COS 484/584

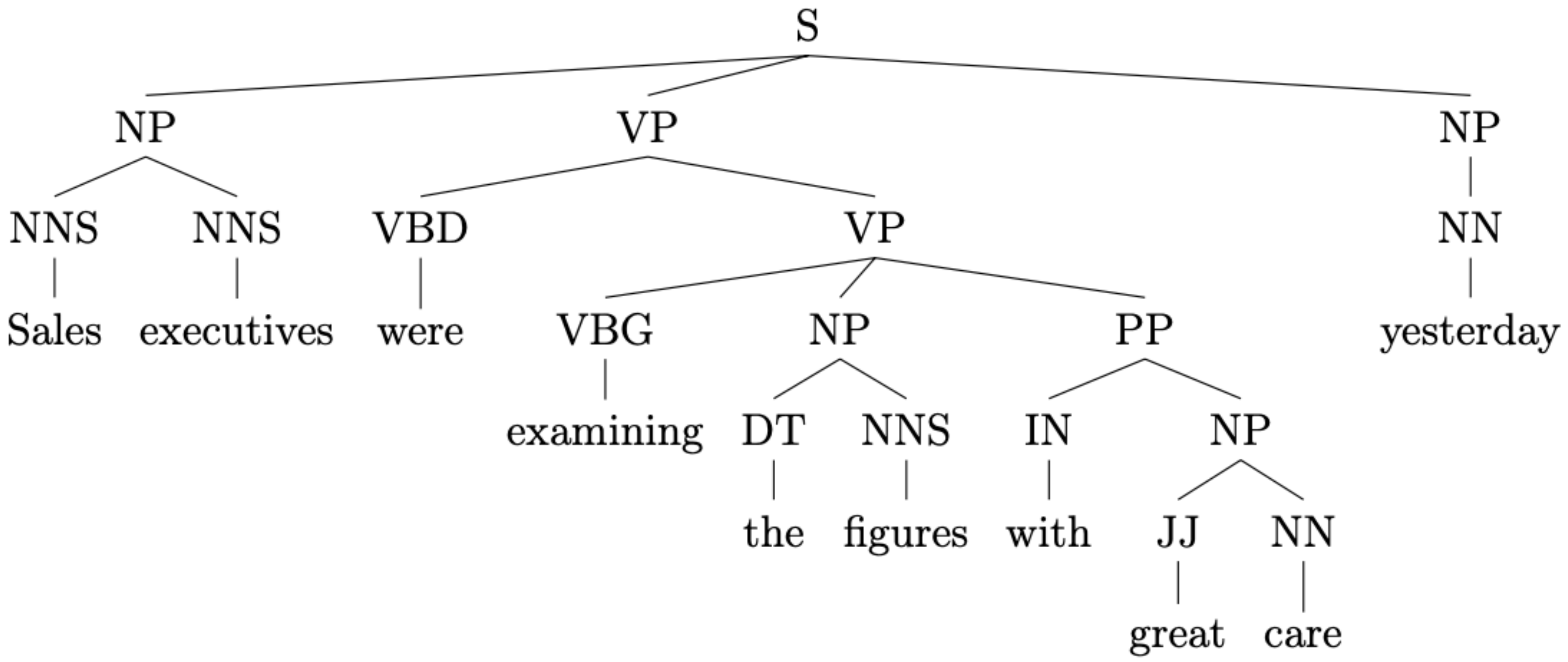
(Advanced) Natural Language Processing

L14: Dependency Parsing

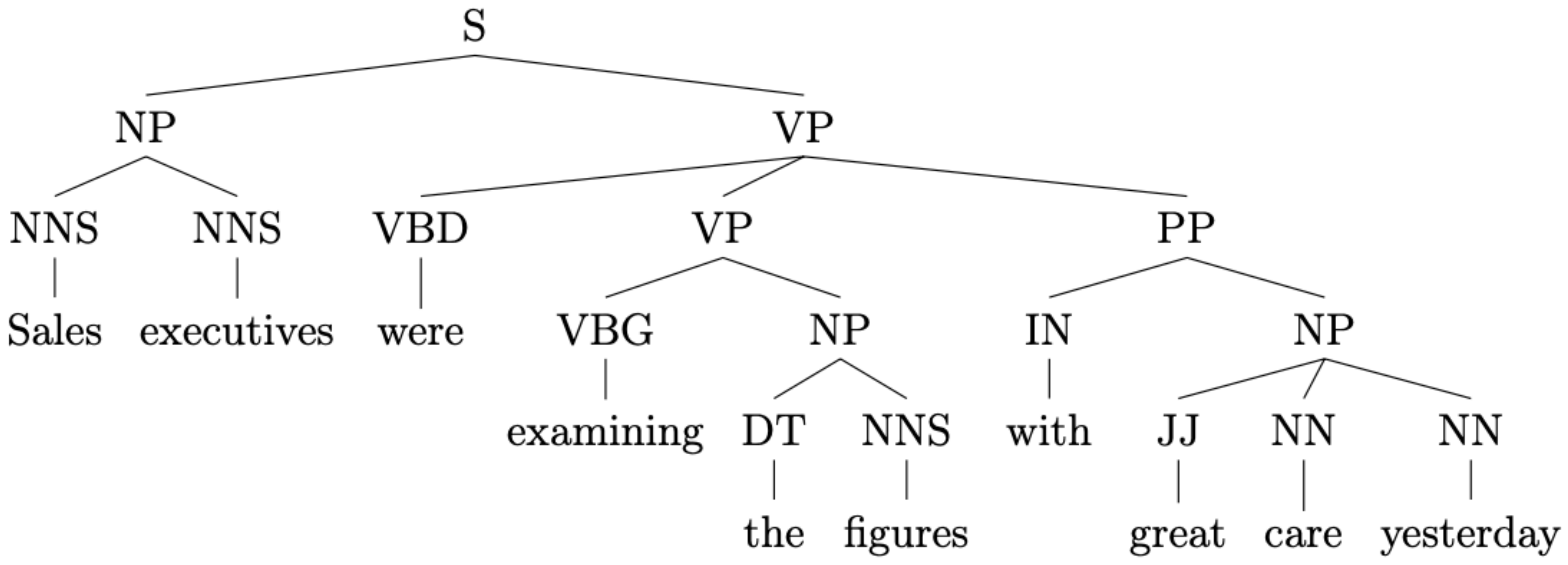
Spring 2021

Constituency parsing (cont'd)

Gold: **(1, 10, S), (1, 2, NP)**, (3, 9, VP), (4, 9, VP), **(5, 6, NP)**, (7, 9, PP), (8, 9, NP), (10, 10, NP)



Predicted: **(1, 10, S), (1, 2, NP)**, (3, 10, VP), (4, 6, VP), **(5, 6, NP)**, (7, 10, PP), (8, 10, NP)



Evaluating constituency parsing

- Recall: (# correct constituents in candidate) / (# constituents in gold tree)
- Precision: (# correct constituents in candidate) / (# constituents in candidate)
- Labeled precision/recall require getting the non-terminal label correct
- F1 is the harmonic mean of precision and recall = (2 * precision * recall) / (precision + recall)
- Part-of-speech tagging accuracy is evaluated separately

Zoom poll

Gold: **(1, 10, S), (1, 2, NP)**, (3, 9, VP), (4, 9, VP), **(5, 6, NP)**, (7, 9, PP), (8, 9, NP), (10, 10, NP)

Predicted: **(1, 10, S), (1, 2, NP)**, (3, 10, VP), (4, 6, VP), **(5, 6, NP)**, (7, 10, PP), (8, 10, NP)

What are the **labeled** precision (P) / recall (R) in the above example?

(a) P = 3/8, R = 3/7

(b) P = 3/7, R = 3/8

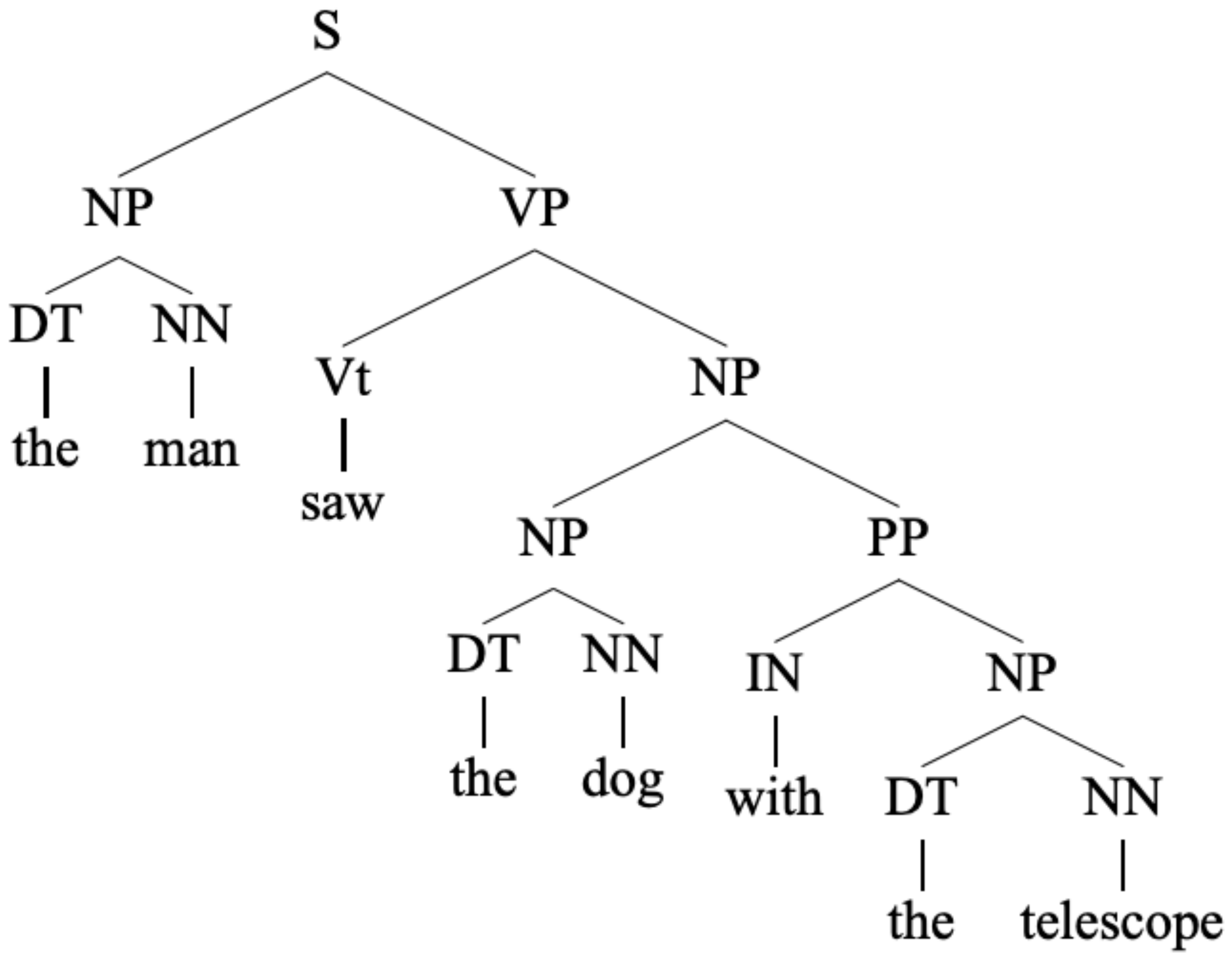
(c) P = 1/2, R = 1/2

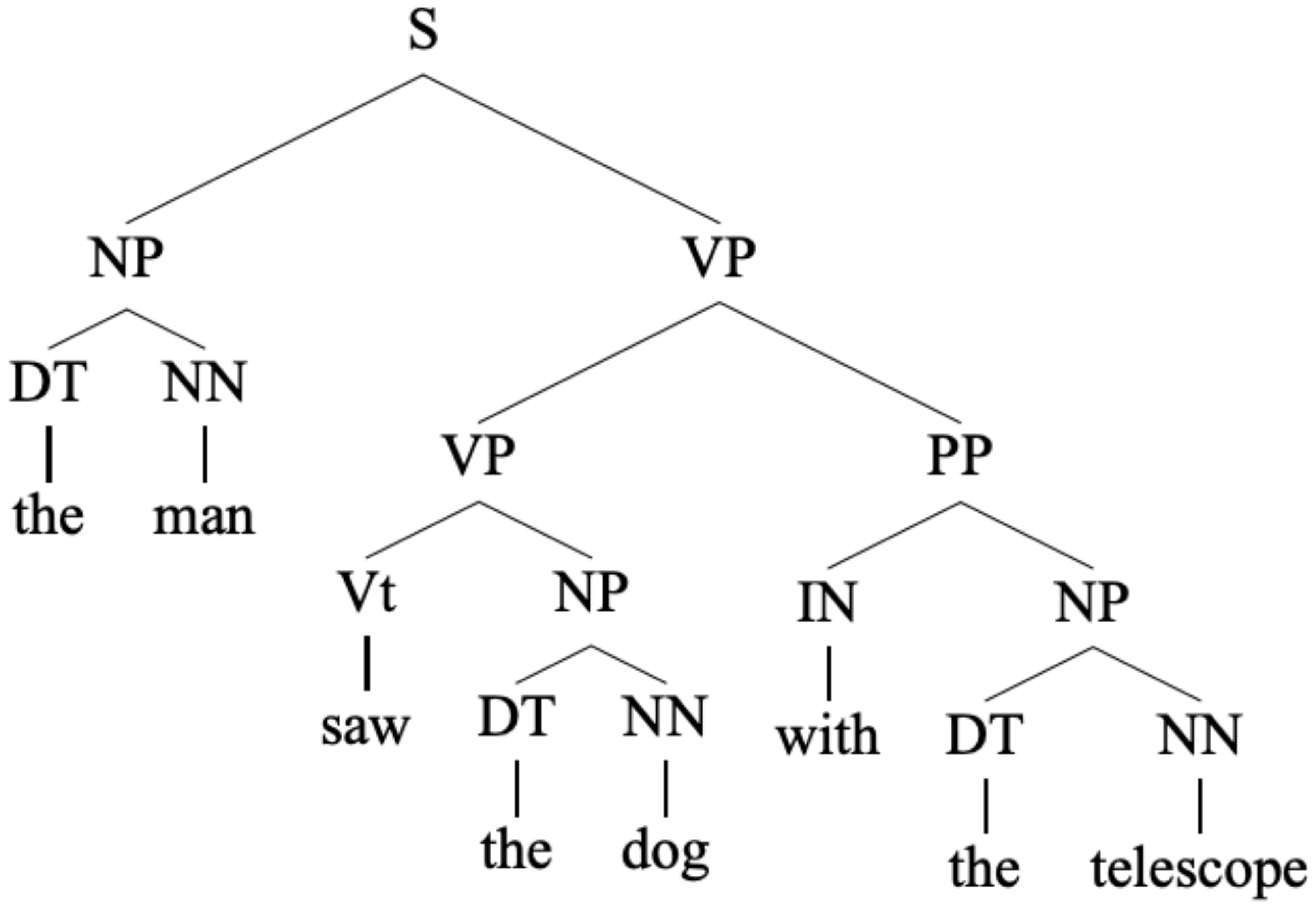
(d) P = 1, R = 1

The answer is (b). F1 = 40%, tagging accuracy = 100%

Weaknesses of PCFGs

Lack of sensitivity to lexical information (words)





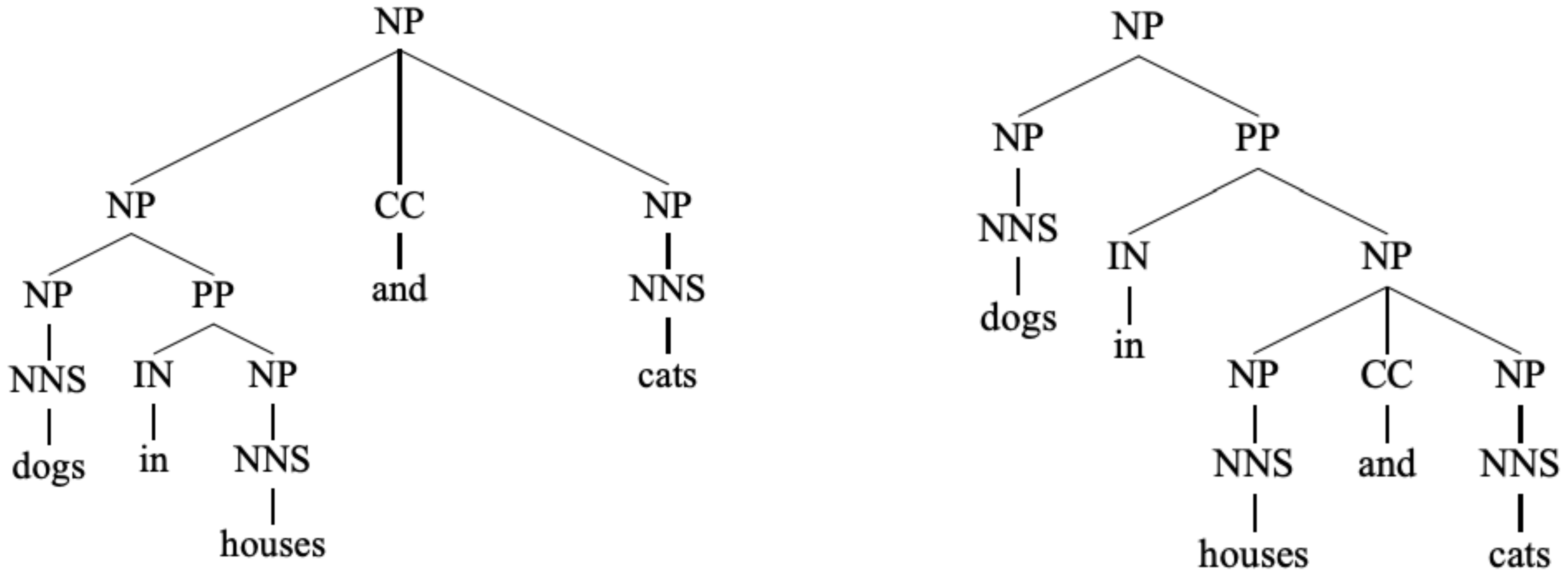
The only difference between these two parses:

$q(\text{NP} \rightarrow \text{NP PP})$ vs $q(\text{VP} \rightarrow \text{VP PP})$

… without looking at the words!

Weaknesses of PCFGs

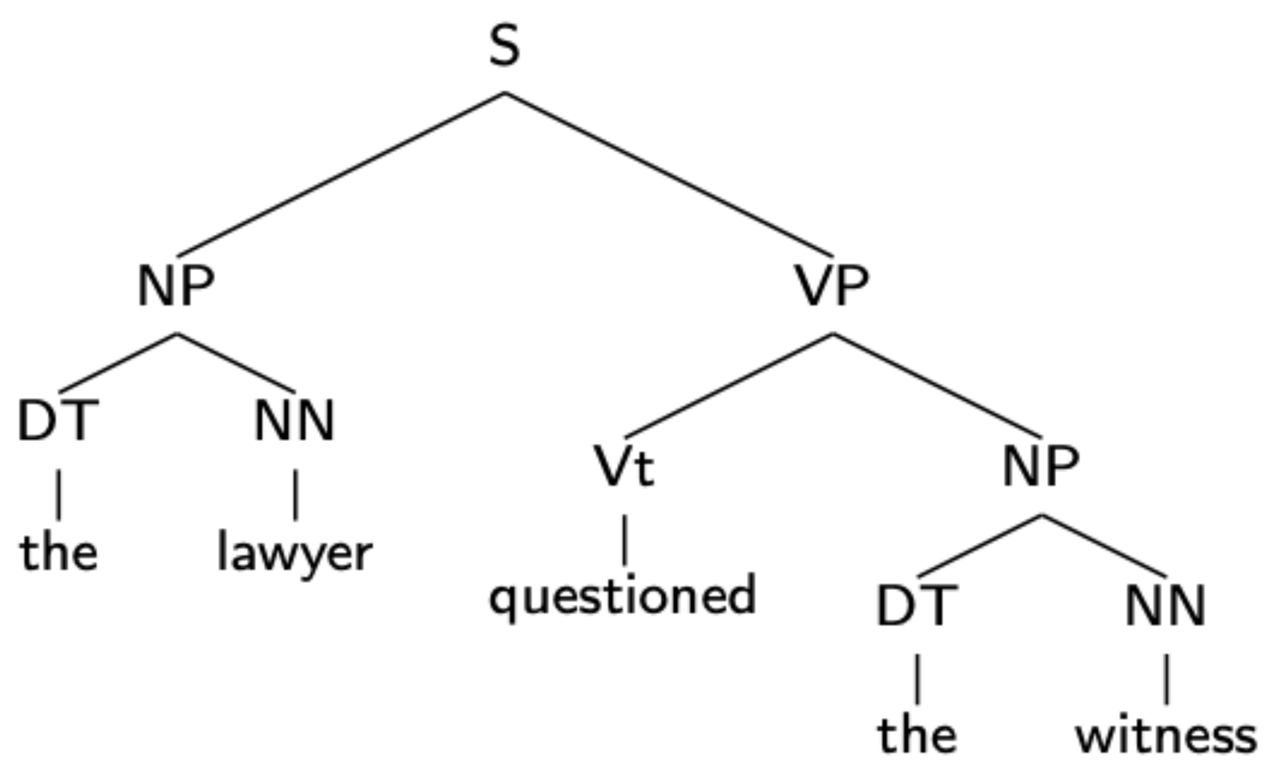
Lack of sensitivity to lexical information (words)

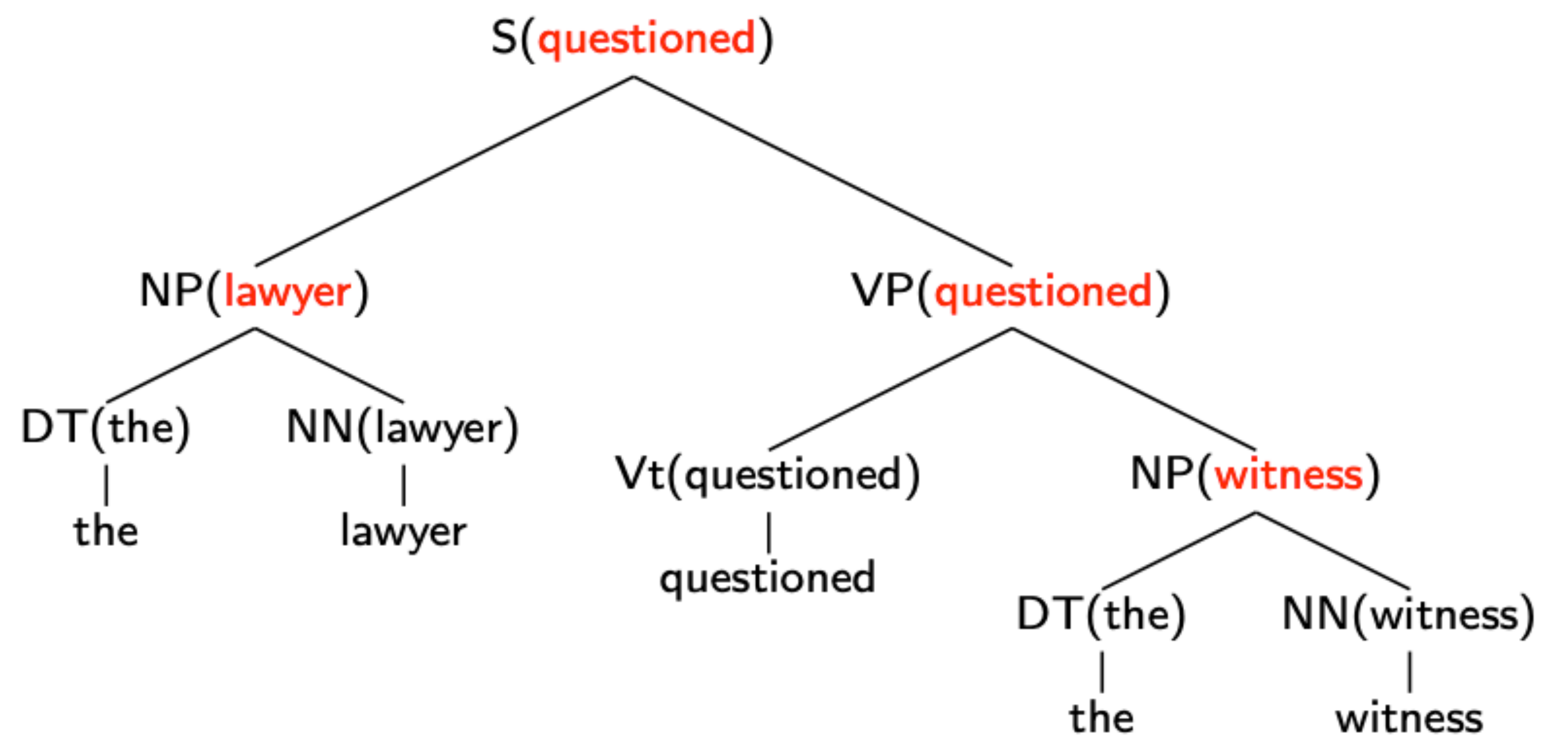


Exactly the same set of context-free rules!

Lexicalized PCFGs [advanced]

- Key idea: add **headwords** to trees





- Each context-free rule has one special child that is the head of the rule (a core idea in syntax)

S	$\Rightarrow$	NP	VP		(VP is the head)
VP	$\Rightarrow$	Vt	NP		(Vt is the head)
NP	$\Rightarrow$	DT	NN	NN	(NN is the head)

The headwords are decided by manual rules!

Lexicalized PCFGs [advanced]

S(saw)	$\rightarrow_2$	NP(man)	VP(saw)
VP(saw)	$\rightarrow_1$	Vt(saw)	NP(dog)
NP(man)	$\rightarrow_2$	DT(the)	NN(man)
NP(dog)	$\rightarrow_2$	DT(the)	NN(dog)
Vt(saw)	$\rightarrow$	saw	
DT(the)	$\rightarrow$	the	
NN(man)	$\rightarrow$	man	
NN(dog)	$\rightarrow$	dog	

- Results for a PCFG: 70.6% recall, 74.8% precision
- Results for a lexicalized PCFG: 88.1% recall, 88.3% precision

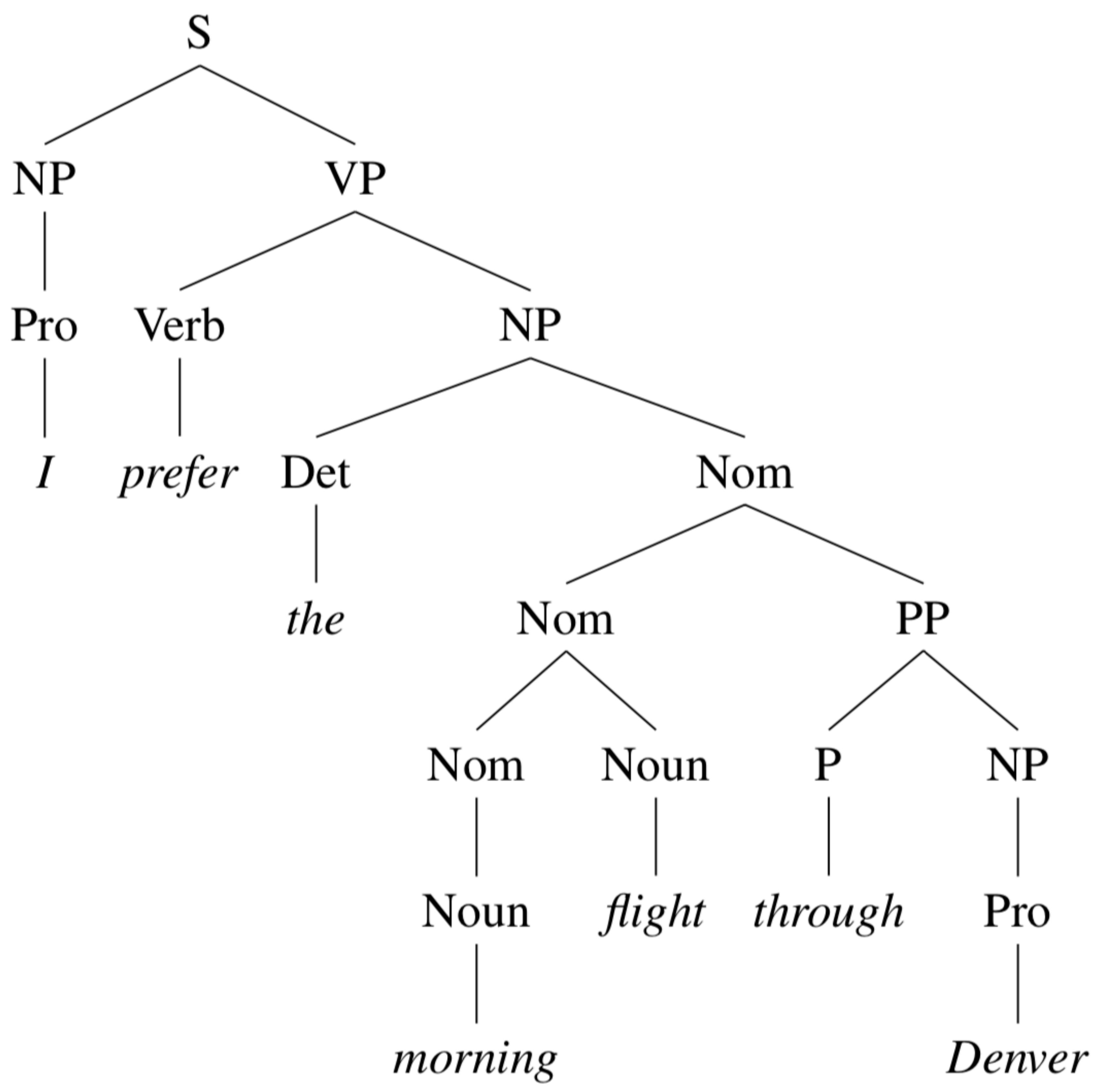
Constituency vs dependency parsing

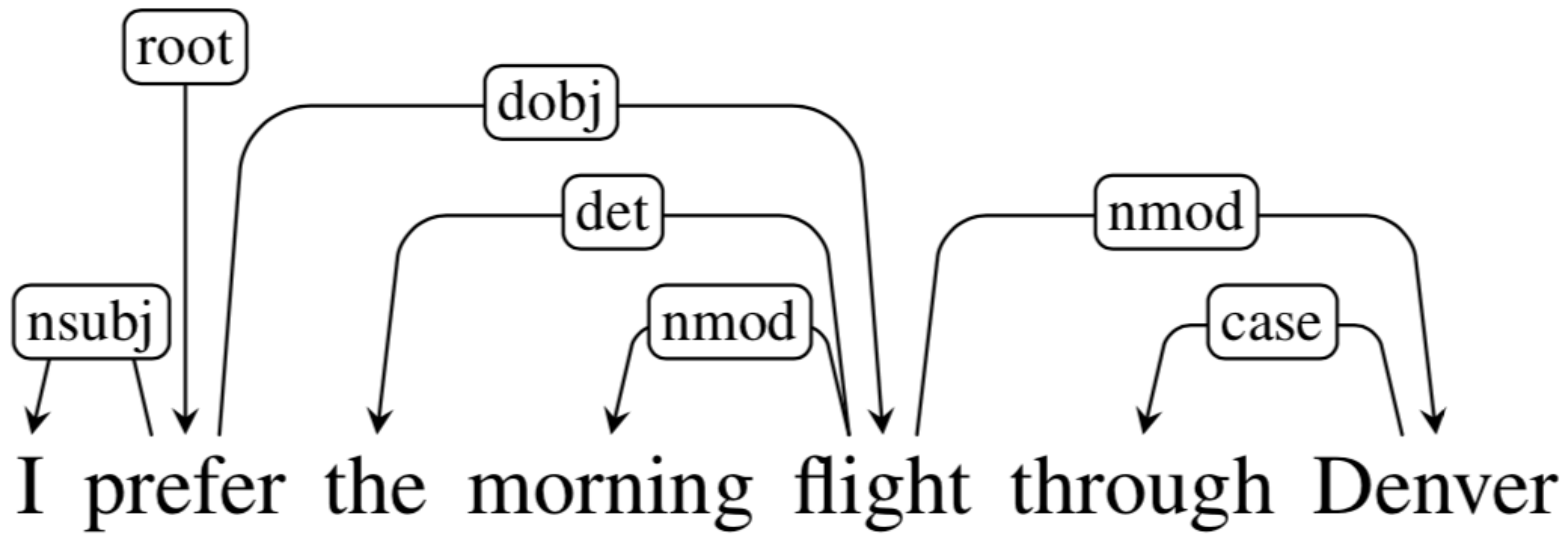
- Constituency structure
- Context-free grammar (CFG)
- Probabilistic context-free grammar (PCFG)
- Treebanks
- The CKY algorithm
- Evaluation
- Lexicalized PCFGs

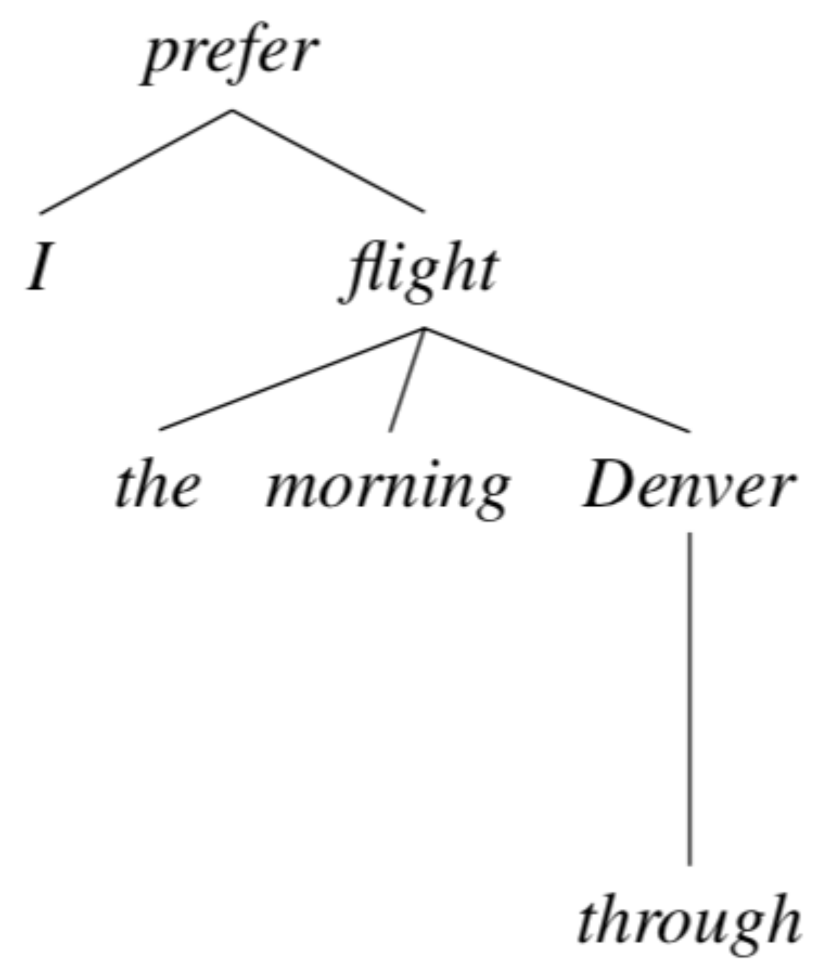
$\longrightarrow$

- Dependency structure
- The Arc-standard algorithm
- Dependency treebanks
- Evaluation

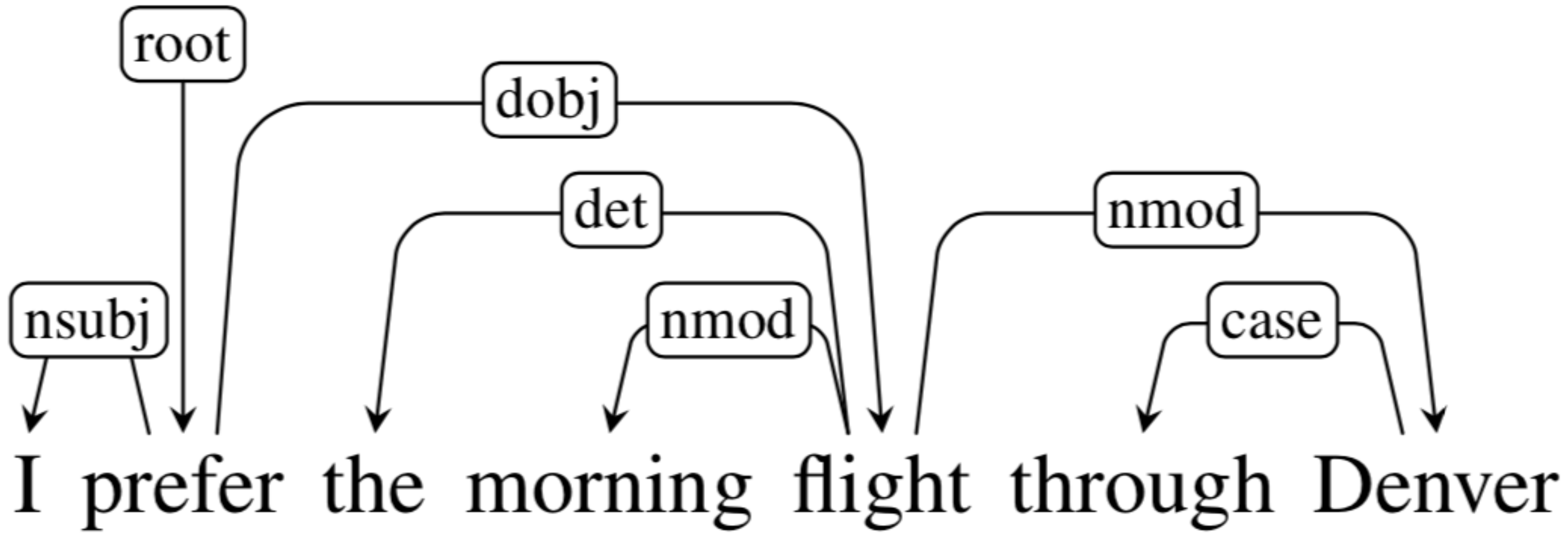
Constituency vs dependency structure







Dependency structure



- Consists of relations between lexical items, normally *binary*, *asymmetric* relations ("arrows") called **dependencies**
- The arrows are commonly **typed** with the name of grammatical relations (subject, prepositional object, apposition, etc)
- The arrow connects a **head** (governor) and a **dependent** (modifier)
- Usually, dependencies form a tree

Dependency relations

Clausal Argument Relations	Description
NSUBJ	Nominal subject
DOBJ	Direct object
IOBJ	Indirect object
CCOMP	Clausal complement
XCOMP	Open clausal complement
Nominal Modifier Relations	**Description**
NMOD	Nominal modifier
AMOD	Adjectival modifier
NUMMOD	Numeric modifier
APPOS	Appositional modifier
DET	Determiner
CASE	Prepositions, postpositions and other case markers
Other Notable Relations	**Description**
CONJ	Conjunct
CC	Coordinating conjunction

Figure 14.2 Selected dependency relations from the Universal Dependency set. (de Marneffe et al., 2014)

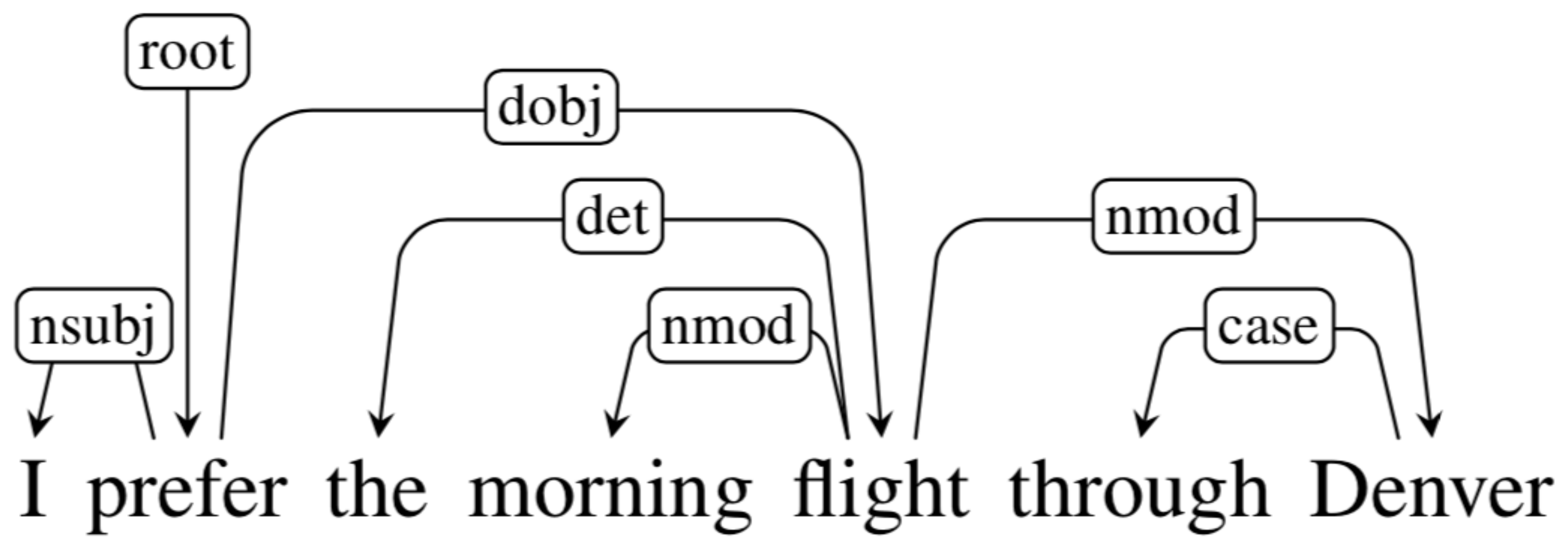
Dependency relations

Relation	Examples with *head* and **dependent**
NSUBJ	**United** *canceled* the flight.
DOBJ	United *diverted* the **flight** to Reno.
	We *booked* her the first **flight** to Miami.
IOBJ	We *booked* **her** the flight to Miami.
NMOD	We took the **morning** *flight*.
AMOD	Book the **cheapest** *flight*.
NUMMOD	Before the storm JetBlue canceled **1000** *flights*.
APPOS	*United*, a **unit** of UAL, matched the fares.
DET	**The** *flight* was canceled.
	Which *flight* was delayed?
CONJ	We *flew* to Denver and **drove** to Steamboat.
CC	We flew to Denver **and** *drove* to Steamboat.
CASE	Book the flight **through** *Houston*.

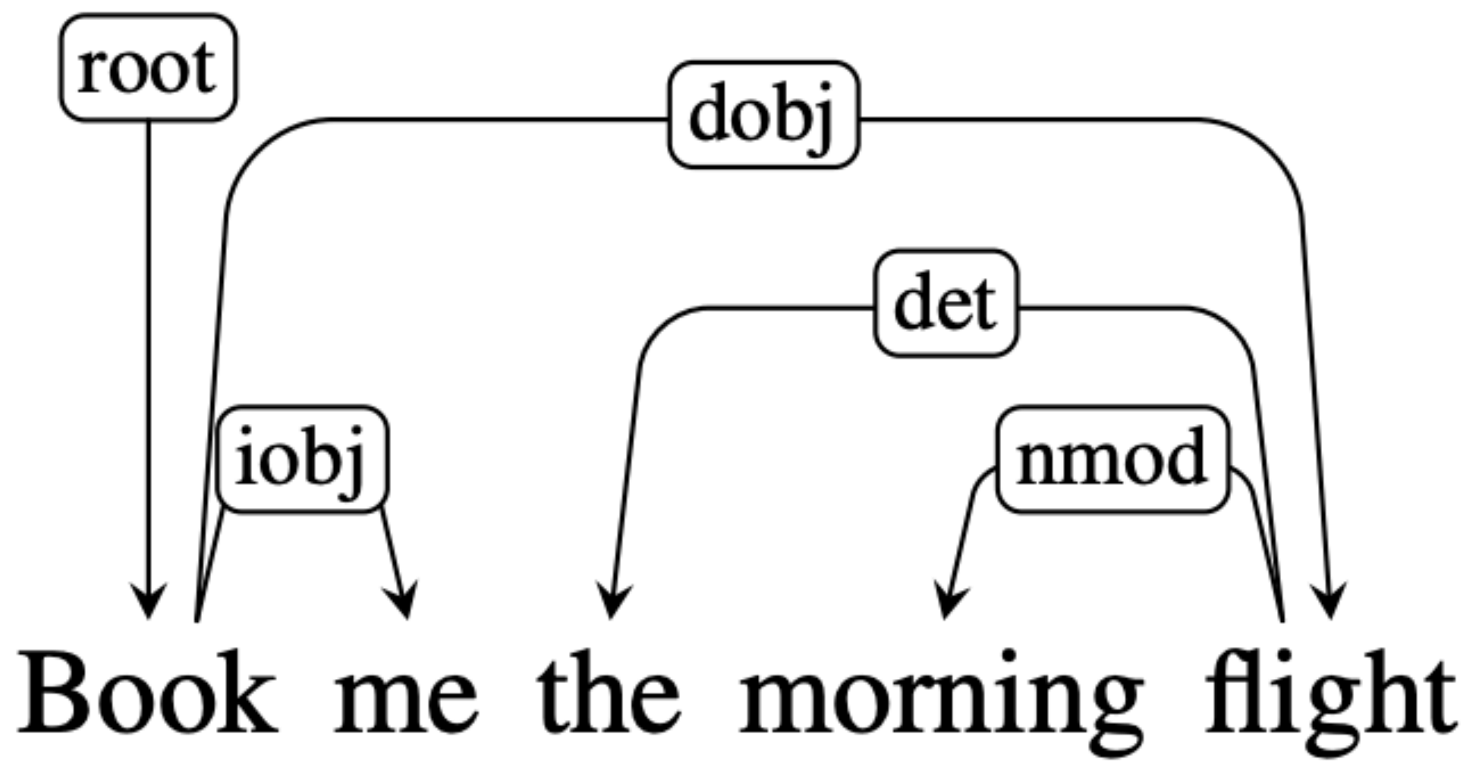
Figure 14.3 Examples of core Universal Dependency relations.

Dependency structure: more examples

I prefer the morning flight through Denver



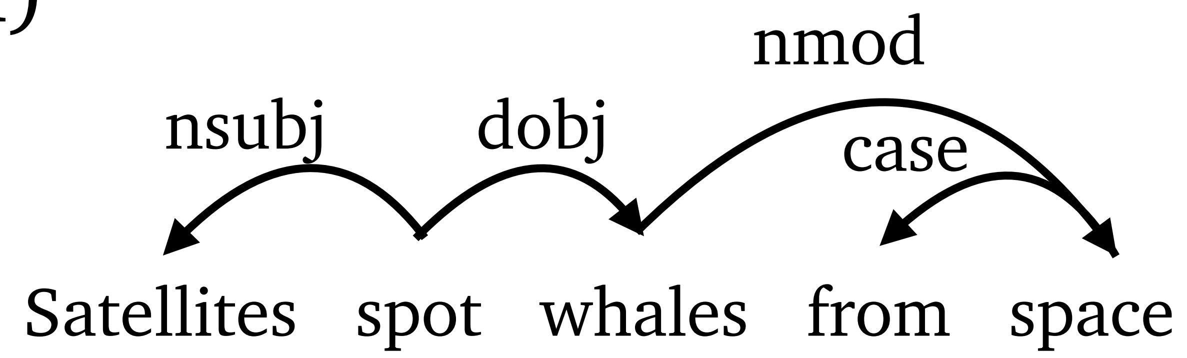
Book me the morning flight



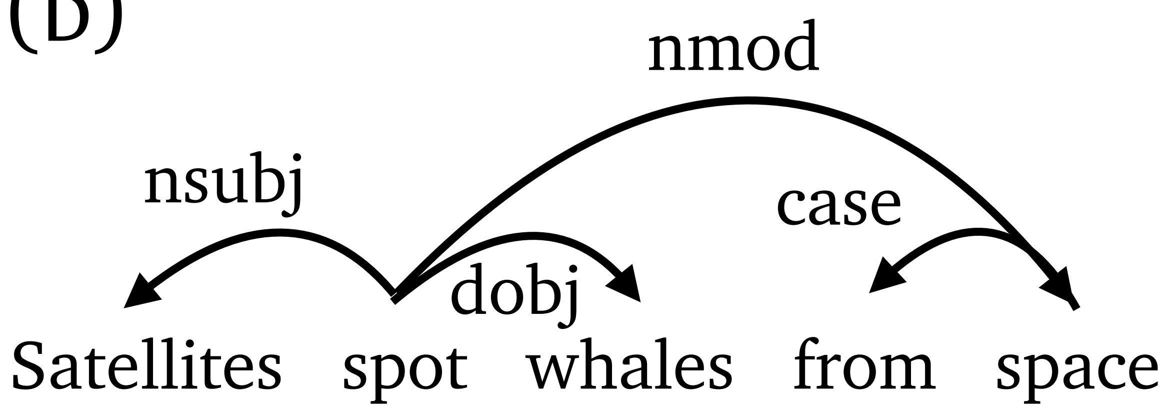
Zoom poll

Which of the following is the correct dependency structure for "Satellites spot whales from space"?

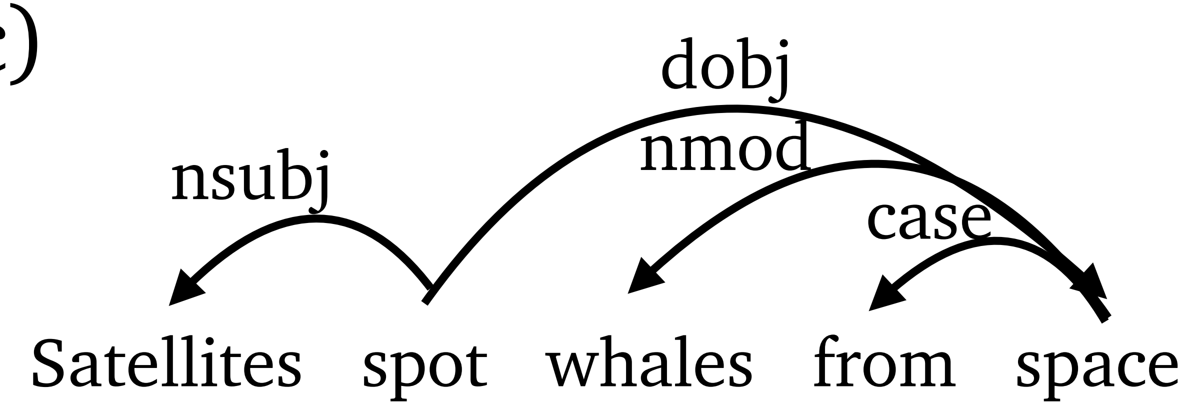
(a)



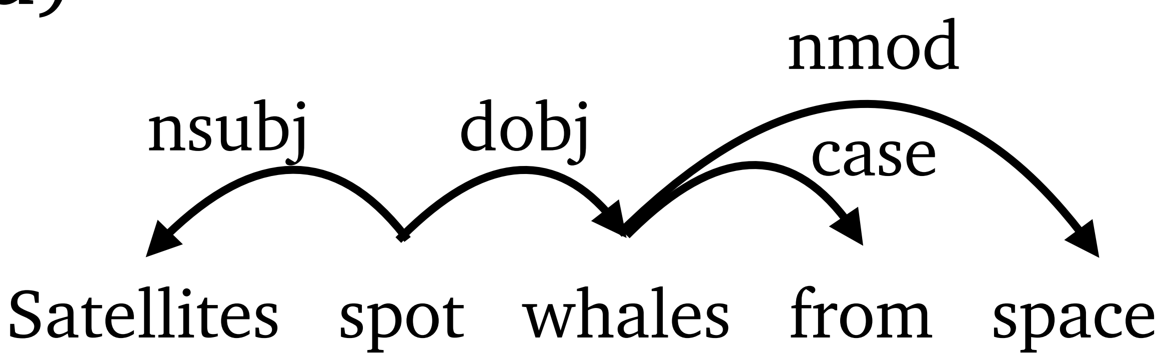
(b)



(c)



(d)



The answer is (b).

Dependency parsing

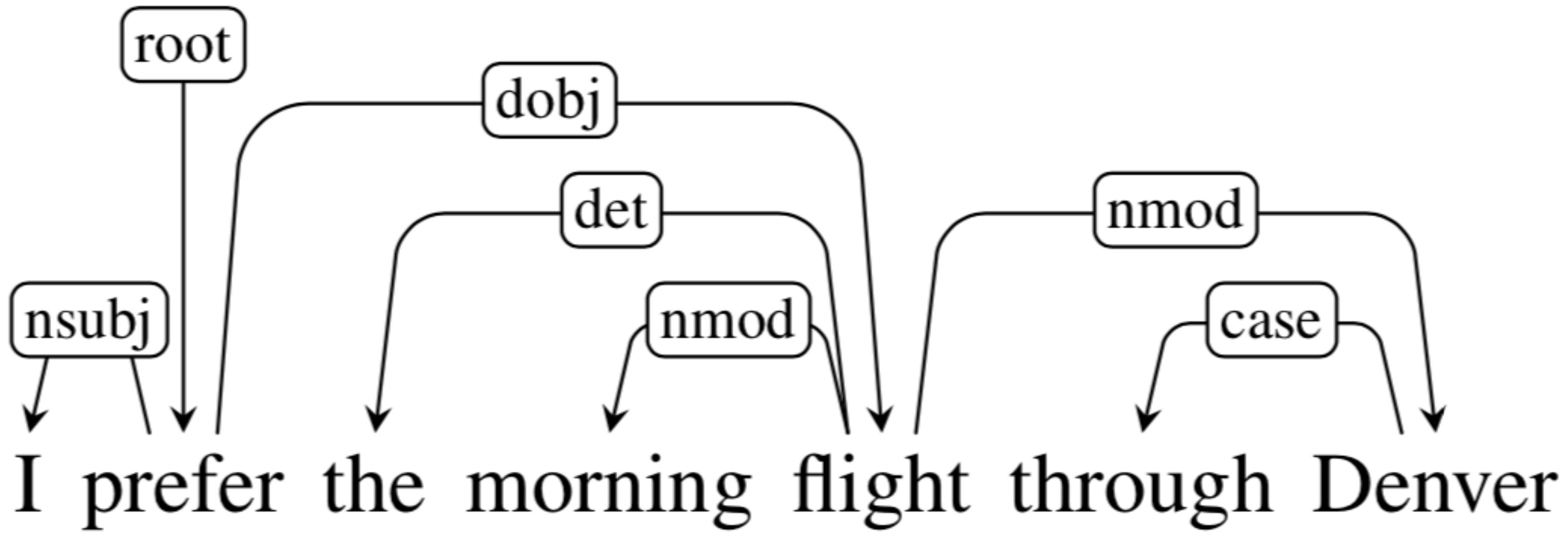
Syntactic parsing is the task of recognizing a sentence and assigning a structure to it.

Dependency parsing is the task of recognizing a sentence and assigning a **dependency** structure to it.

Input

I prefer the morning flight through Denver

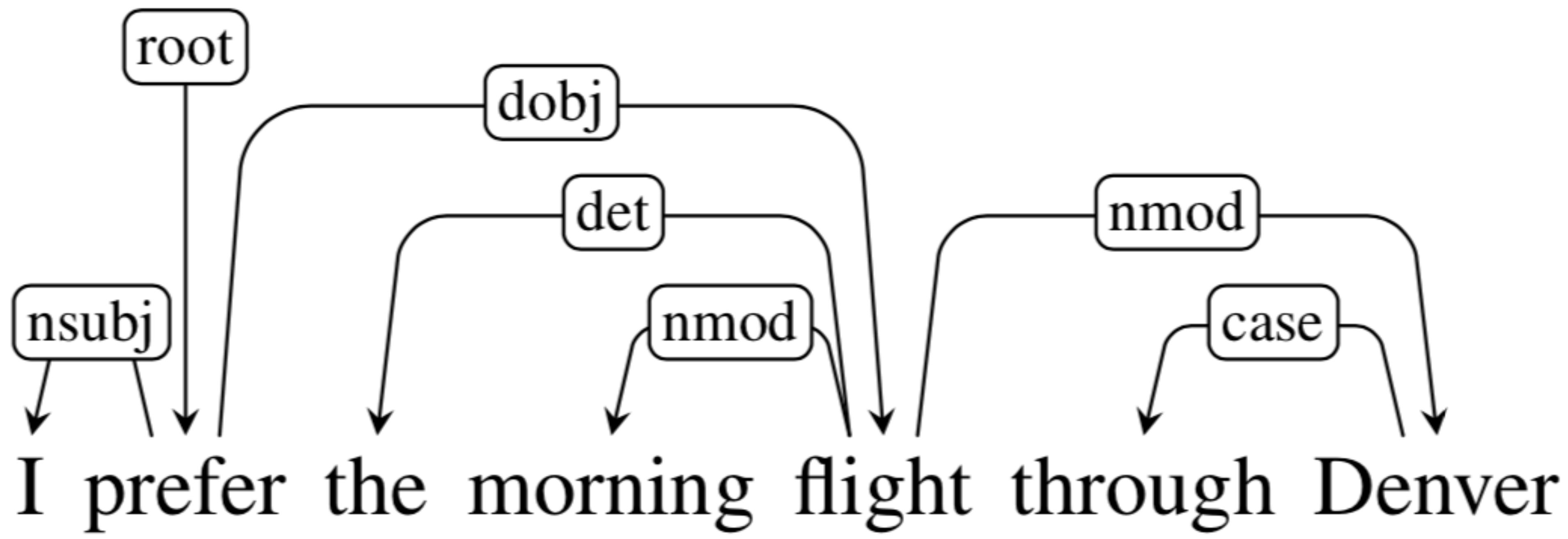
Output



Dependency formalisms

Usually a tree structure

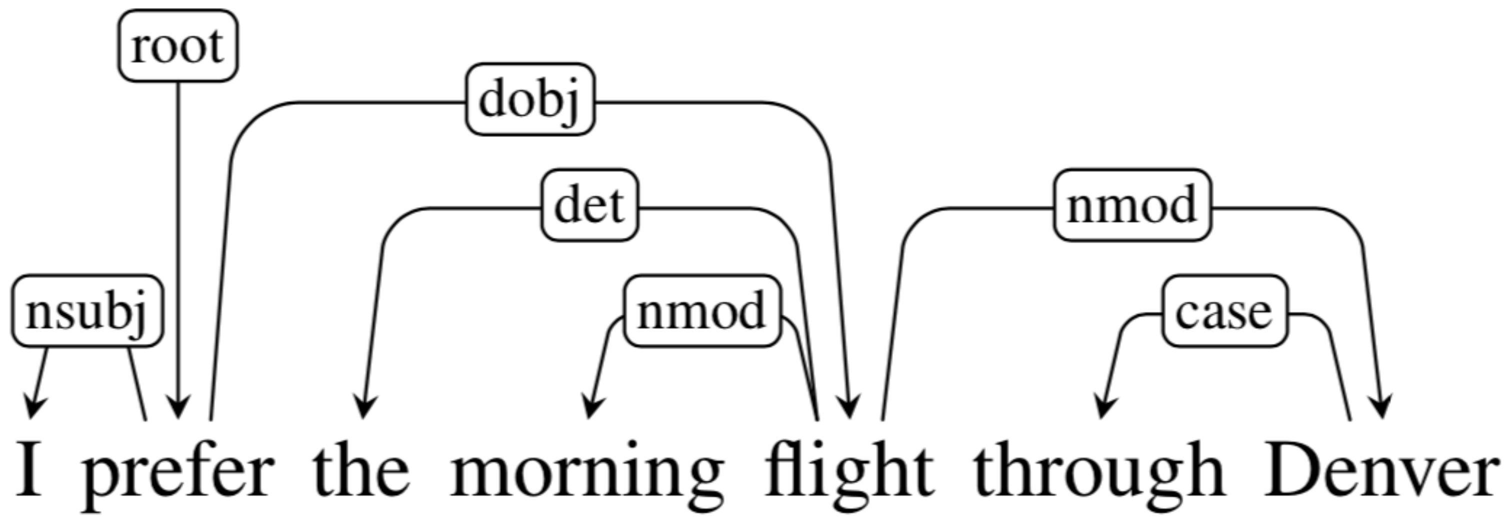
- There is only one root
- Every word except for the root has one head (parent)
  - Alternatively, we can just add a fake node ROOT, so each word has exactly one head
- No cycles: A —> B, B —> C, C —> A



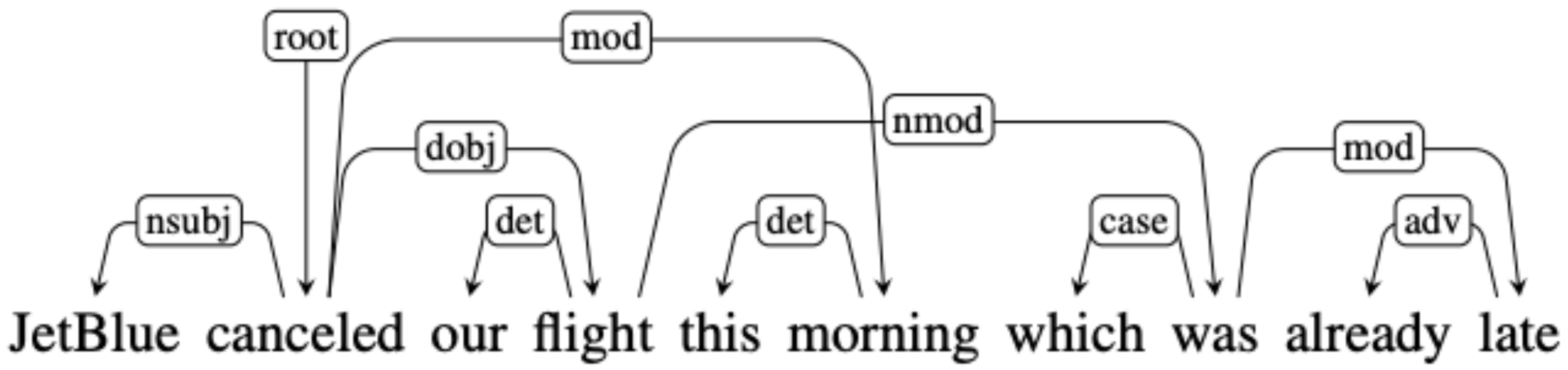
Dependency formalisms

Additional constraint: **projectivity**

- **Definition**: there are no crossing dependency arcs when the words are laid out in their linear order, with all arcs above the words



projective



non-projective

Non-projectivity arises due to long distance dependencies or in languages with flexible word order.

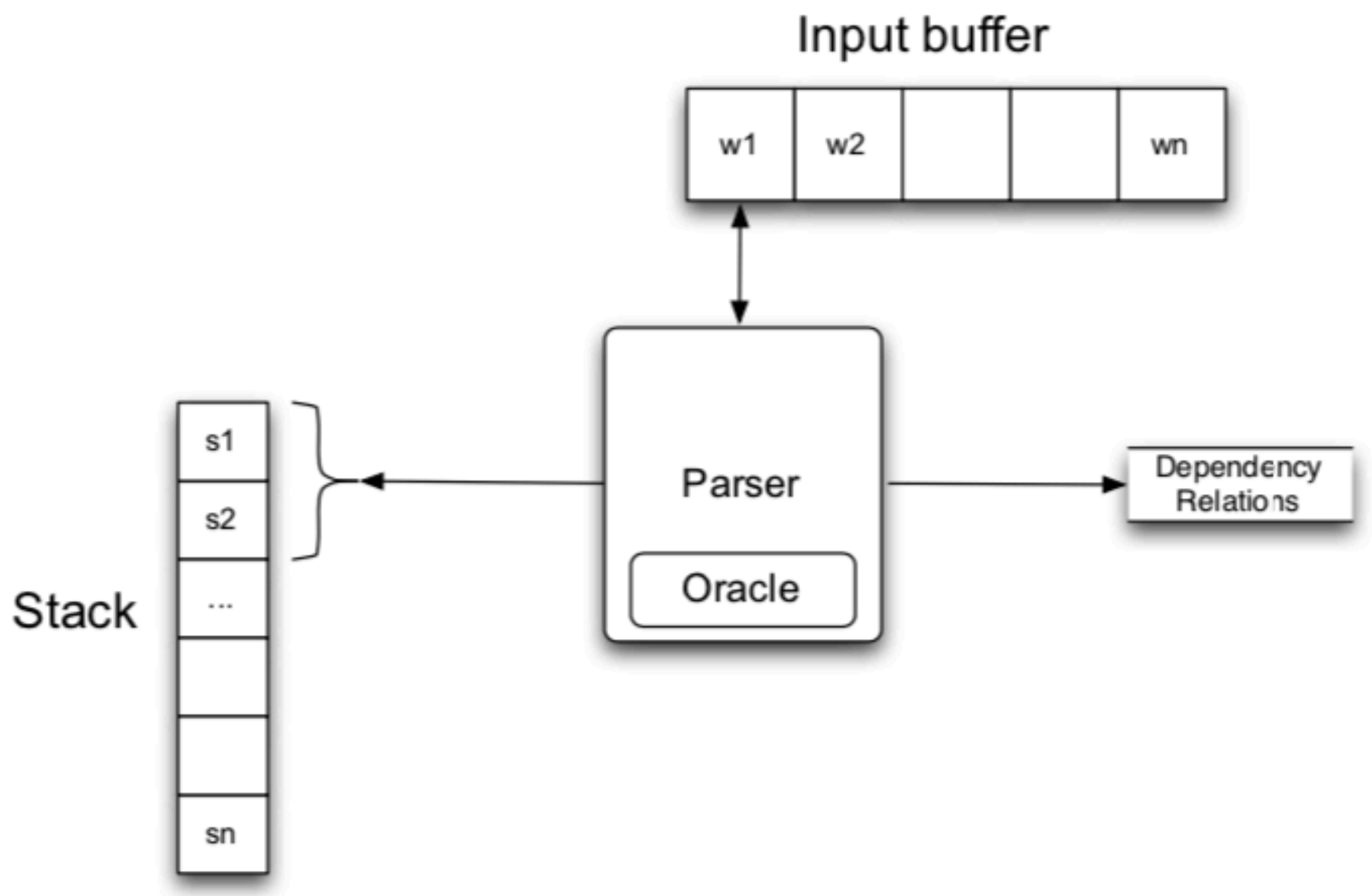
We only focus on projective parsing

Dataset	# Sentences	(%) Projective
English	39,832	99.9
Chinese	16,091	100.0
Czech	72,319	76.9
German	38,845	72.2

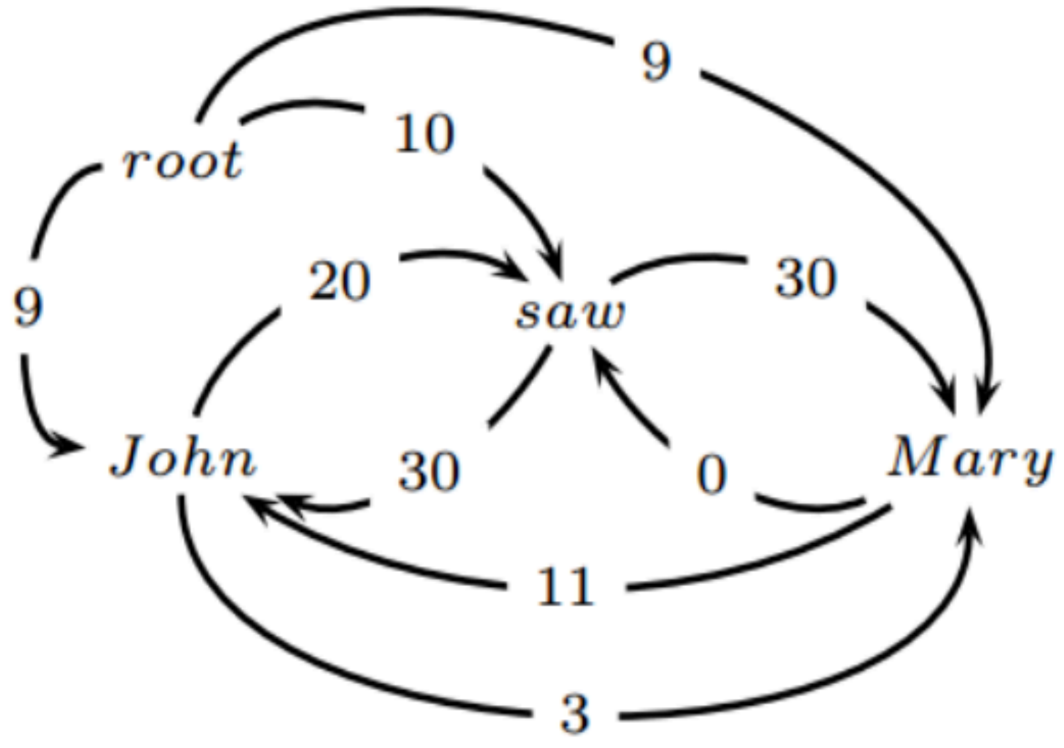
Two families of algorithms

Transition-based dependency parsing

- Also called “shift-reduce parsing”



Graph-based dependency parsing



The Arc-standard algorithm

- Given: a sentence of $w_1, w_2, \ldots, w_n$
- The parsing process is modeled as a sequence of transitions
- A configuration consists of a stack s, a buffer b and a set of dependency arcs A:
  $c = (s, b, A)$
- Initially, $s = [\text{ROOT}]$, $b = [w_1, w_2, \ldots, w_n]$, $A = \varnothing$
- Three types of transitions: LEFT-ARC (r), RIGHT-ARC (r), SHIFT

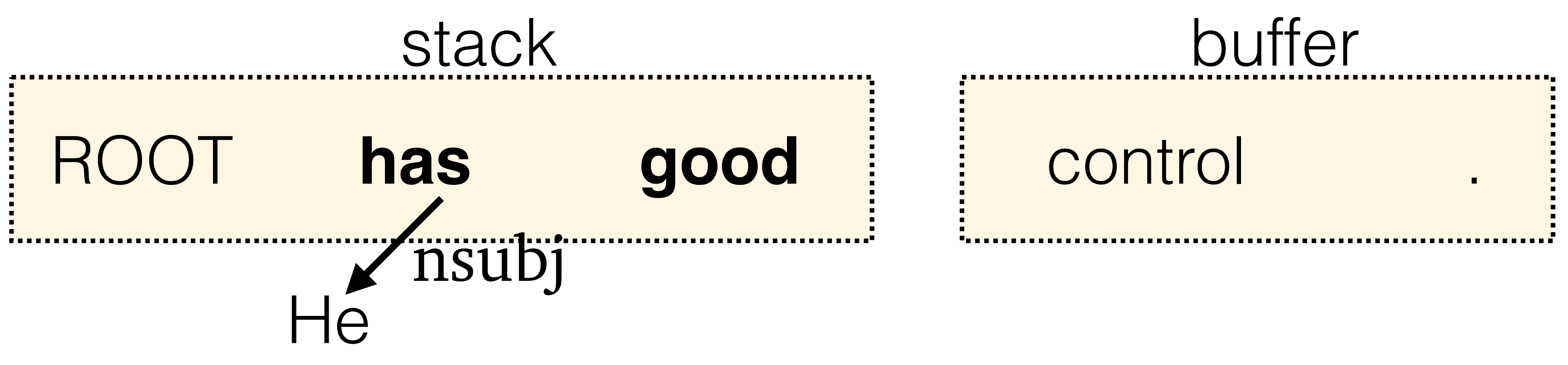
  I will define them in the next slides!
- A configuration is terminal if $s = [\text{ROOT}]$ and $b = \varnothing$

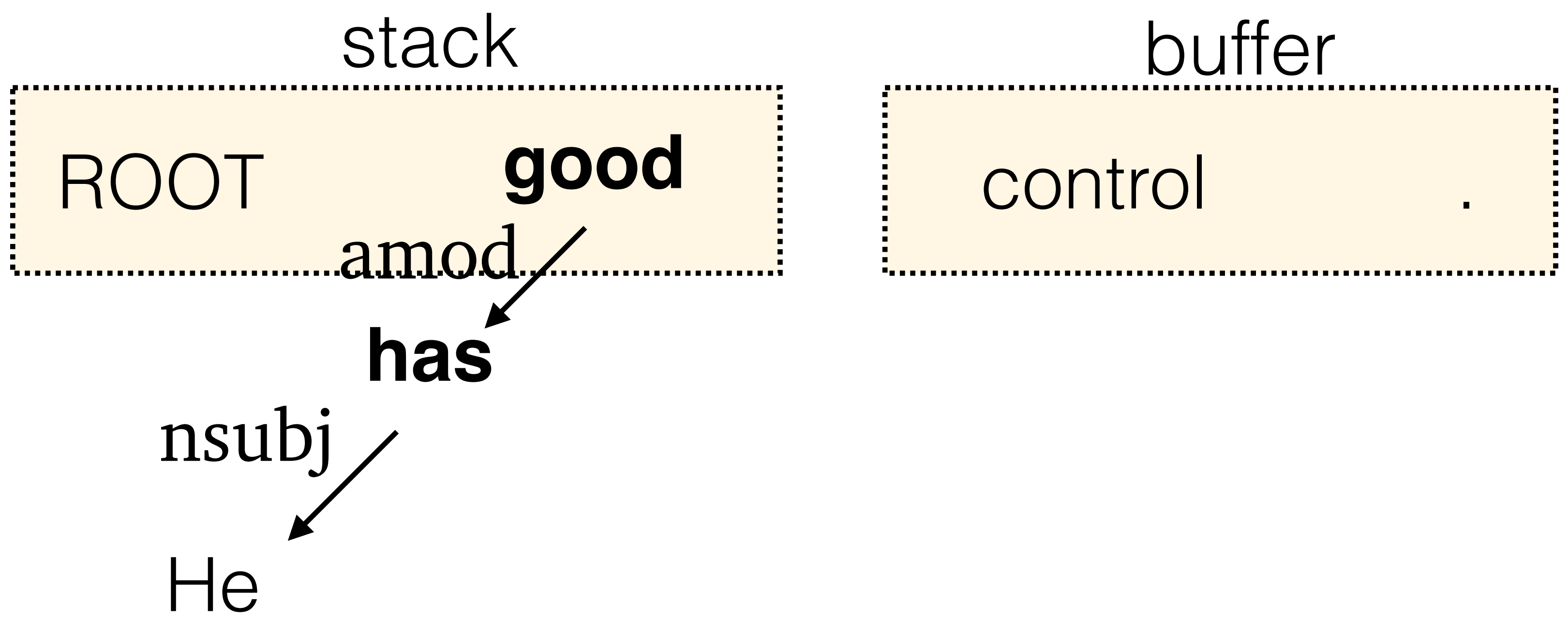
The Arc-standard algorithm

s_1, s_2: the top 2 words on the stack (s_1 = good, s_2 = has);

b_1: the first word in the buffer (b_1 = control)

LEFT-ARC (r): add an arc ($s_1 \xrightarrow{r} s_2$) to A, remove s_2 from the stack



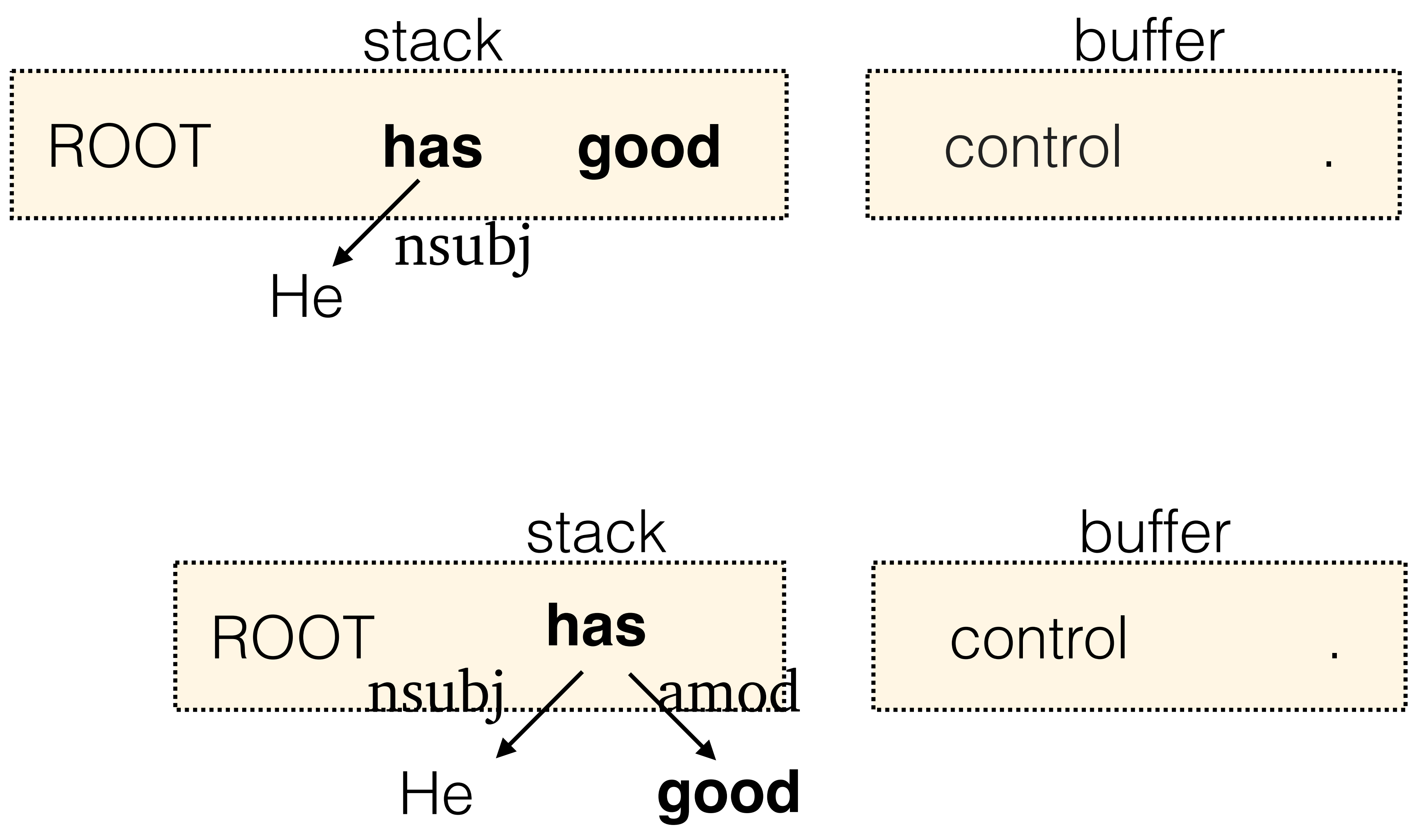


The Arc-standard algorithm

s_1, s_2: the top 2 words on the stack (s_1 = good, s_2 = has);

b_1: the first word in the buffer (b_1 = control)

RIGHT-ARC (r): add an arc ($s_2 \xrightarrow{r} s_1$) to A, remove s_1 from the stack

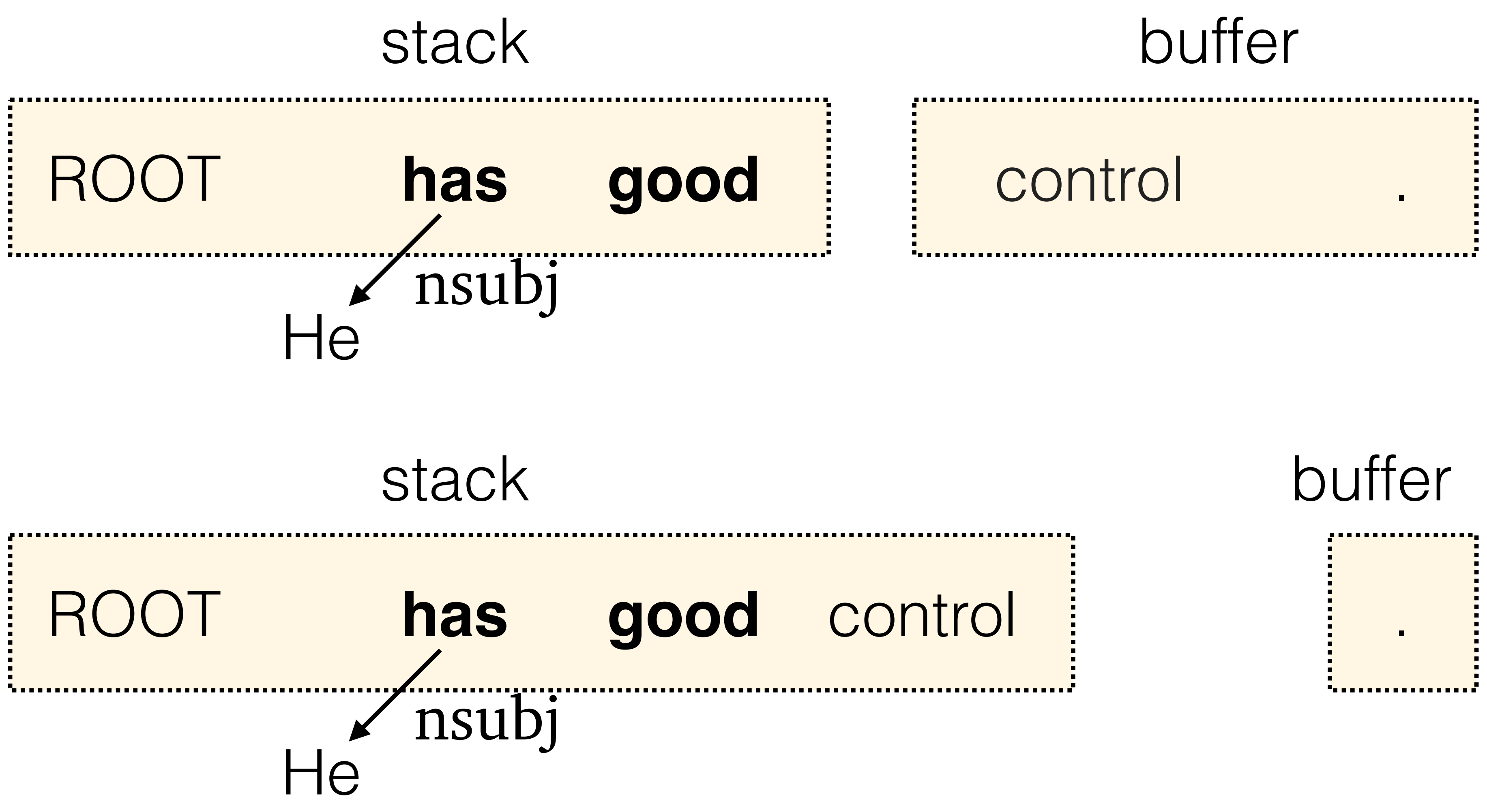


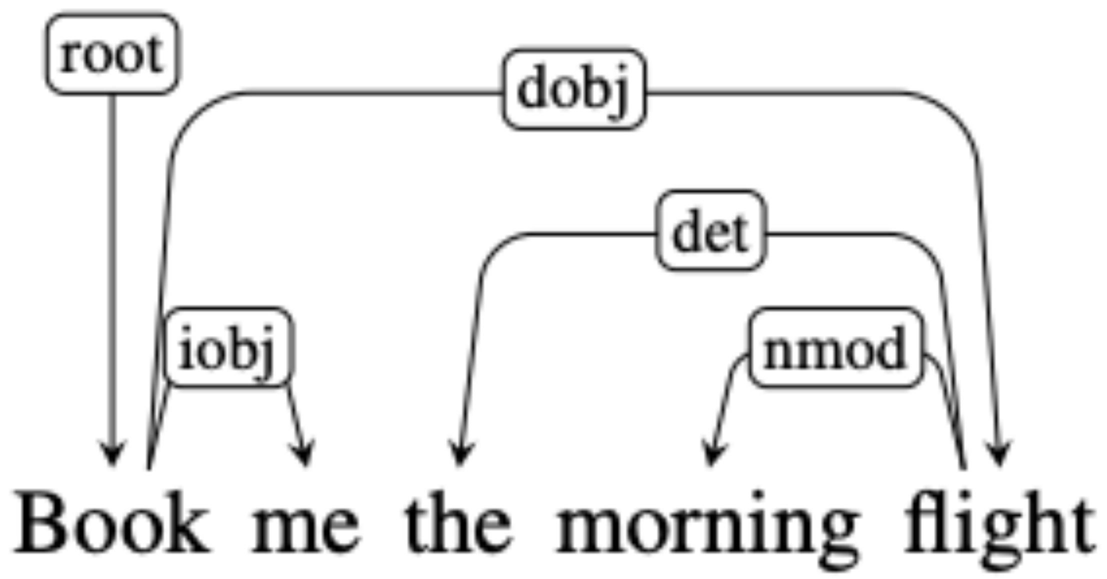
The Arc-standard algorithm

s_1, s_2: the top 2 words on the stack (s_1 = good, s_2 = has);

b_1: the first word in the buffer (b_1 = control)

SHIFT: move b_1 from the buffer to the stack



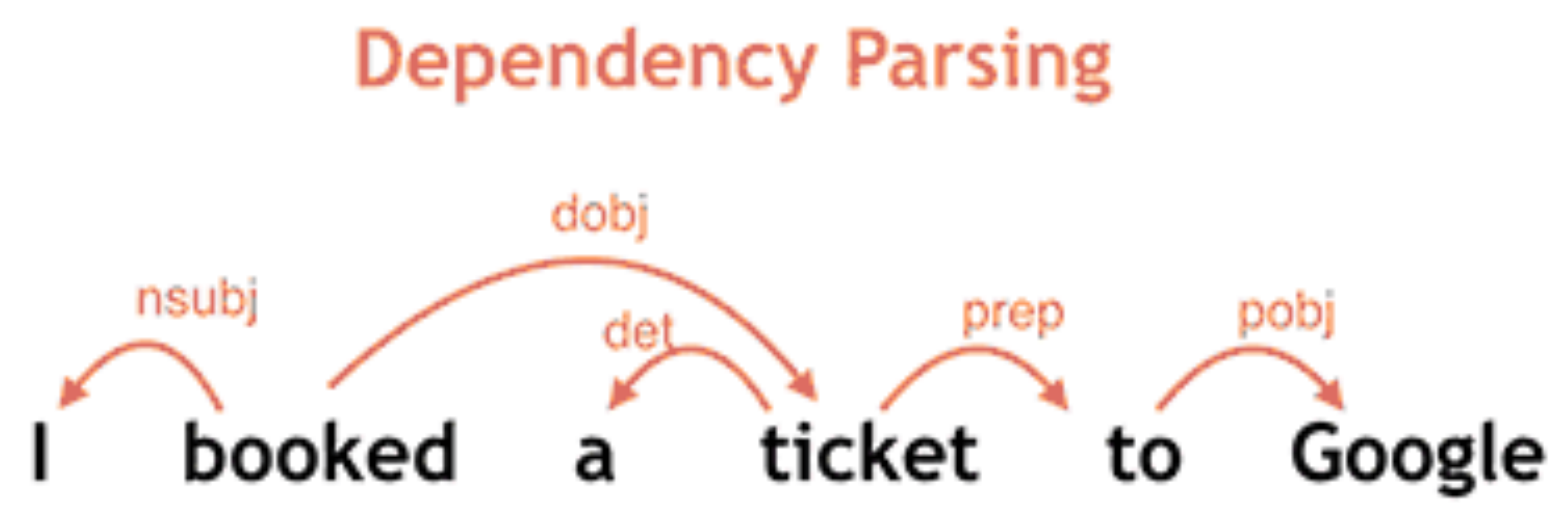


“Book me the morning flight”

A running example

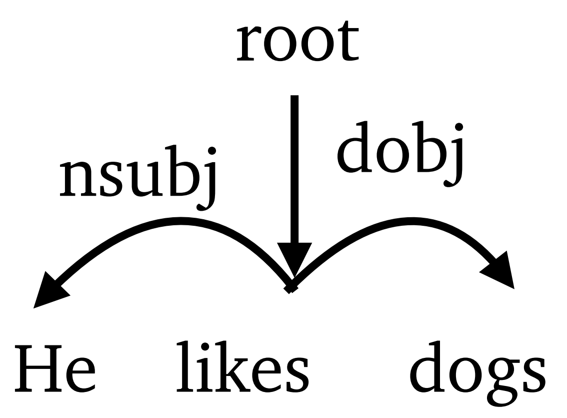
	stack	buffer	action	added arc
0	[ROOT]	[Book, me, the, morning, flight]	SHIFT	
1	[ROOT, Book]	[me, the, morning, flight]	SHIFT	
2	[ROOT, Book, me]	[the, morning, flight]	RIGHT-ARC(iobj)	(Book, iobj, me)
3	[ROOT, Book]	[the, morning, flight]	SHIFT	
4	[ROOT, Book, the]	[morning, flight]	SHIFT	
5	[ROOT, Book, the, morning]	[flight]	SHIFT	
6	[ROOT, Book, the,morning,flight]	[]	LEFT-ARC(nmod)	(flight,nmod,morning)
7	[ROOT, Book, the, flight]	[]	LEFT-ARC(det)	(flight,det,the)
8	[ROOT, Book, flight]	[]	RIGHT-ARC(dobj)	(Book,dobj,flight)
9	[ROOT, Book]	[]	RIGHT-ARC(root)	(ROOT,root,Book)
10	[ROOT]	[]		

Transition-based dependency parsing



https://ai.googleblog.com/2016/05/announcing-syntaxnet-worlds-most.html

Zoom poll



Which of the following transition sequences is correct for the sentence “He likes dogs”?

(a) SHIFT, SHIFT, RIGHT-ARC(dobj), SHIFT, LEFT-ARC(nsubj), RIGHT-ARC(root)

(b) SHIFT, SHIFT, SHIFT, RIGHT-ARC(dobj), LEFT-ARC(nsubj), RIGHT-ARC(root)

(c) SHIFT, SHIFT, LEFT-ARC(nsubj), SHIFT, RIGHT-ARC(dobj), RIGHT-ARC(root)

(d) SHIFT, SHIFT, SHIFT, LEFT-ARC(nsubj), RIGHT-ARC(dobj), RIGHT-ARC(root)

Both (b) and (c) are correct.

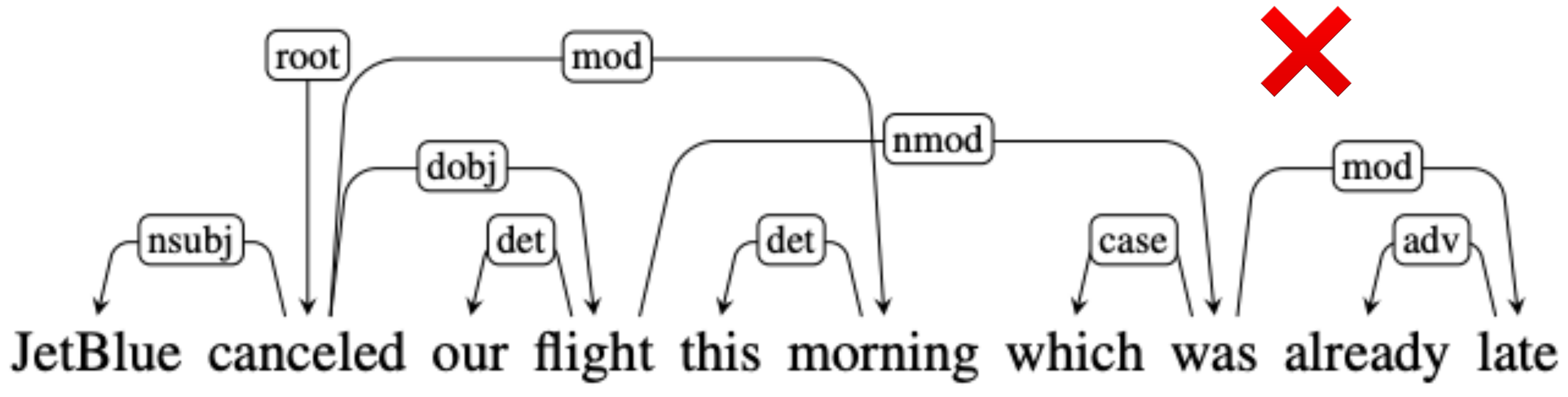
Transition-based dependency parsing

Given: a sentence of $w_1, w_2, \ldots, w_n$

Q: How many transitions are needed? How many times of SHIFT?

Correctness [advanced]

- For every complete transition sequence, the resulting graph is a projective dependency forest (soundness)
- For every projective dependency tree G, there is a transition sequence that generates G (completeness)



<u>However, one parse tree can have multiple valid transition sequences.</u>

How to decide which transitions to take?

Key idea: we can learn a statistical machine learning model from dependency treebanks!

- The major English dependency treebank: converting from Penn Treebank using rule-based algorithms
  - (De Marneffe et al, 2006): Generating typed dependency parses from phrase structure parses
  - (Johansson and Nugues, 2007): Extended Constituent-to-dependency Conversion for English

- Universal Dependencies: nearly 200 treebanks in 100 languages were collected since 2016

Universal Dependencies

Universal Dependencies (UD) is a framework for consistent annotation of grammar (parts of speech, morphological features, and syntactic dependencies) across different human languages. UD is an open community effort with over 300 contributors producing nearly 200 treebanks in over 100 languages. If you're new to UD, you should start by reading the first part of the Short Introduction and then browsing the annotation guidelines.

https://universaldependencies.org/

Universal Dependencies

Current UD Languages

Information about language families (and genera for families with multiple branches) is mostly taken from WALS Online (IE = Indo-European).

Abaza	1	<1K	Northwest Caucasian
Afrikaans	1	49K	IE, Germanic
Akkadian	2	23K	Afro-Asiatic, Semitic
Akuntsu	1	<1K	Tupian, Tupari
Albanian	1	<1K	IE, Albanian
Amharic	1	10K	Afro-Asiatic, Semitic
Ancient Greek	2	416K	IE, Greek
Apurina	1	<1K	Arawakan
Arabic	3	1,042K	Afro-Asiatic, Semitic
Armenian	1	52K	IE, Armenian
Assyrian	1	<1K	Afro-Asiatic, Semitic
Bambara	1	13K	Mande
Basque	1	121K	Basque
Belarusian	1	275K	IE, Slavic
Bhojpuri	2	6K	IE, Indic
Breton	1	10K	IE, Celtic
Bulgarian	1	156K	IE, Slavic
Buryat	1	10K	Mongolic
Cantonese	1	13K	Sino-Tibetan
Catalan	1	531K	IE, Romance
Chinese	5	285K	Sino-Tibetan
Chukchi	1	6K	Chukotko-Kamchatkan
Classical Chinese	1	233K	Sino-Tibetan
Coptic	1	48K	Afro-Asiatic, Egyptian
Croatian	1	199K	IE, Slavic
Czech	5	2,227K	IE, Slavic
Danish	2	100K	IE, Germanic
Dutch	2	306K	IE, Germanic
English	9	648K	IE, Germanic

https://universaldependencies.org/

Train a classifier to predict transitions

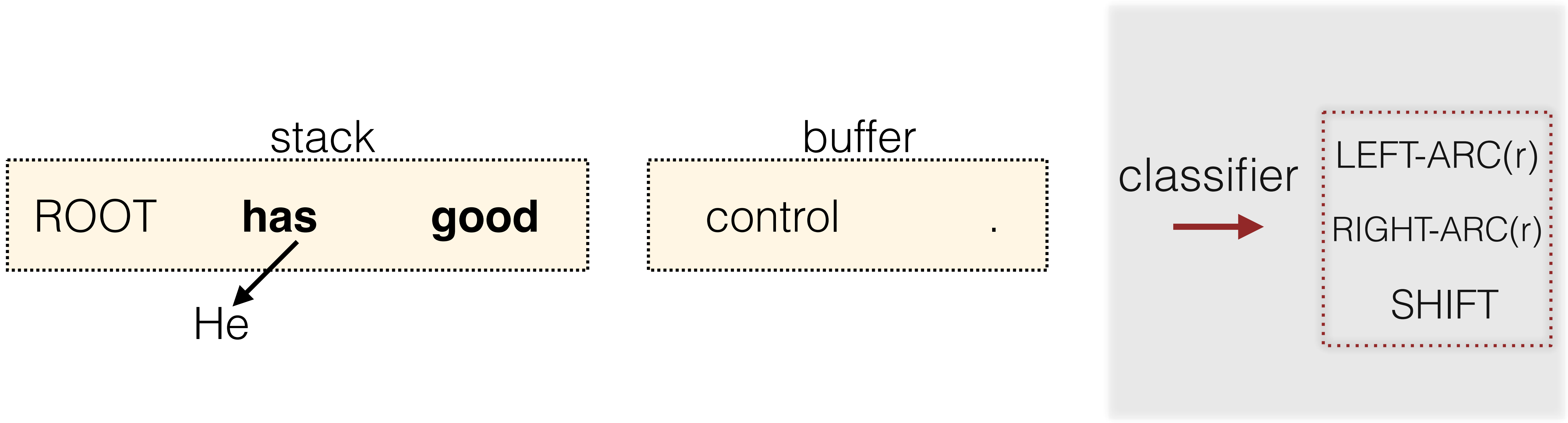
- Given $\{x_i, y_i\}$ where x_i is a sentence and y_i is a dependency parse

- For each x_i with n words, we can construct a transition sequence of length $2n$ which generates y_i, so we can generate 2n training examples: $\{(c_k, t_k)\}$

  c_k: configuration, t_k: transition

  - "shortest stack" strategy: prefer LEFT-ARC over SHIFT.

- The goal becomes how to learn a classifier from c_k to t_k



(2|R| + 1) -way classification!

R: dependency labels

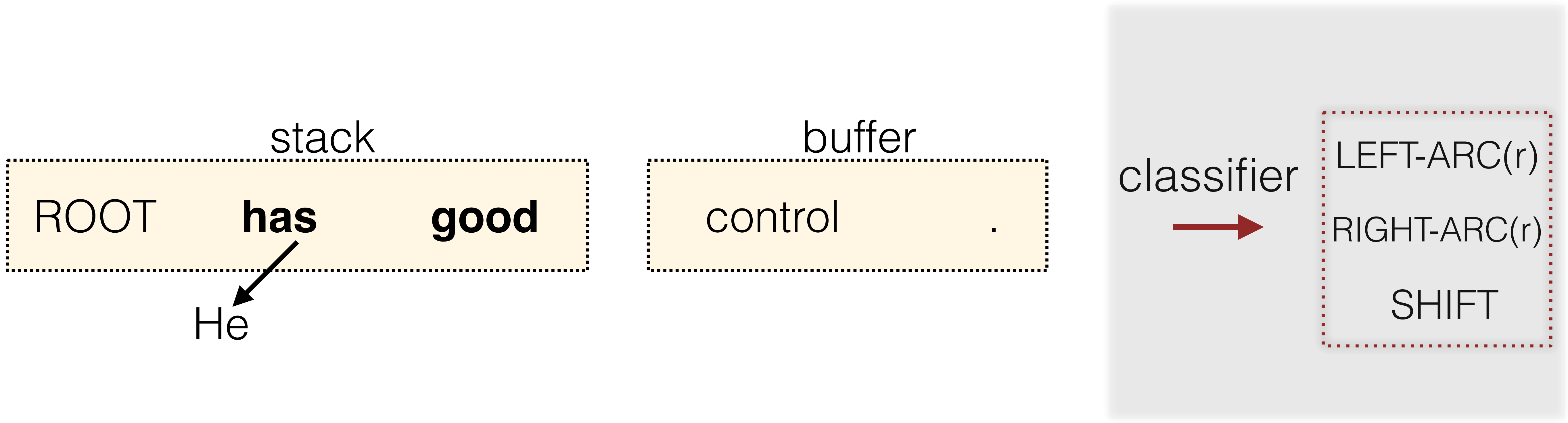
Train a classifier to predict transitions

During testing, we use the classifier to repeat predicting the transition, until we reach a terminal configuration

function DEPENDENCYPARSE(*words*) **returns** dependency tree

    state ← {[root], [*words*], [] } ; initial configuration
    while *state* **not final**
        t ← **Classifier** (*state*) ; choose a transition operator to apply
        state ← APPLY(*t*, *state*) ; apply it, creating a new state
    return *state*

Feature extraction



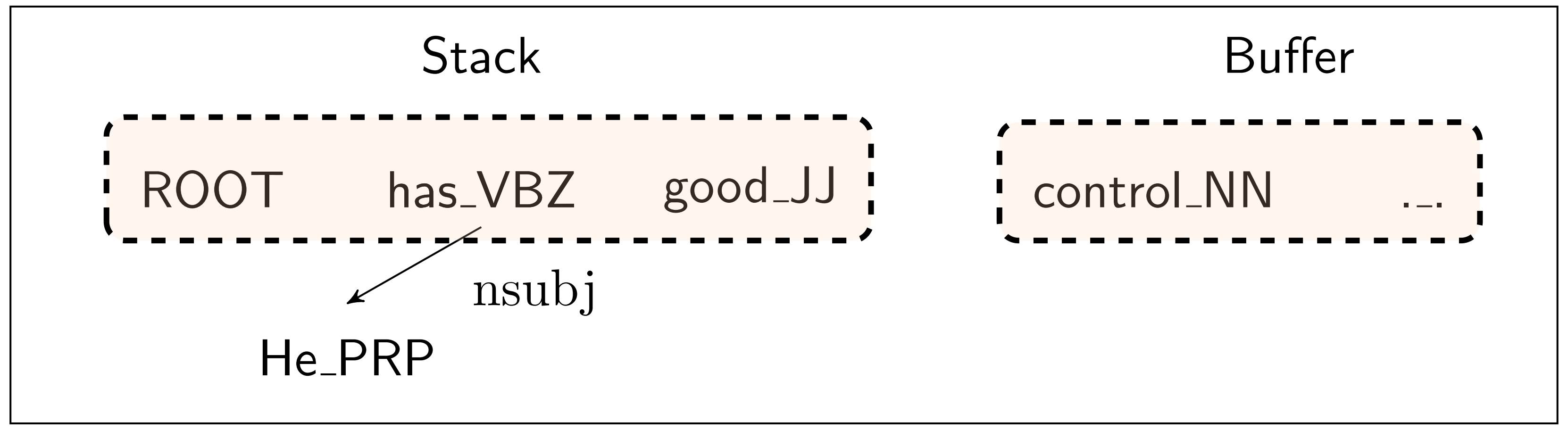
- Extract features from the configuration
- Use your favorite classifier: logistic regression, SVM, FFNNs, ...

Source	Feature templates		
One word	$s_1.w$	$s_1.t$	$s_1.wt$
	$s_2.w$	$s_2.t$	$s_2.wt$
	$b_1.w$	$b_1.w$	$b_0.wt$
Two word	$s_1.w \circ s_2.w$	$s_1.t \circ s_2.t$	$s_1.t \circ b_1.w$
	$s_1.t \circ s_2.wt$	$s_1.w \circ s_2.w \circ s_2.t$	$s_1.w \circ s_1.t \circ s_2.t$
	$s_1.w \circ s_1.t \circ s_2.t$	$s_1.w \circ s_1.t$	

w: word, t: part-of-speech tag

(Nivre 2008): Algorithms for Deterministic Incremental Dependency Parsing

Feature extraction



w: words, t: part-of-speech tags

Feature templates

$s_2 . w \circ s_2 . t$

$s_1 . w \circ s_1 . t \circ b_1 . w$

Features

$s_2 . w = \text{has} \circ s_2 . t = \text{VBZ}$

$s_1 . w = \text{good} \circ s_1 . t = \text{JJ} \circ b_1 . w = \text{control}$

Today we can use neural networks to extract features!

(Nivre 2008): Algorithms for Deterministic Incremental Dependency Parsing

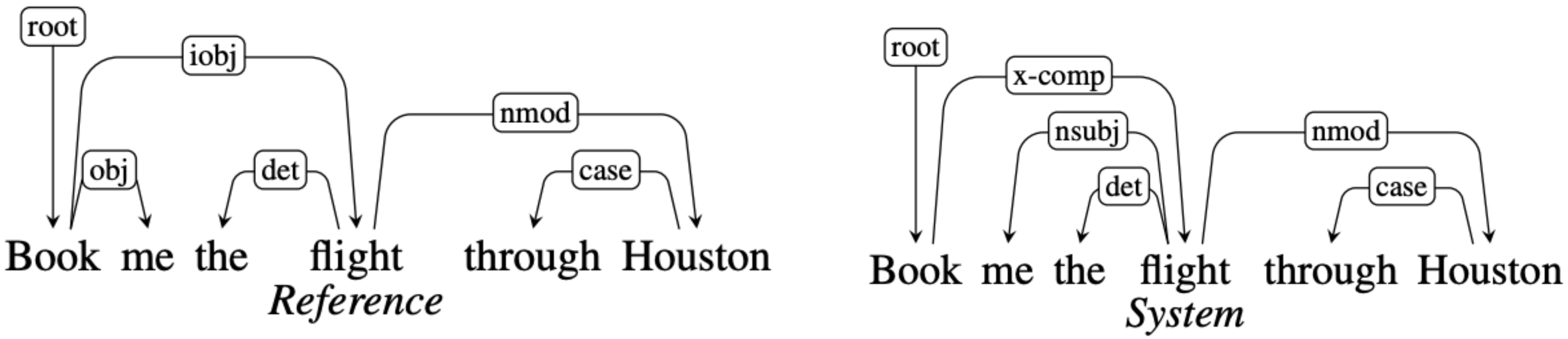
Evaluating dependency parsing

- Unlabeled attachment score (UAS)

  = percentage of words that have been assigned the correct head

- Labeled attachment score (LAS)

  = percentage of words that have been assigned the correct head & label



UAS = 5/6 LAS = 2/3

Evaluating dependency parsing

Parser		Test UAS	Test LAS
(Chen and Manning, 2014)	T	91.8	89.6
(Dyer et al., 2015)	T	93.1	90.9
(Ballesteros et al., 2016)	T	93.56	92.41
(Weiss et al., 2015)	T	94.26	91.42
(Andor et al., 2016)	T	94.61	92.79
(Ma et al., 2018) §	T	95.87	94.19
(Kiperwasser and Goldberg, 2016a) §	G	93.0	90.9
(Kiperwasser and Goldberg, 2016b)	G	93.1	91.0
(Wang and Chang, 2016)	G	94.08	91.82
(Cheng et al., 2016)	G	94.10	91.49
(Kuncoro et al., 2016)	G	94.26	92.06
(Zheng, 2017) §	G	95.53	93.94
(Dozat and Manning, 2017)	G	95.74	94.08

T: transition-based / G: graph-based