sent-mid punc	: ; ... – -

45 tags

(Marcus et al., 1993)

based on Wall Street Journal (WSJ)

Other corpora: Brown, Switchboard

Part of speech tagging

- Tag each word in a sentence with its part of speech
- Disambiguation task: each word might have different functions in different contexts
  - The/DT man/NN bought/VBD a/DT boat/NN
  - The/DT old/NN man/VBP the/DT boat/NN

Same word, different tags

earnings growth took a **back/JJ** seat
a small building in the **back/NN**
a clear majority of senators **back/VBP** the bill
Dave began to **back/VB** toward the door
enable the country to buy **back/RP** about debt
I was twenty-one **back/RB** then

Some words have many functions!

JJ: adjective, NN: single or mass noun, VBP: Verb, non-3rd person singular present
VB: Verb, base form, RP: particle, RB: adverb

Part of speech tagging

- Tag each word in a sentence with its part of speech
- Disambiguation task: each word might have different senses/functions

		WSJ	Brown
Types:			
Unambiguous	(1 tag)	44,432 (**86%**)	45,799 (**85%**)
Ambiguous	(2+ tags)	7,025 (**14%**)	8,050 (**15%**)
Tokens:			
Unambiguous	(1 tag)	577,421 (**45%**)	384,349 (**33%**)
Ambiguous	(2+ tags)	711,780 (**55%**)	786,646 (**67%**)

Unambiguous types:
Jane NNP,
hesitantly RB

- Types = distinct words in the corpus
- Tokens = all words in the corpus (can be repeated)

A simple baseline

- Many words might be easy to tag
- **Most frequent class:** Assign each word to the class it occurred most in the training set. (e.g. man/NN)

How accurate do you think this baseline would be at tagging words?

A) <50%
B) 50-75%
C) 75-90%
D) >90%

The answer is (D)

A simple baseline

- Many words might be easy to tag
- **Most frequent class:** Assign each word to the class it occurred most in the training set. (e.g. man/NN)
- Accurately tags **92.34%** of word tokens on Wall Street Journal (WSJ)!
- State of the art ~ 97%
- Average English sentence ~14 words
  - Sentence level accuracies: 0.92^{14} = **31%** vs 0.97^{14} = **65%**
- POS tagging not solved yet!

Some observations

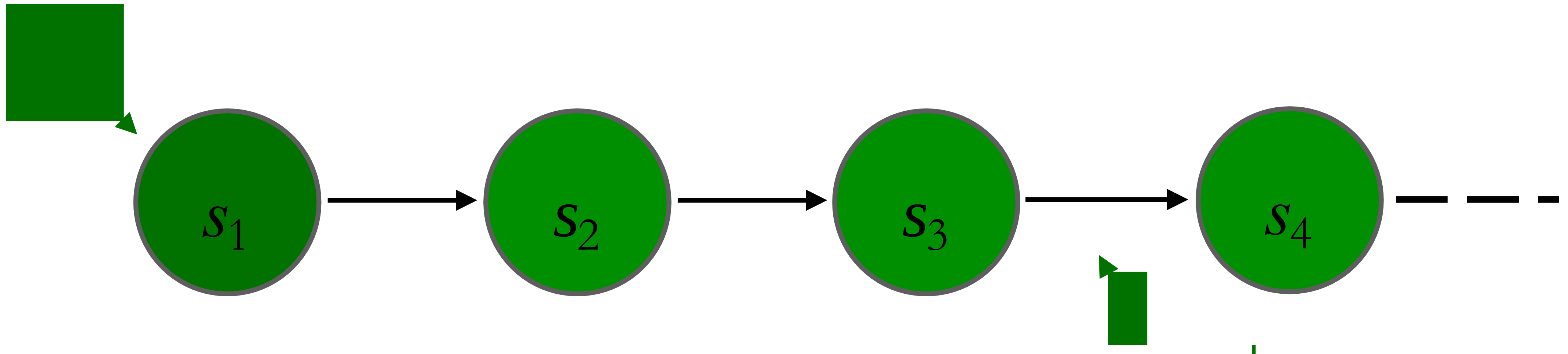
- The function (or POS) of a word depends on its context
  - The/DT old/JJ man/NN bought/VBP the/DT boat/NN
  - The/DT old/NN man/VBP the/DT boat/NN
- Certain POS combinations are extremely unlikely
  - *<JJ, DT>* ("good the") or *<DT, IN>* ("the in")
- Better to make decisions on entire sentences instead of individual words

Hidden Markov Models

Markov chains

$\pi(s_1)$: initial distribution

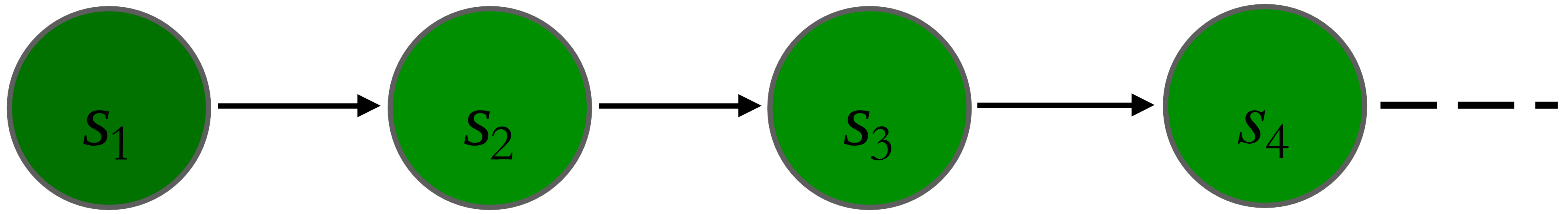
Where have we seen this before?
N-gram language models!



$p(s_t \mid s_{t-1})$: transition probability

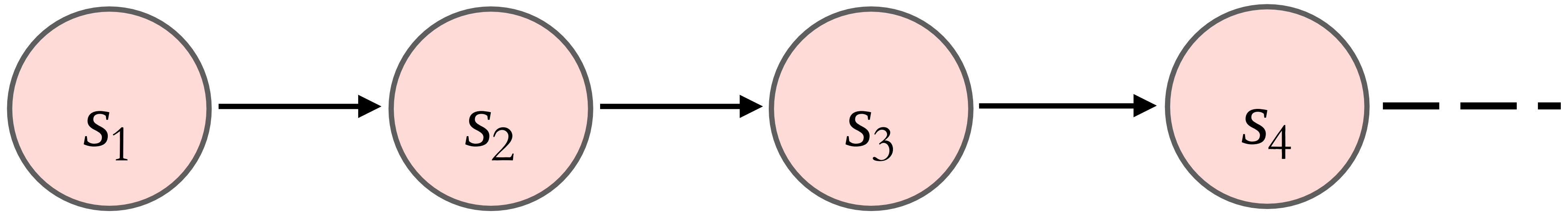
- Model probabilities of **sequences** of variables
- Each state can take one of K values (can assume {1, 2, ..., K} for simplicity)
- Markov assumption: $P(s_t | s_1, s_2, \ldots, s_{t-1}) \approx P(s_t | s_{t-1})$
- A Markov chain is specified by
  - Initial probability distribution $\pi(s), \forall s \in \{1, \ldots, K\}$
  - Transition probability matrix $(K \times K)$

Markov chains



The/DT cat/NN sat/VBD on/IN the/DT mat/NN

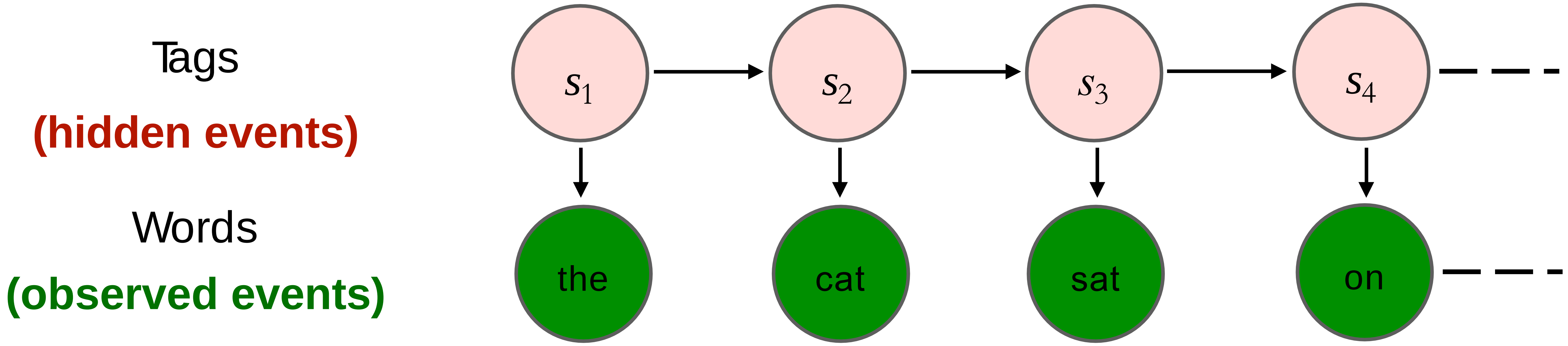
Markov chains can help us model entire sentences.



The/?? cat/?? sat/?? on/?? the/?? mat/??

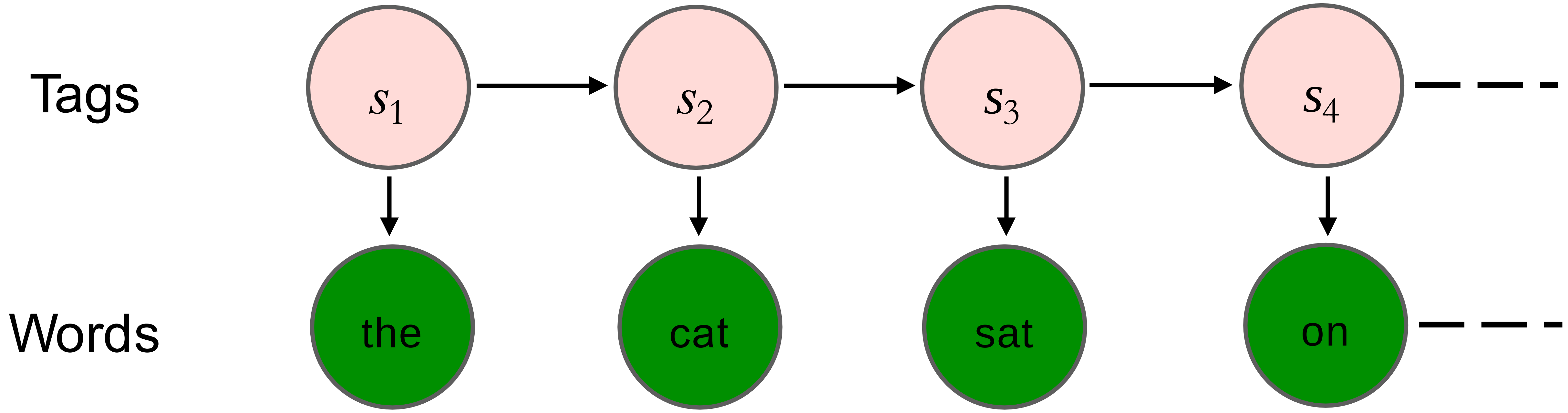
BUT we don't normally see sequences of POS tags appearing in text

Hidden Markov Model (HMM)



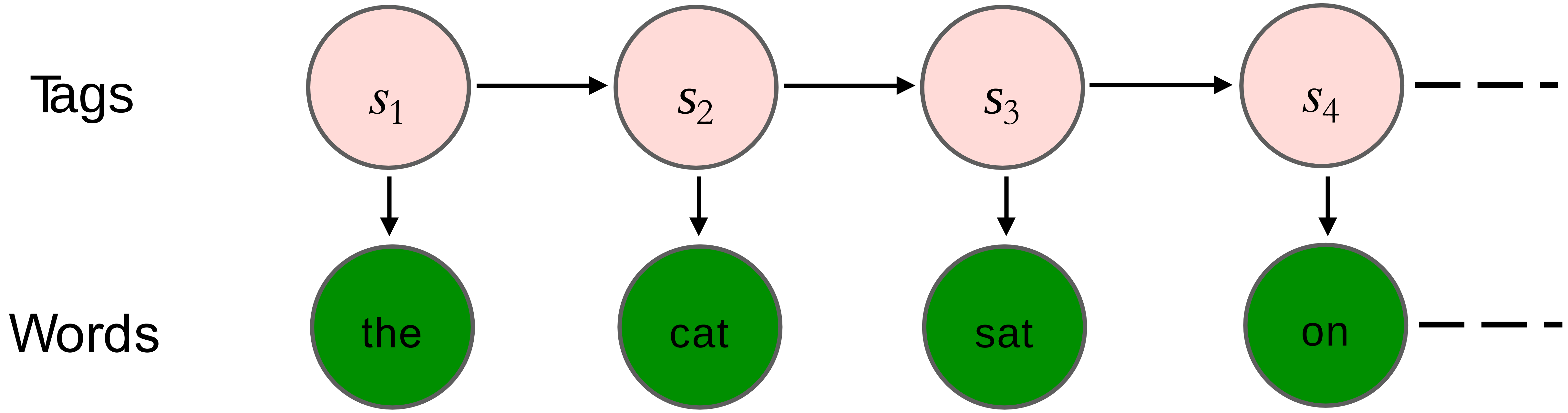
- We don’t normally see sequences of POS tags in text
- However, we do observe the words!
- The HMM allows us to *jointly reason* over both **hidden** and **observed** events.
  - Assume that each position has a tag that generates a word

Components of an HMM



1. Set of states S = {1, 2, ..., K} and set of observations $O = \{o_1, \ldots, o_n\}$
   $o_i \in V$
2. **Initial state probability distribution** $\pi(s_1)$
3. **Transition probabilities** $P(s_{t+1} \mid s_t)$
4. **Emission probabilities** $P(o_t \mid s_t)$

Assumptions



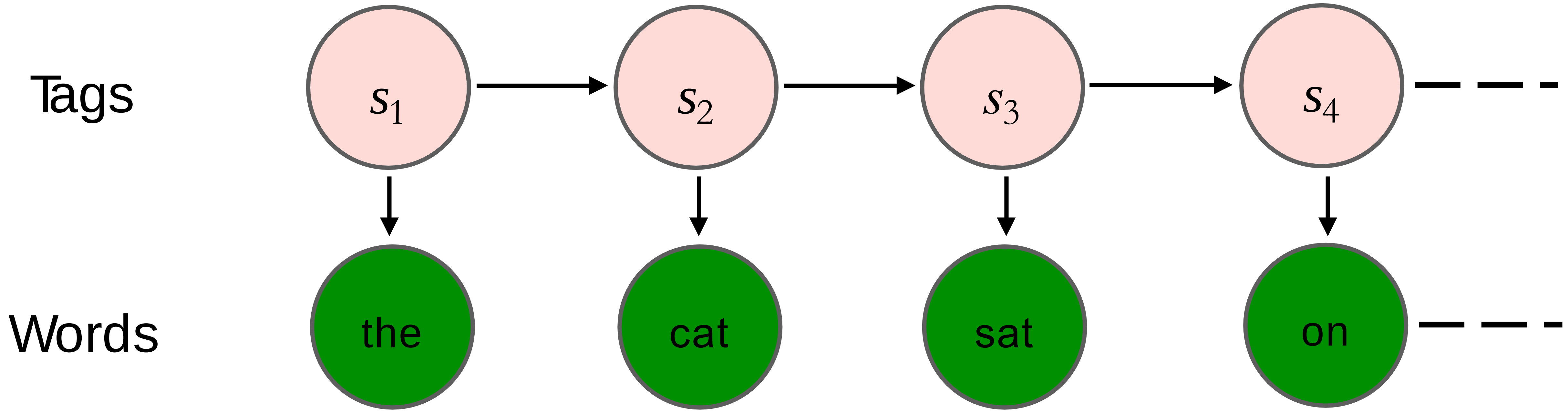
1. Markov assumption:

$$P(s_t \mid s_1, \ldots, s_{t-1}) \approx P(s_t \mid s_{t-1})$$

2. Output independence:

$$P(o_t \mid s_1, \ldots, s_t) \approx P(o_t \mid s_t)$$

Sequence likelihood



$$P(S, O) = P(s_1, s_2, \ldots, s_n, o_1, o_2, \ldots, o_n)$$

$$= \pi(s_1) p(o_1 \mid s_1) \prod_{i=2}^{n} P(s_i \mid s_{i-1}) P(o_i \mid s_i)$$

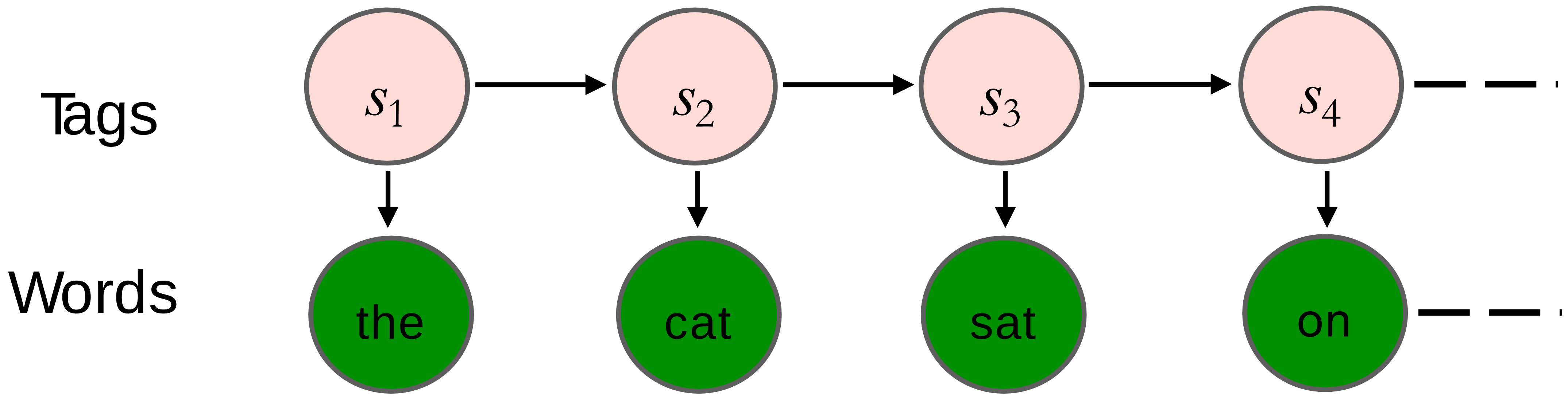
transition probability

emission probability

If we add a dummy state $s_0 = \varnothing$ at the beginning,

$$P(S, O) = \prod_{i=1}^{n} P(s_i \mid s_{i-1}) P(o_i \mid s_i) \qquad [\, \pi(s_1) = P(s_1 \mid \varnothing)]$$

Example: Sequence likelihood



Dummy start state

s_t \ s_{t+1}

	DT	NN
$\varnothing$	0.8	0.2
DT	0.2	0.8
NN	0.3	0.7

s_t \ o_t

	the	cat
DT	0.9	0.1
NN	0.5	0.5

What is the joint probability $P($*the cat*, *DT NN*$)$*?*

A) $(0.8 * 0.8) * (0.9 * 0.5)$
B) $(0.2 * 0.8) * (0.9 * 0.5)$
C) $(0.3 * 0.7) * (0.5 * 0.5)$
D) $(0.8 * 0.2) * (0.5 * 0.1)$

The answer is (A).

Learning

Training set:

1 Pierre/NNP Vinken/NNP ,/, 61/CD years/NNS old/JJ ,/, will/MD join/VB the/DT board/NN as/IN a/DT nonexecutive/JJ director/NN Nov./NNP 29/CD ./.
2 Mr./NNP Vinken/NNP is/VBZ chairman/NN of/IN Elsevier/NNP N.V./NNP ,/, the/DT Dutch/NNP publishing/VBG group/NN ./.
3 Rudolph/NNP Agnew/NNP ,/, 55/CD years/NNS old/JJ and/CC chairman/NN of/IN Consolidated/NNP Gold/NNP Fields/NNP PLC/NNP ,/, was/VBD named/VBN a/DT nonexecutive/JJ director/NN of/IN this/DT British/JJ industrial/JJ conglomerate/NN ./.
...
38,219 It/PRP is/VBZ also/RB pulling/VBG 20/CD people/NNS out/IN of/IN Puerto/NNP Rico/NNP ,/, who/WP were/VBD helping/VBG Huricane/NNP Hugo/NNP victims/NNS ,/, and/CC sending/VBG them/PRP to/TO San/NNP Francisco/NNP instead/RB ./.

Maximum likelihood estimates:

$$P(s_i \mid s_j) = \frac{Count(s_j, s_i)}{Count(s_j)}$$

$$P(o \mid s) = \frac{Count(s, o)}{Count(s)}$$

Q: How many probabilities to estimate?

A: transition probabilities - (K + 1)   K

emission probabilities - $|V| \times K$

Learning example

1. The/DT cat/NN sat/VBD on/IN the/DT mat/NN

2. Princeton/NNP is/VBZ in/IN New/NNP Jersey/NNP

3. The/DT old/NN man/VBP the/DT boat/NN

Maximum likelihood estimates:

$$P(s_i \mid s_j) = \frac{Count(s_j, s_i)}{Count(s_j)}$$

$$P(o \mid s) = \frac{Count(s, o)}{Count(s)}$$

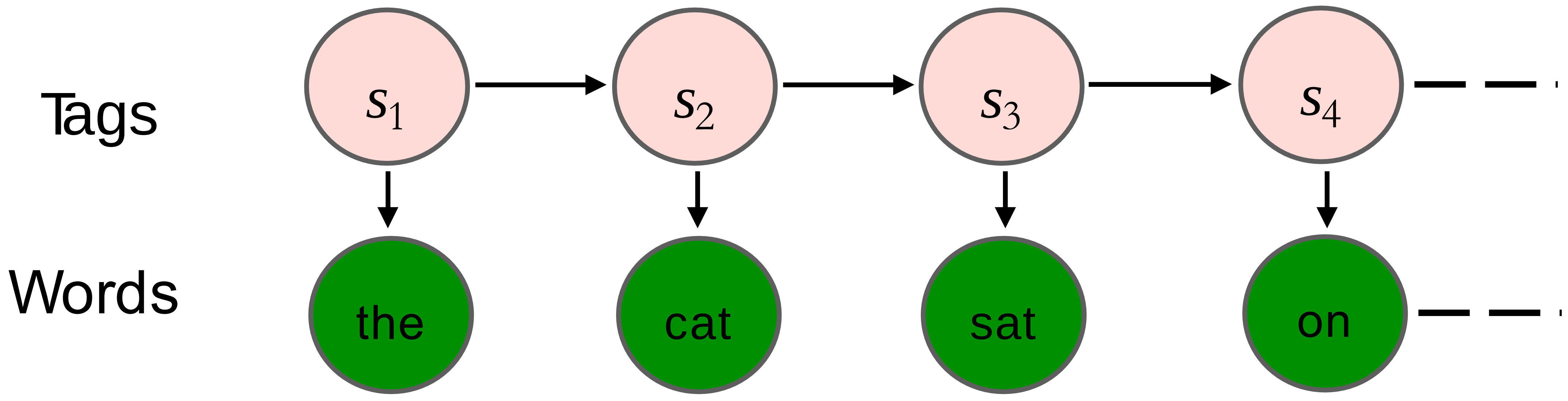
$\pi(DT) = P(DT \mid \varnothing) =$ 2/3

$P(NN \mid DT) =$ 4/4 $\quad P(DT \mid IN) =$ 1/2

$P(cat \mid NN) =$ 1/4 $\quad P(the \mid DT) =$ 2/4

(assuming we differentiate cased vs uncased words)

Decoding with HMMs



Task: Find the most probable sequence of states $S = s_1, s_2, \ldots, s_n$ given the observations $O = o_1, o_2, \ldots, o_n$

$$\hat{S} = \arg\max_{S} P(S \mid O) = \arg\max_{S} \frac{P(O \mid S)P(S)}{P(O)}$$

[Bayes' Rule]

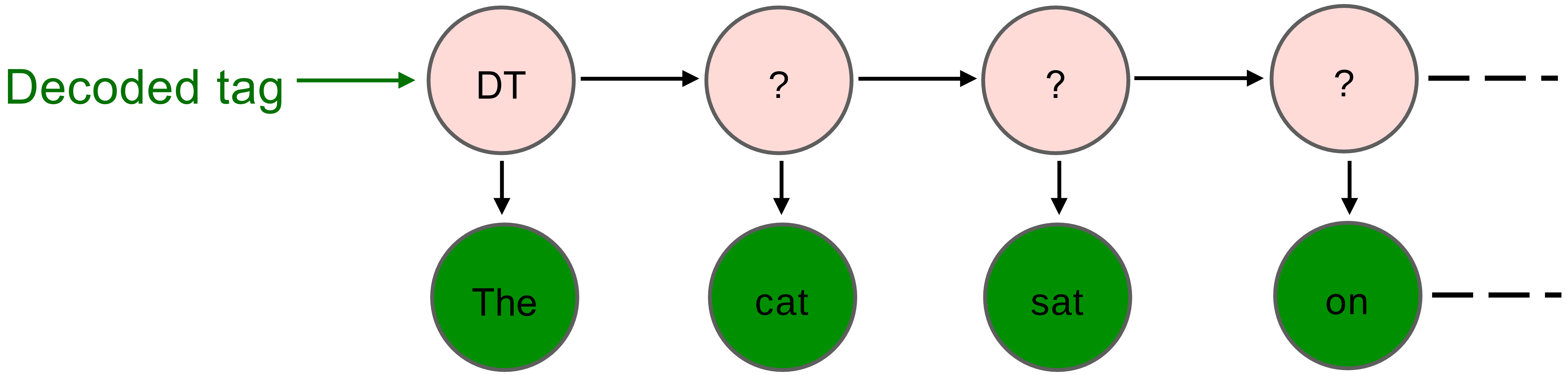
$$= \arg\max_{S} P(O \mid S)P(S)$$

$$= \arg\max_{s_1,\ldots,s_n} \prod_{i=1}^{n} P(s_i \mid s_{i-1})P(o_i \mid s_i)$$

How can we maximize this?
Search over all state sequences?

Greedy search

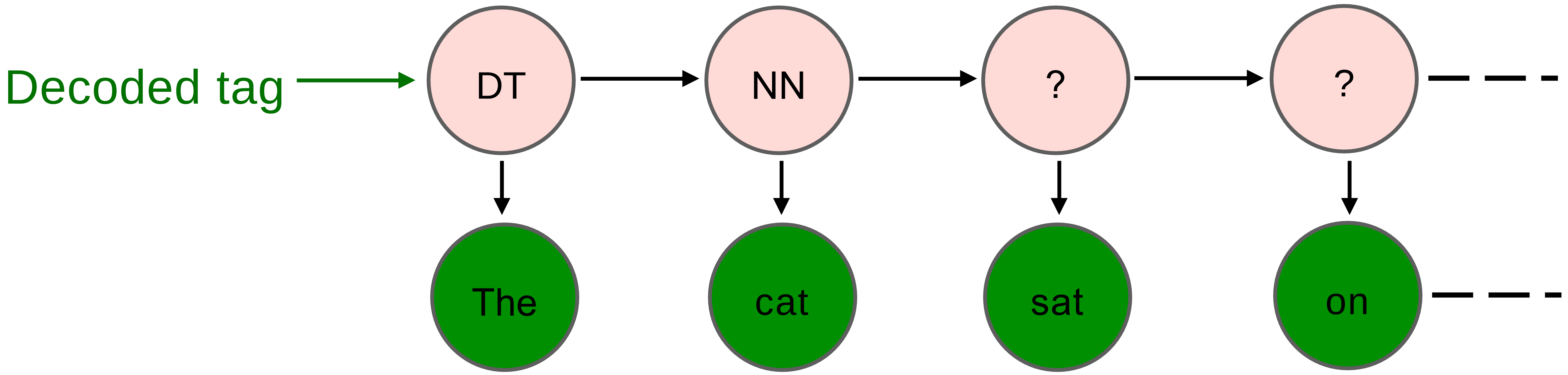
- Decode one state at at time



$$\arg\max_{s} \pi(s_1 = s)p(\text{The} \mid s) = \text{DT}$$

Greedy search

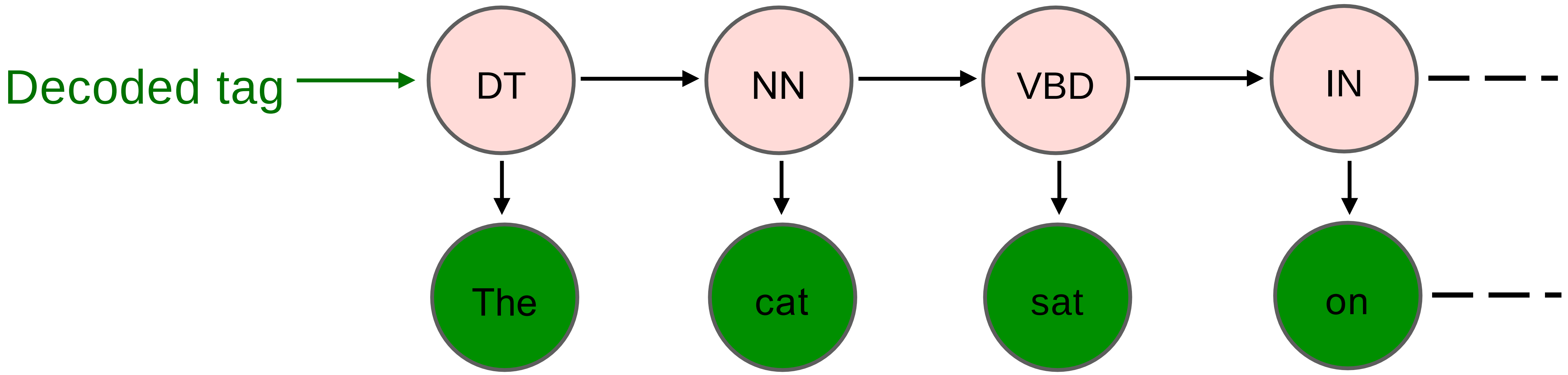
- Decode one state at at time



$$\arg\max_{s} p(s \mid DT)p(\text{cat} \mid s) = \text{NN}$$

Greedy search

- Decode one state at at time



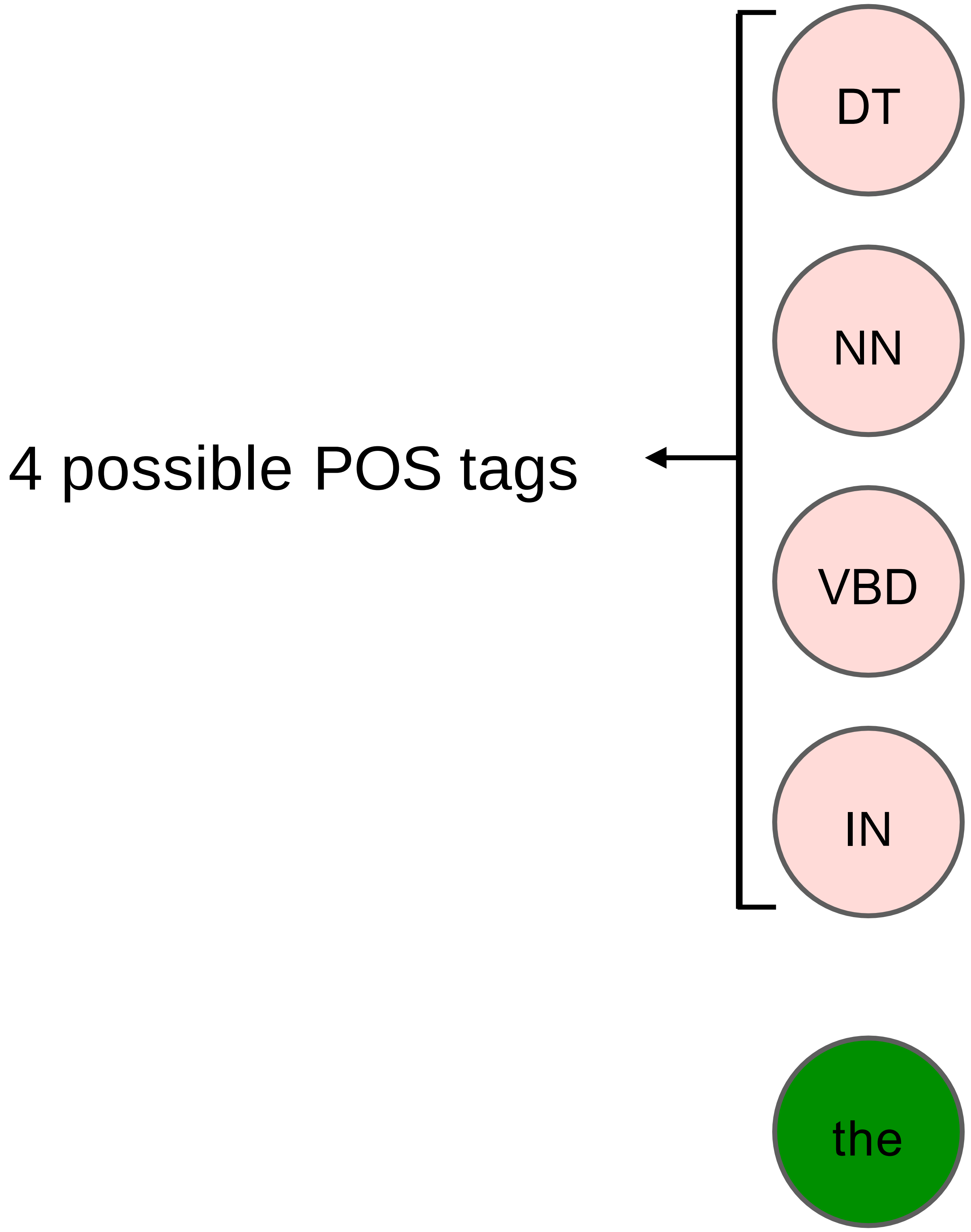
$$\hat{s}_t = \arg\max_s p(s \mid \hat{s}_{t-1}) p(o_t \mid s)$$

Very efficient but it doesn't guarantee to produce the overall optimal sequence

Viterbi decoding

- Use **dynamic programming**!
- Maintain some extra data structures
- Probability lattice, $M[T, K]$ and backtracking matrix, $B[T, K]$
  - T : Number of time steps
  - K : Number of states
- $M[i, j]$ stores joint probability of most probable sequence of states ending with state j at time i,
- $B[i, j]$ is the tag at time i-1 in the most probable sequence ending with tag j at time i

Viterbi decoding



$$M[1,DT] = \pi(DT)\ P(\text{the} \mid DT)$$

$$M[1,NN] = \pi(NN)\ P(\text{the} \mid NN)$$

$$M[1,VBD] = \pi(VBD)\ P(\text{the} \mid VBD)$$

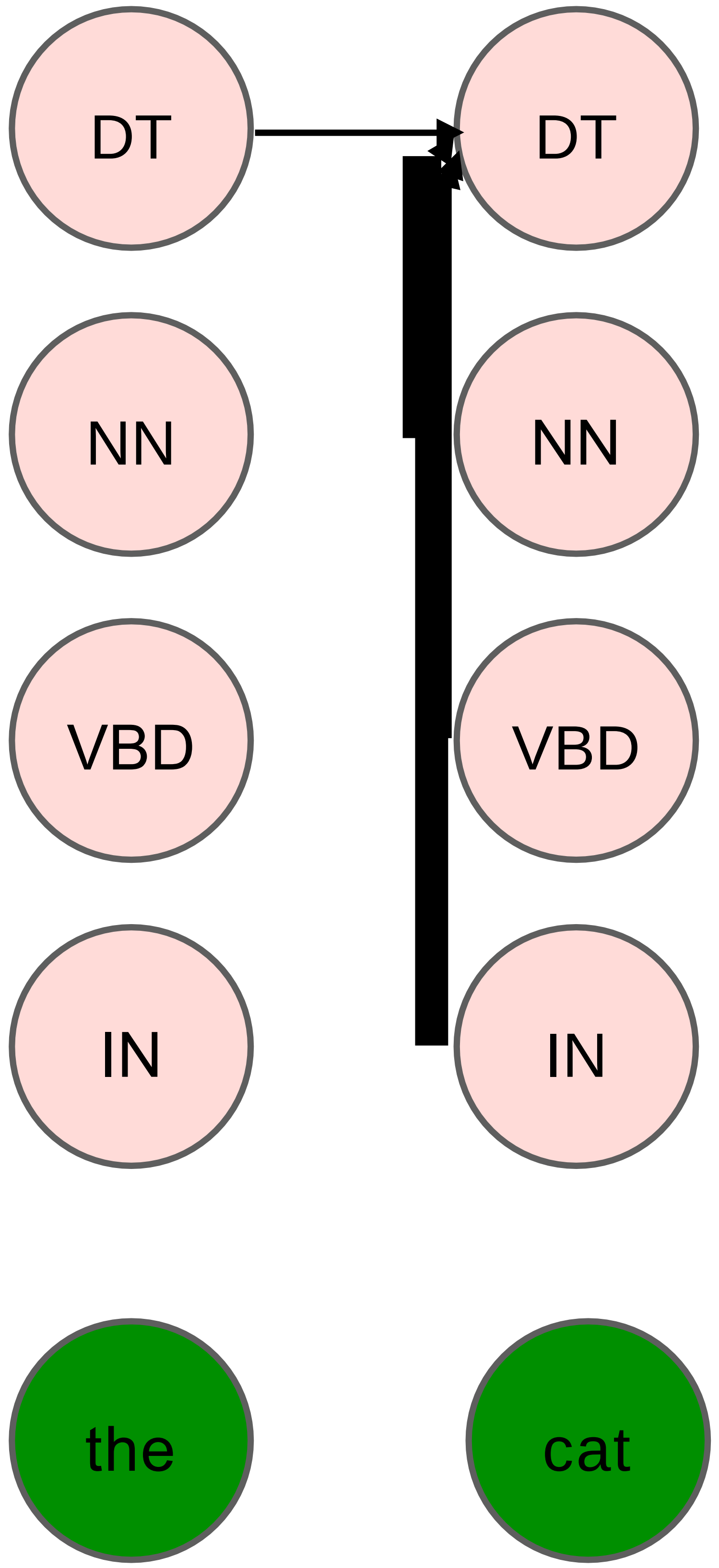
$$M[1,IN] = \pi(IN)\ P(\text{the} \mid IN)$$

Initialize the table

Forward

Viterbi decoding

Consider all possible previous tags



$$M[2,DT] = \max_{k} M[1,k]\ P(DT \mid k)\ P(\text{cat} \mid DT)$$

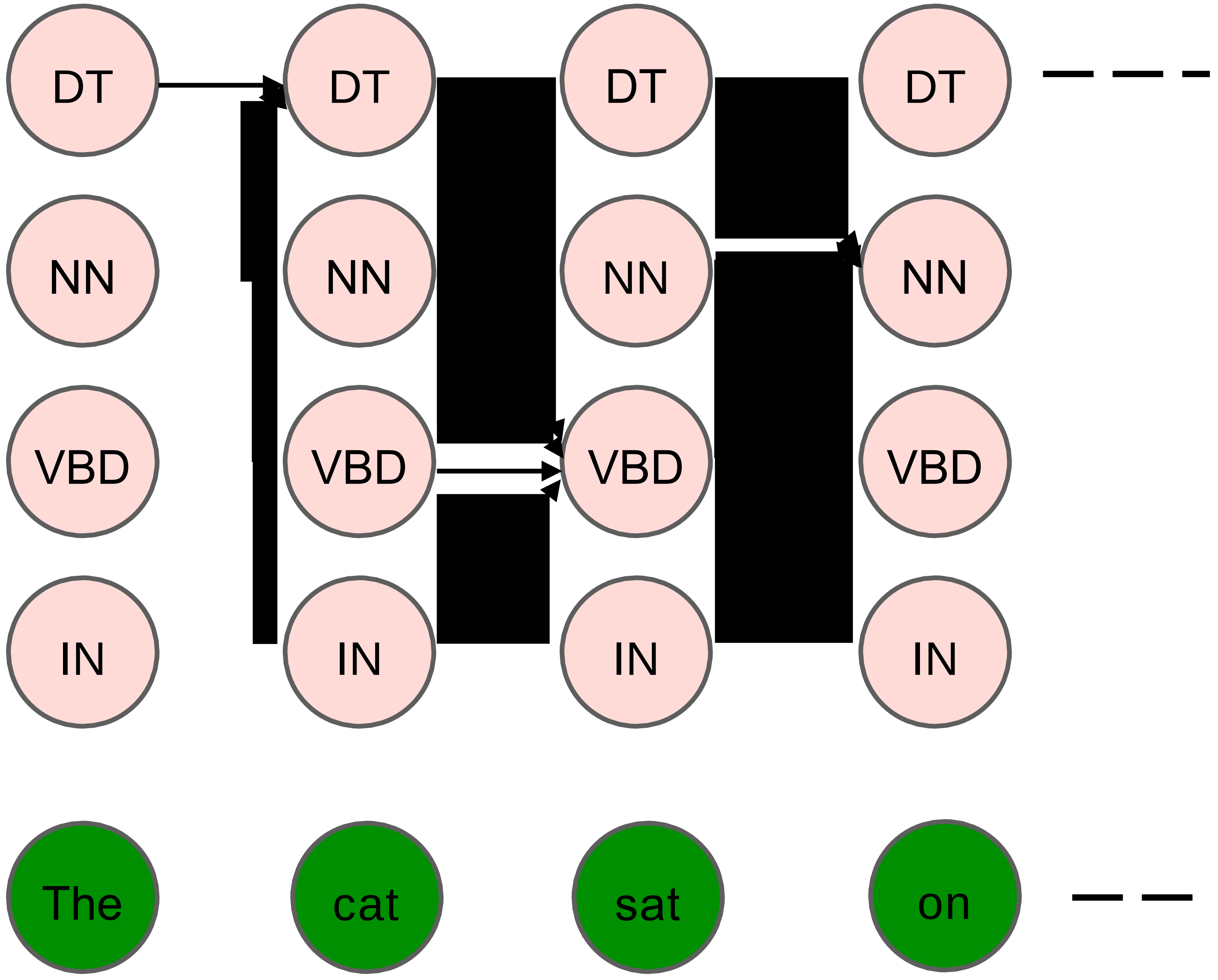
$$M[2,NN] = \max_{k} M[1,k]\ P(NN \mid k)\ P(\text{cat} \mid NN)$$

$$M[2,VBD] = \max_{k} M[1,k]\ P(VBD \mid k)\ P(\text{cat} \mid VBD)$$

$$M[2,IN] = \max_{k} M[1,k]\ P(IN \mid k)\ P(\text{cat} \mid IN)$$

Forward

Viterbi decoding



What is the time complexity of this algorithm?

A) $O(n)$
B) $O(nK)$
C) $O(nK^2)$
D) $O(n^2K)$

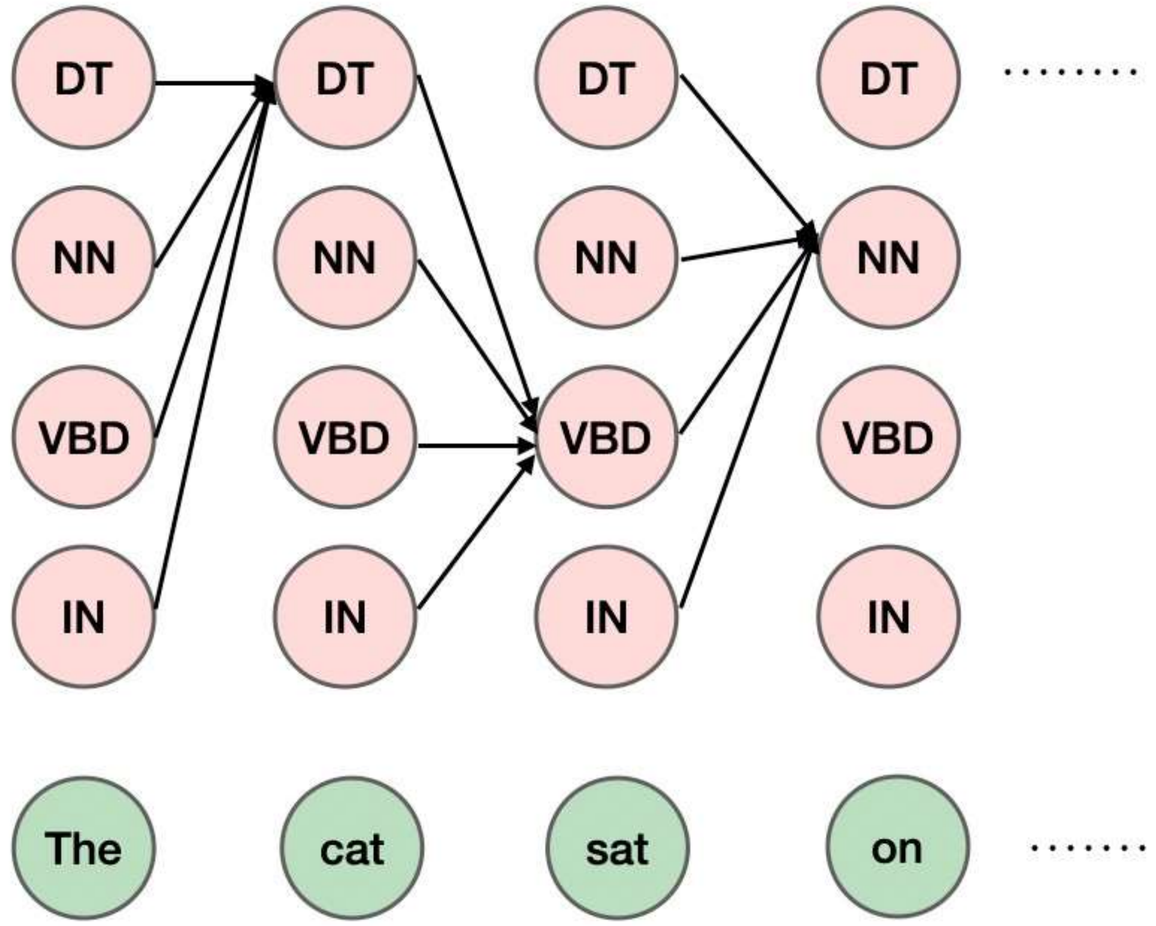
The answer is (C).

n = number of timesteps
K = number of states

$$M[i,j] = \max_k M[i-1,k]\ P(s_j \mid s_k)\ P(o_i \mid s_j) \qquad 1 \leq k \leq K \quad 1 \leq i \leq n$$

Viterbi decoding

Backward: Pick $\max_k M[n, k]$ and backtrack using B



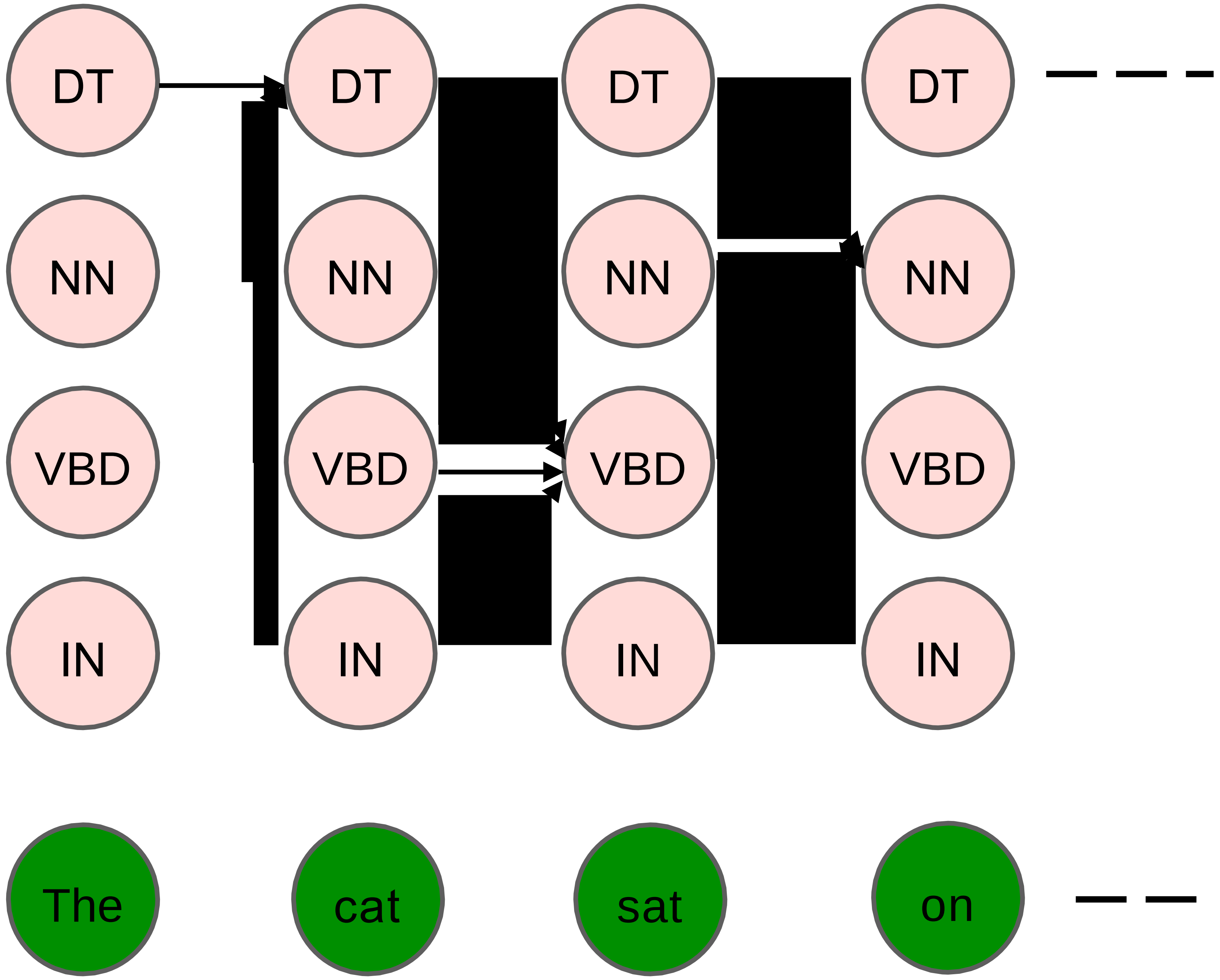
- In practice, we maximize sum of log probabilities (or minimize the sum of negative log probabilities) instead of maximize the product of probabilities

$$M[2,NN] = \max_k \{M[1,k]\ P(NN \mid k)\ P(\text{cat} \mid NN)\}$$

$$M[2,NN] = \max_k \{M[1,k] + \log P(NN \mid k) + \log P(\text{cat} \mid NN)\}$$

Beam search

If K (number of possible hidden states) is too large, Viterbi is too expensive!



Beam search

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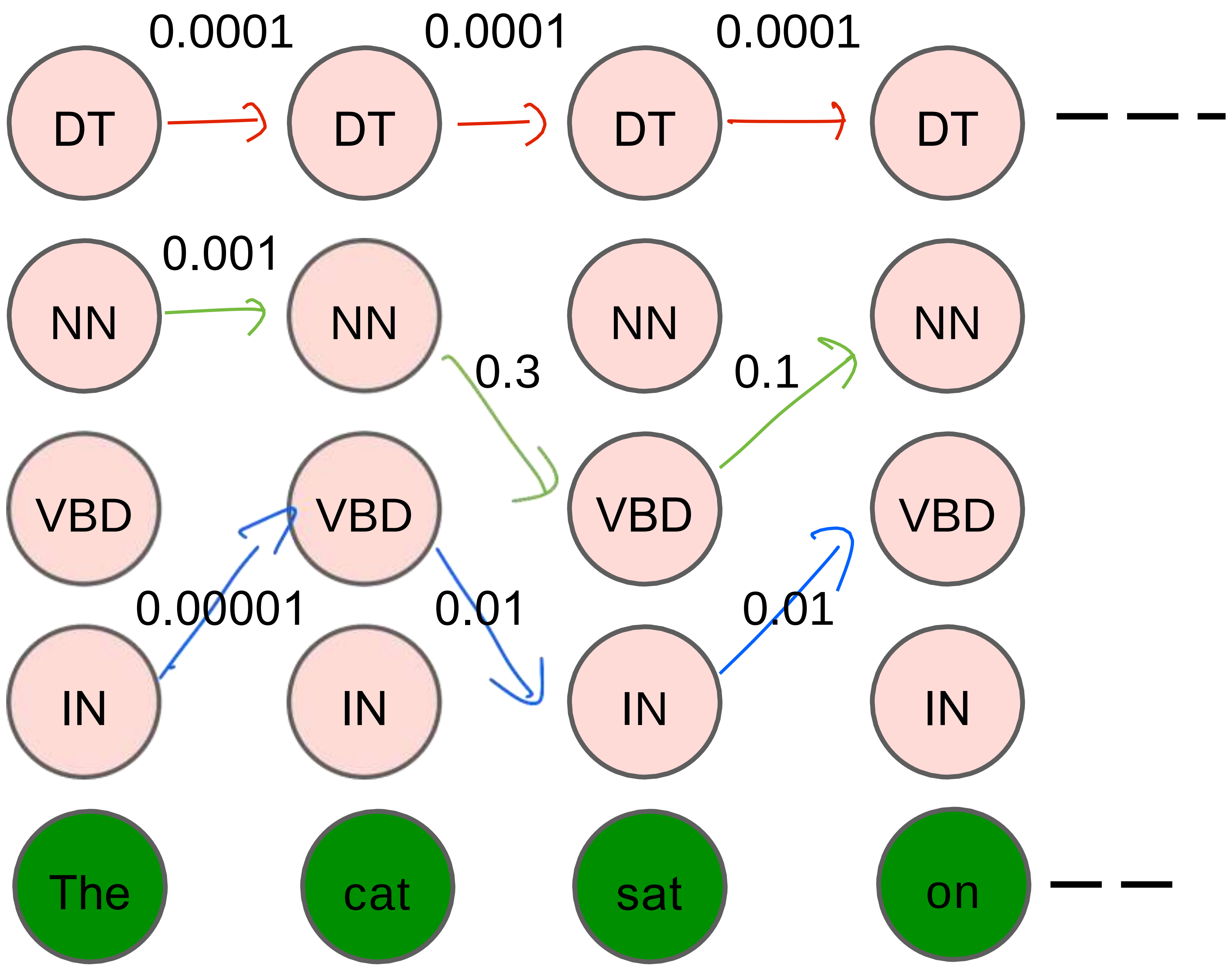


Observation: *Many paths have very low likelihood!*

Beam search

- Keep a fixed number of hypotheses at each point
- Beam width, β

log probabilities

DT $score = -0.1$

NN $score = -9.8$

$\beta = 2$

VBD $score = -0.7$

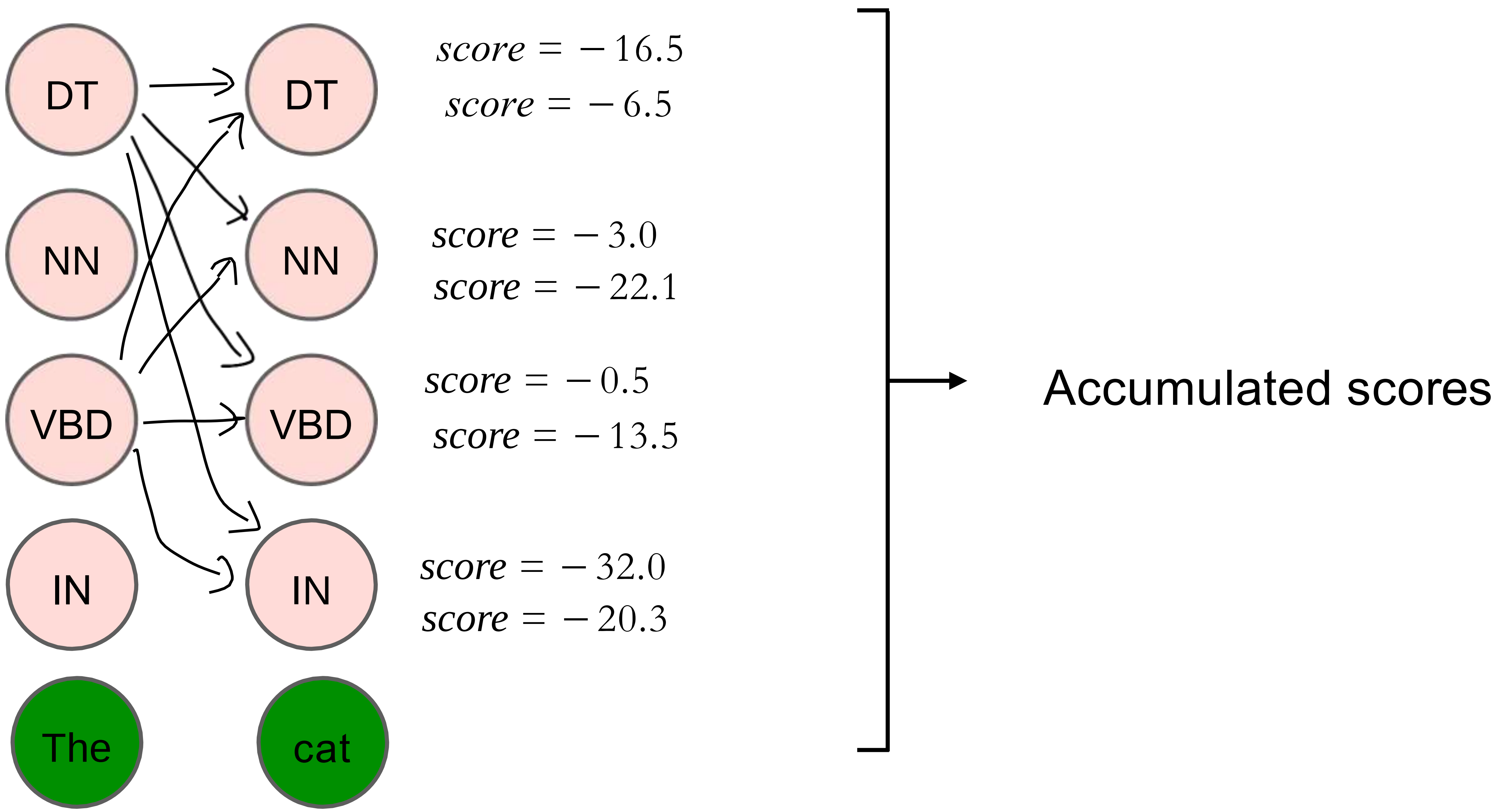
IN $score = -10.1$

The

Beam search

- Keep a fixed number of hypotheses at each point
- Beam width, β

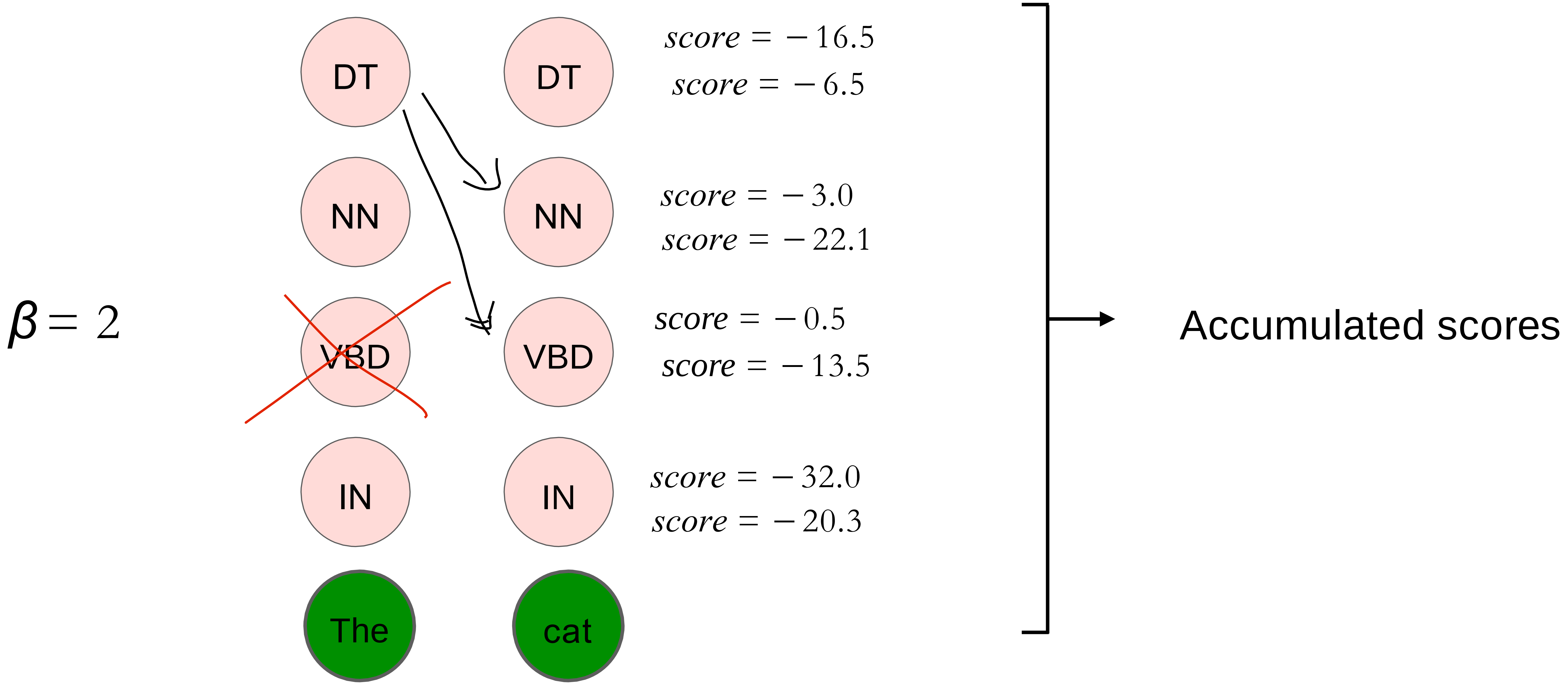
$\beta = 2$



Step 1: Expand all partial sequences in current beam

Beam search

- Keep a fixed number of hypotheses at each point
- Beam width, β

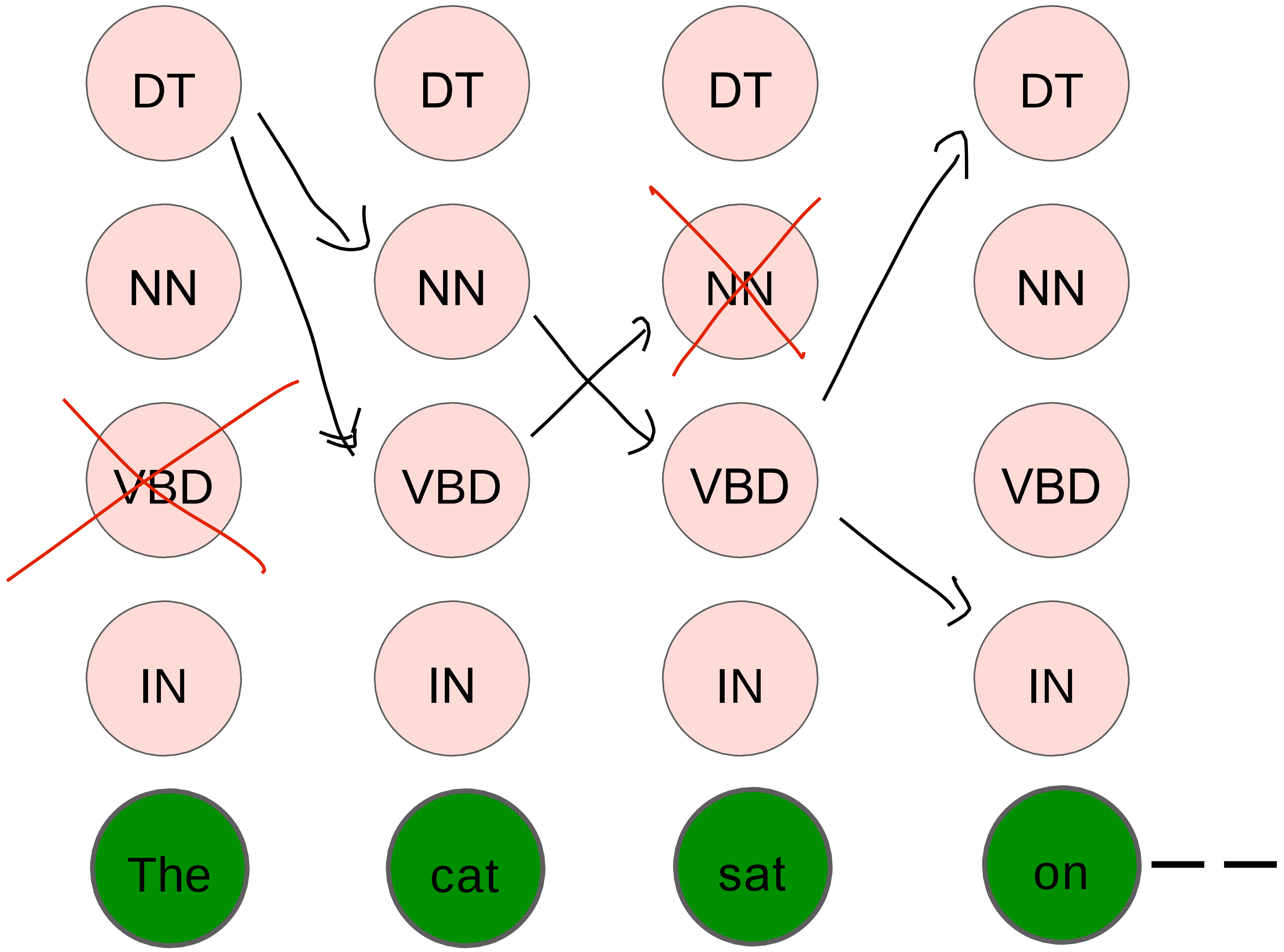


Step 2: Prune set back to top β sequences (sort and select) … and Repeat!

Beam search

- Keep a fixed number of hypotheses at each point
- Beam width, β

$\beta = 2$



Pick $\max_k M[n, k]$ from within beam and backtrack

What is the time complexity of this algorithm?

n = number of timesteps
K = number of states
β = beam width

A: $O(nK\beta)$

Beam Search

- If K (number of states) is too large, Viterbi is too expensive!
- Keep a fixed number of hypotheses at each point
  - Beam width, β
- Trade-off (some) accuracy for computational savings

- **Final remark**: beam search is a common decoding method for any language generation tasks (e.g., n-gram LMs, GPT-3)

Greedy: choose the most likely word!

To predict the next word given a context of two words w_1, w_2:

$$w_3 = \arg\max_{w \in V} P(w \mid w_1, w_2)$$