

# L9: Dependency Parsing

- COS 484
- Natural Language Processing

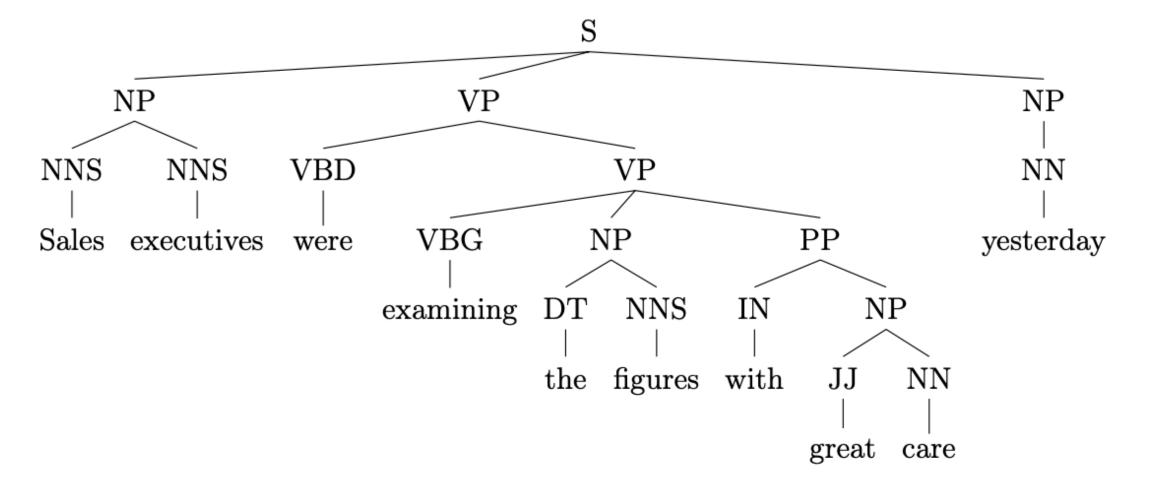
Spring 2022

# Midterm

- Take-home, administered online through Gradescope
- 3 hour exam (can be taken within a period of around 24 hours Thu-Fri)
  - Includes grace period for you to scan + upload your answers
- Exact logistics will be announced on Canvas in 1-2 days
- Next Tuesday: Midterm review session
  - No precept this Friday

## Recap: Constituency parsing

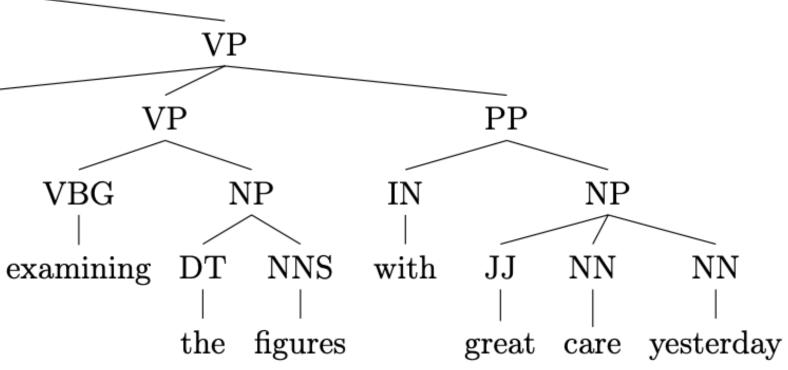
Gold: (1, 10, S), (1, 2, NP), (3, 9, VP), (4, 9, VP), (5, 6, NP), (7, 9, PP), (8, 9, NP), (10, 10, NP)



Predicted: (1, 10, S), (1, 2, NP), (3, 10, VP), (4, 6, VP), (5, 6, NP), (7, 10, PP), (8, 10, NP)  $\mathbf{S}$ NPNNS VBD NNS

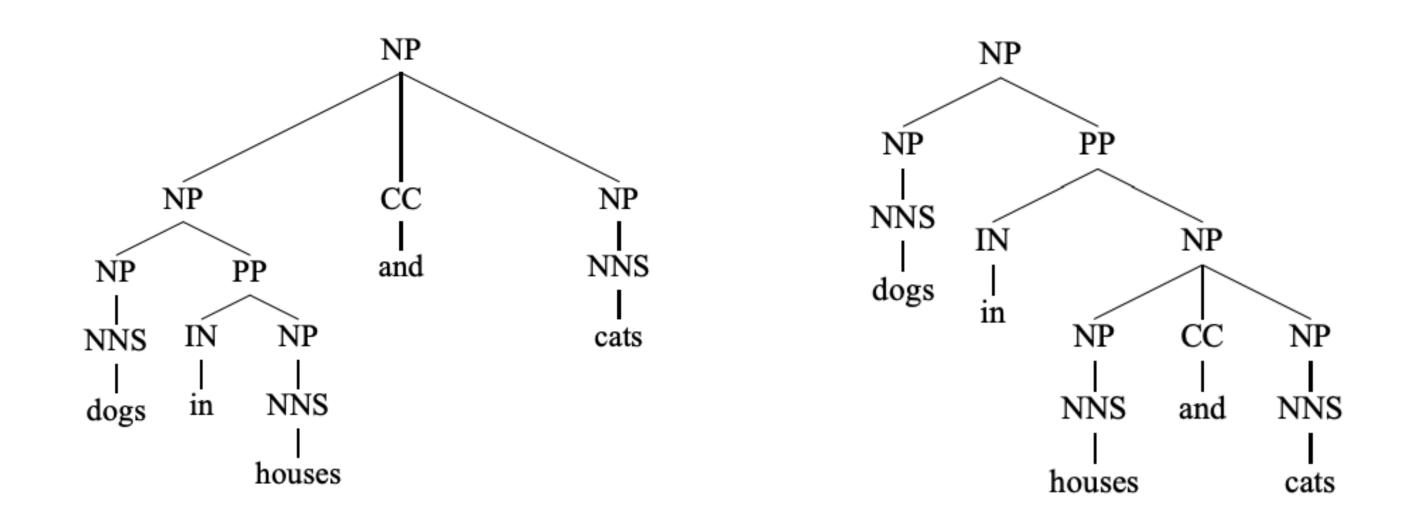
**a** 1

Sales executives were



## Weaknesses of PCFGs

Lack of sensitivity to lexical information (words)



Exactly the same set of context-free rules!

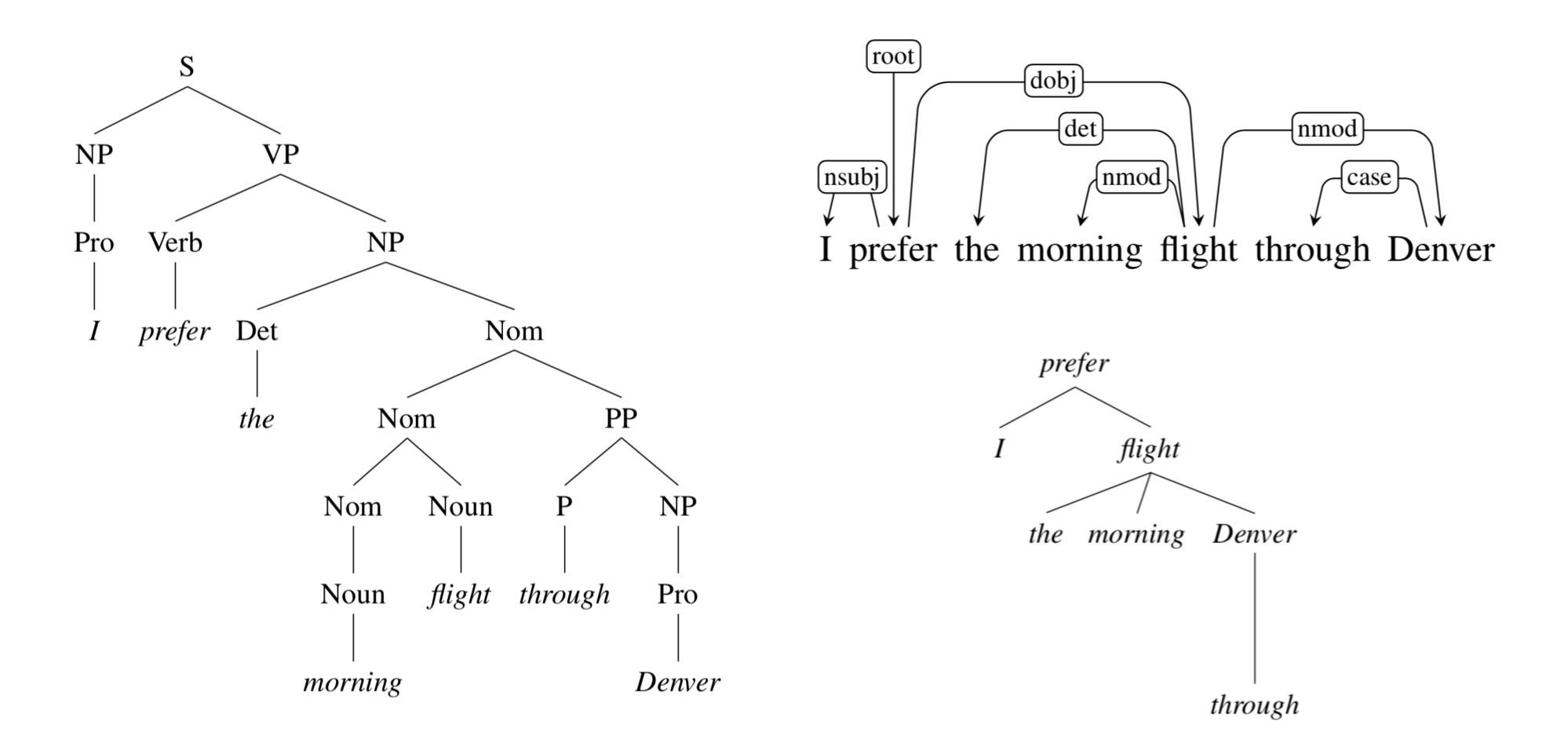
# Constituency vs dependency parsing

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

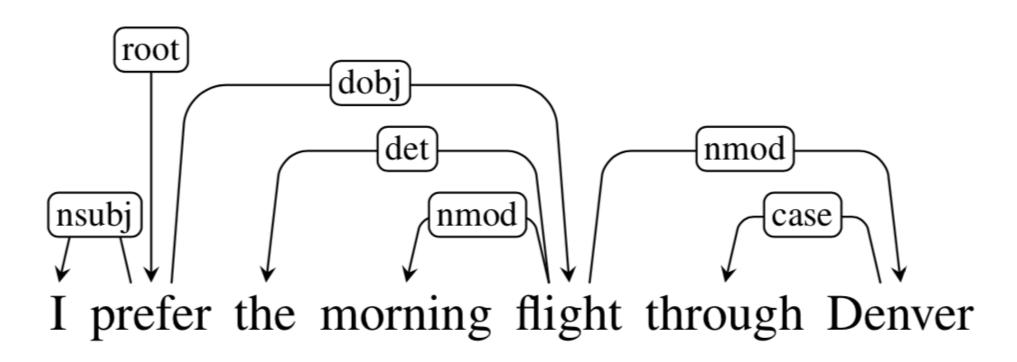


- Dependency structure
- The Arc-standard algorithm
- Dependency treebanks
- Evaluation

#### Constituency vs dependency structure



# Dependency structure



- called **dependencies**
- object, apposition, etc)
- The arrow connects a **head** (governor) and a **dependent** (modifier)
- Usually, dependencies form a tree

Consists of relations between lexical items, normally *binary*, *asymmetric* relations ("arrows")

• The arrows are commonly **typed** with the name of grammatical relations (subject, prepositional

# Dependency relations

<b>Clausal Argument Relations</b>	Descr
NSUBJ	Nomi
DOBJ	Direct
IOBJ	Indire
ССОМР	Claus
XCOMP	Open
Nominal Modifier Relations	Descr
NMOD	Nomi
AMOD	Adjec
NUMMOD	Nume
APPOS	Appo
DET	Deter
CASE	Prepo
Other Notable Relations	Descr
CONJ	Conju
CC	Coord
Figure 14.2 Selected dependence	y relati
effe et al., 2014)	

ription
inal subject
et object
ect object
sal complement
n clausal complement
ription
inal modifier
ctival modifier
eric modifier
ositional modifier
rminer
ositions, postpositions and other case markers
ription
unct
dinating conjunction
tions from the Universal Dependency set. (de Marn-

# Dependency relations

Relation	Examples with <i>l</i>
NSUBJ	United canceled
DOBJ	United diverted
	We booked her t
IOBJ	We booked her
NMOD	We took the <b>mo</b>
AMOD	Book the cheap
NUMMOD	Before the storn
APPOS	United, a <b>unit</b> of
DET	The flight was c
	Which <i>flight</i> wa
CONJ	We <i>flew</i> to Denv
CC	We flew to Denv
CASE	Book the flight f
Figure 14.3	Examples of core Univer

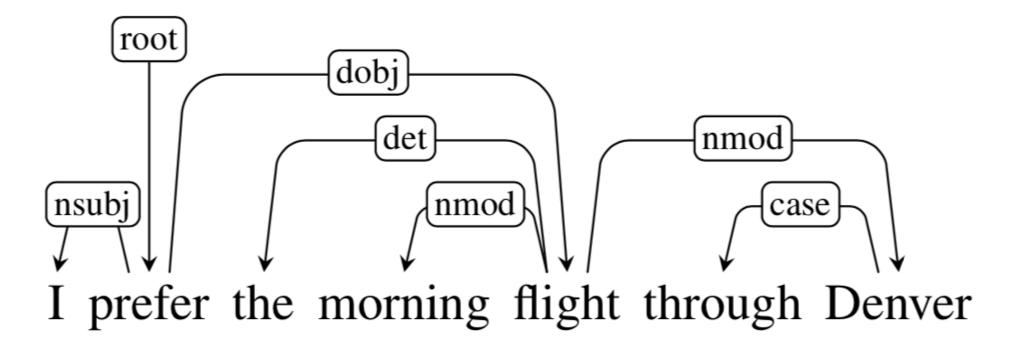
#### *head* and **dependent**

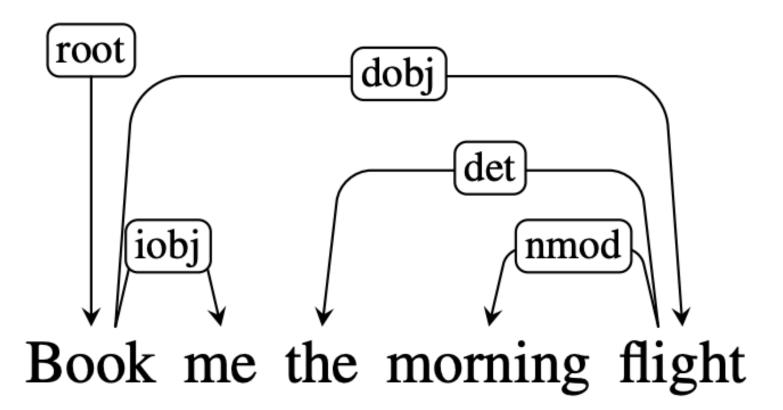
- d the flight. the **flight** to Reno. the first **flight** to Miami. the flight to Miami. orning flight. **best** flight. n JetBlue canceled 1000 flights. of UAL, matched the fares. canceled. as delayed? ver and drove to Steamboat. ver **and** *drove* to Steamboat. through *Houston*.
- rsal Dependency relations.

## Dependency structure: more examples

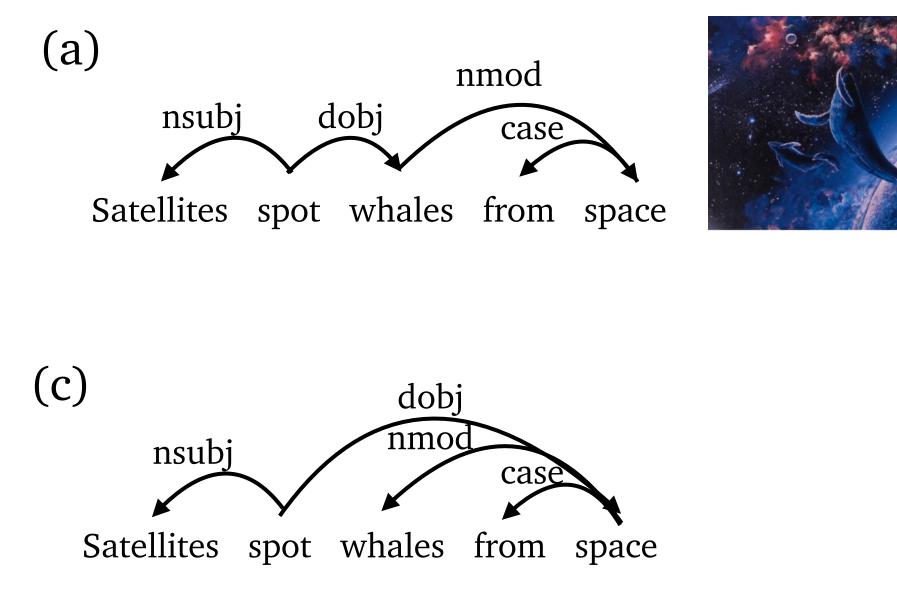
#### I prefer the morning flight through Denver

Book me the morning flight





# Zoom poll

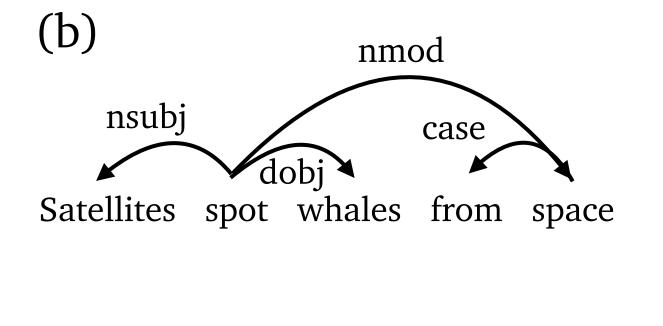


The answer is (b).

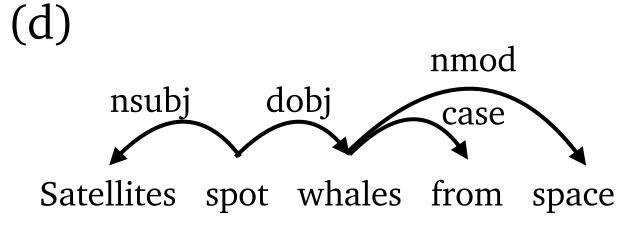


#### Which of the following is the correct dependency structure for "Satellites spot whales from space"?













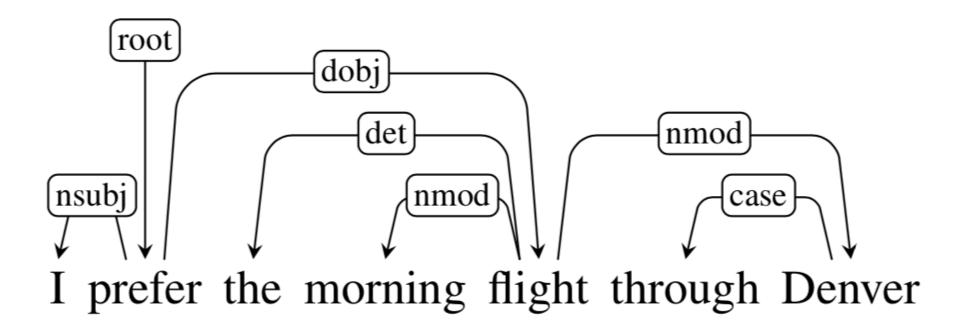
# Dependency parsing

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

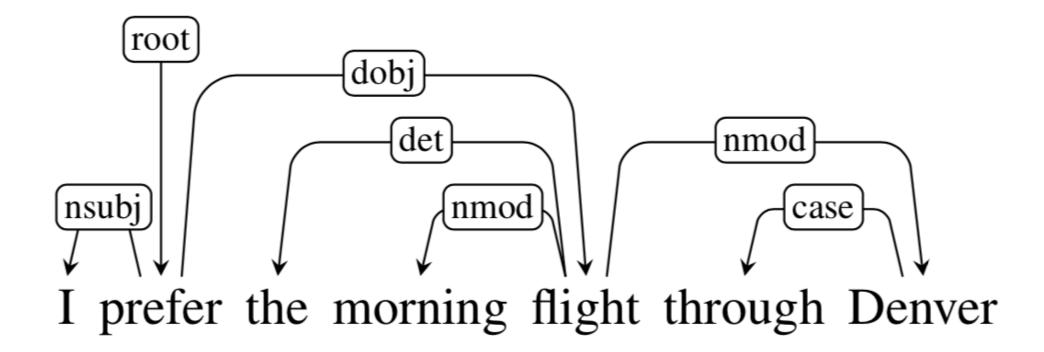


# Dependency formalisms

Usually a tree structure

- There is only one root
- Every word except for the root has one head (parent)
- No cycles:  $A \longrightarrow B$ ,  $B \longrightarrow C$ ,  $C \longrightarrow A$

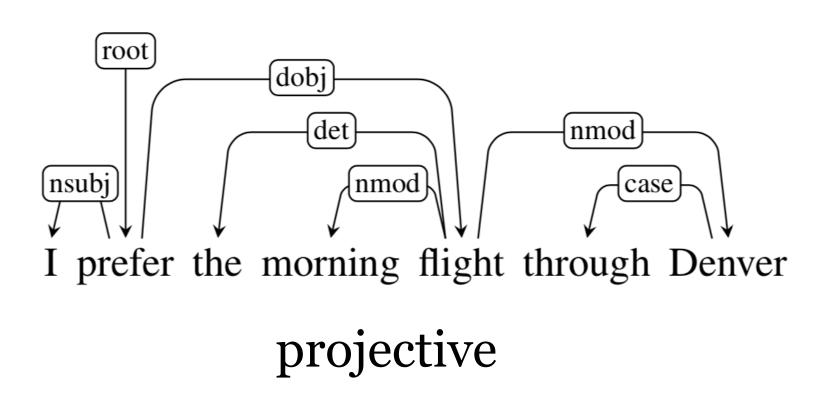
• Alternatively, we can just add a fake node ROOT, so each word has exactly one head



# Dependency formalisms

#### Additional constraint: **projectivity**

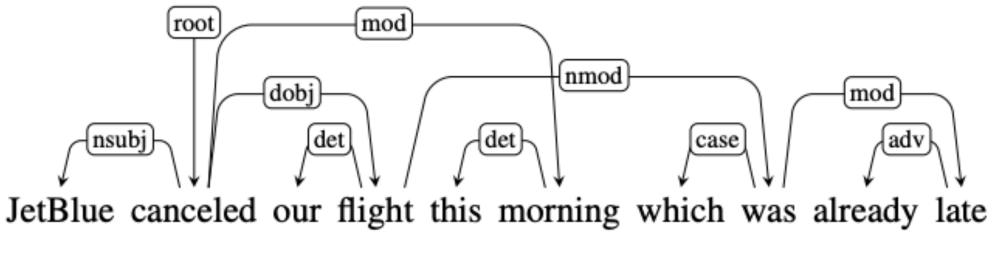
linear order, with all arcs above the words



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

We will focus on projective parsing

#### • **Definition**: there are no crossing dependency arcs when the words are laid out in their



#### non-projective

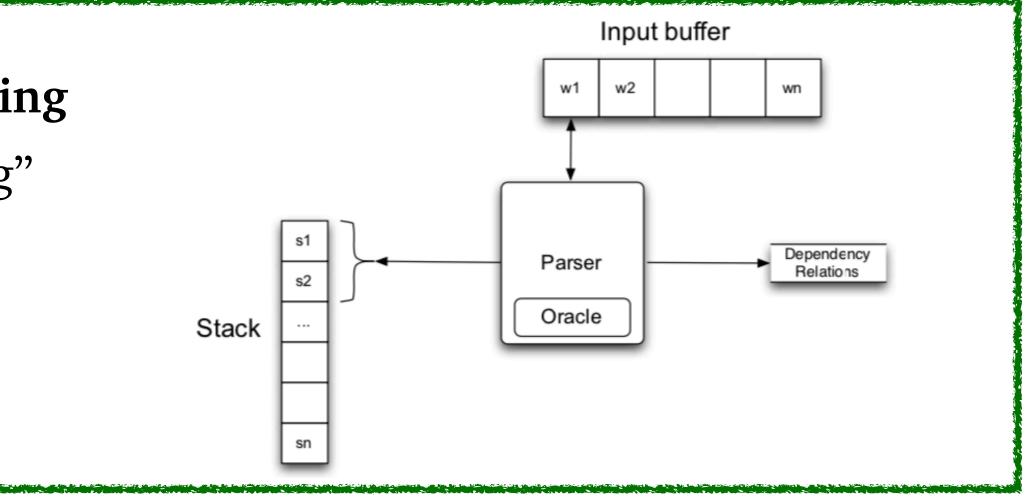
Dataset	# Sentences	(%) Projective
English	39,832	99.9
Chinese	16,091	100.0
Czech	72,319	76.9
German	38,845	72.2

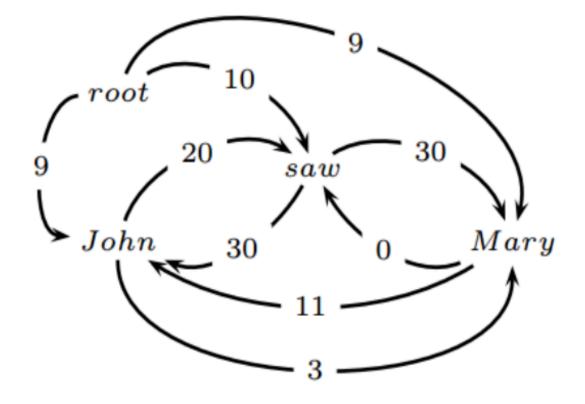
# Two families of algorithms

#### **Transition-based dependency parsing**

• Also called "shift-reduce parsing"

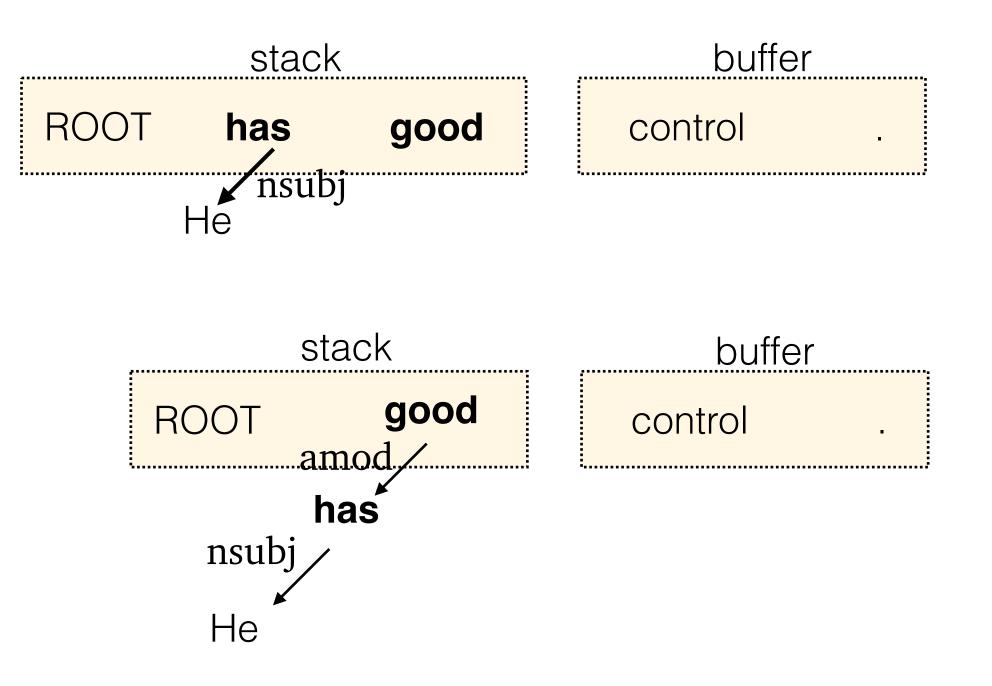
#### Graph-based dependency parsing





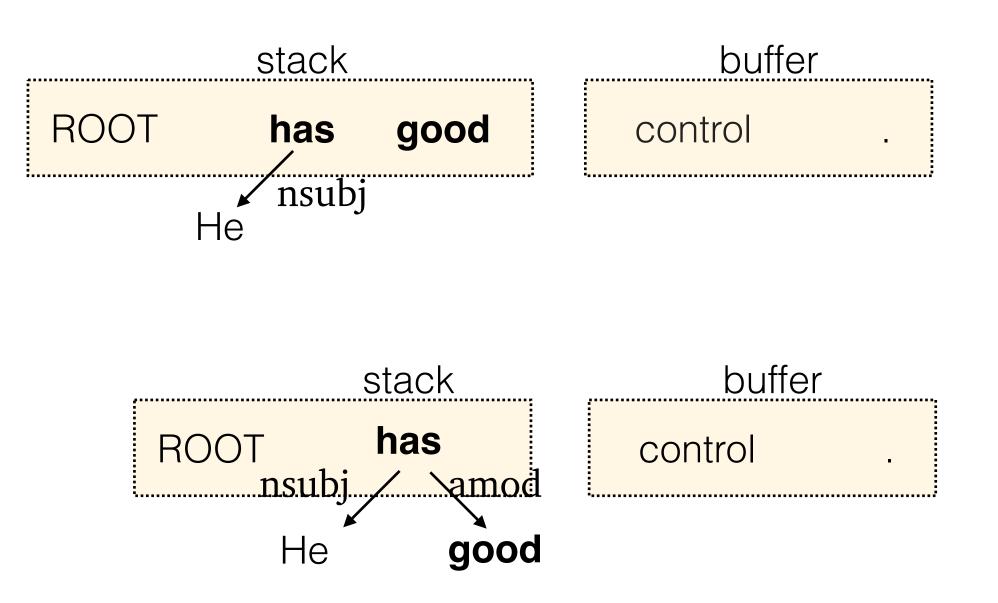
- Given: a sentence of  $w_1, w_2, \dots, w_n$
- The parsing process is modeled as a sequence of transitions
- A configuration (state) consists of a stack s, a buffer b and a set of dependency arcs A:
  c = (s, b, A)
- Initially,  $s = [ROOT], b = [w_1, w_2, ..., w_n], A = \emptyset$
- A configuration is terminal if s = [ROOT] and  $b = \emptyset$
- Three types of transitions: LEFT-ARC (*r*), RIGHT-ARC (*r*), SHIFT

 $s_1, s_2$ : the top 2 words on the stack ( $s_1 = \text{good}, s_2 = \text{has}$ );  $b_1$ : the first word in the buffer ( $b_1$  = control)

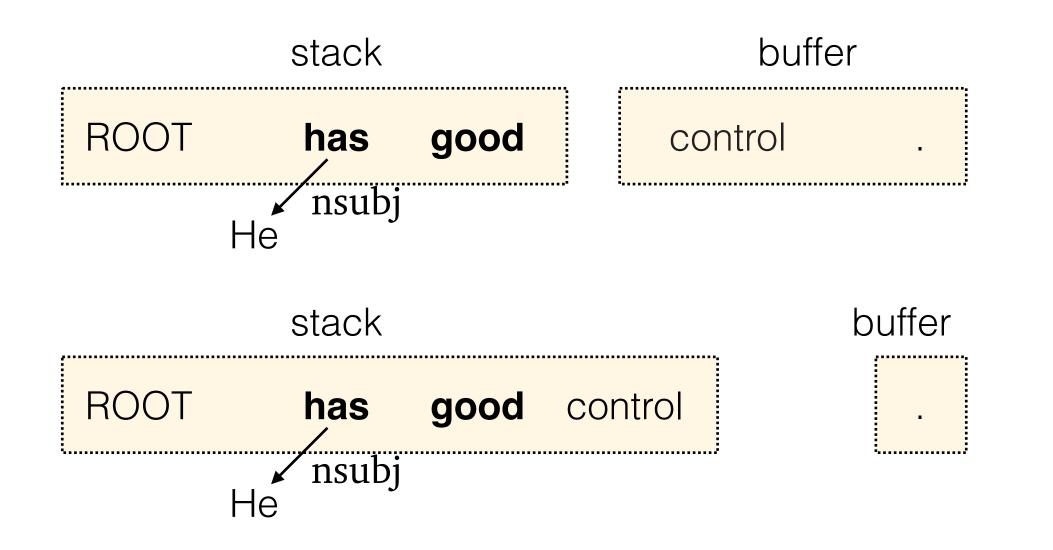


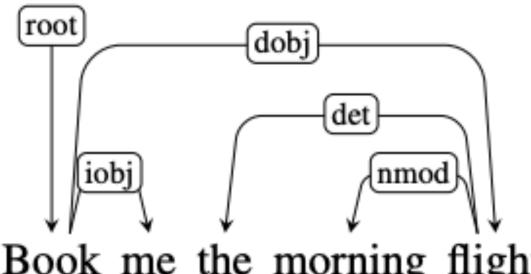
LEFT-ARC (*r*): add an arc ( $s_1 \xrightarrow{r} s_2$ ) to *A*, remove  $s_2$  from the stack

 $s_1, s_2$ : the top 2 words on the stack ( $s_1 = \text{good}, s_2 = \text{has}$ );  $b_1$ : 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



 $s_1, s_2$ : the top 2 words on the stack ( $s_1 = \text{good}, s_2 = \text{has}$ );  $b_1$ : the first word in the buffer ( $b_1$  = control) **SHIFT**: move  $b_1$  from the buffer to the stack



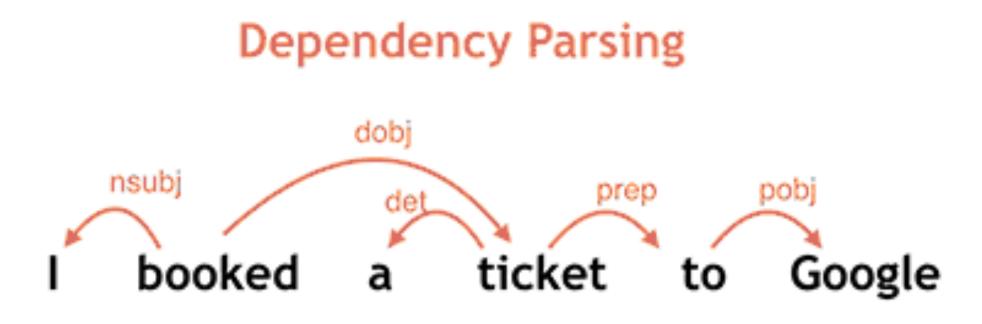


#### "Book me the morning flight" A running example

Book me the morning flight

	stack	buffer	action	added arc
0	[ROOT]	[Book, me, the, morning, flight]	SHIFT	
1		[me, the, morning, flight]	SHIFT	
2	[ROOT, Book, me]	[the, morning, flight]	RIGHT-ARC(iobj)	(Book, iobj, me)
3		[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)	
9	[ROOT, Book]	[]	RIGHT-ARC(root)	
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"?

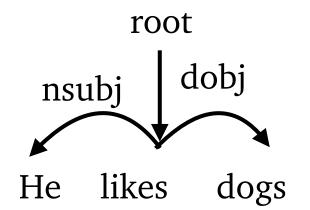
(a) SHIFT, SHIFT, RIGHT-ARC(dobj), SHIFT, LEFT-ARC(nsubj), RIGHT-ARC(root)

(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.





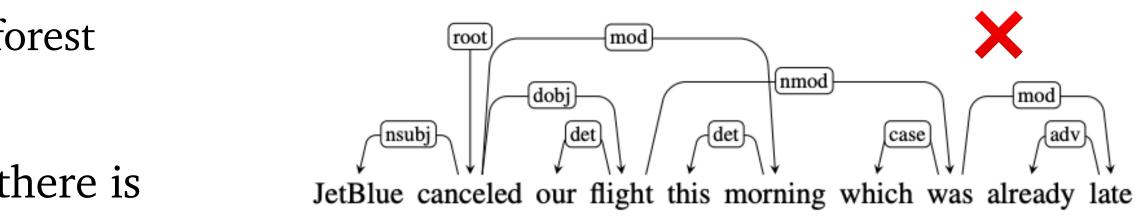
### Transition-based dependency parsing

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)



However, one parse tree can have multiple valid transition sequences.

### How to decide which transitions to take?

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

- English dependency treebank: converted from Penn Treebank using rule-based algorithms

#### 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.



(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

https://universaldependencies.org/

#### Current UD Languages

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

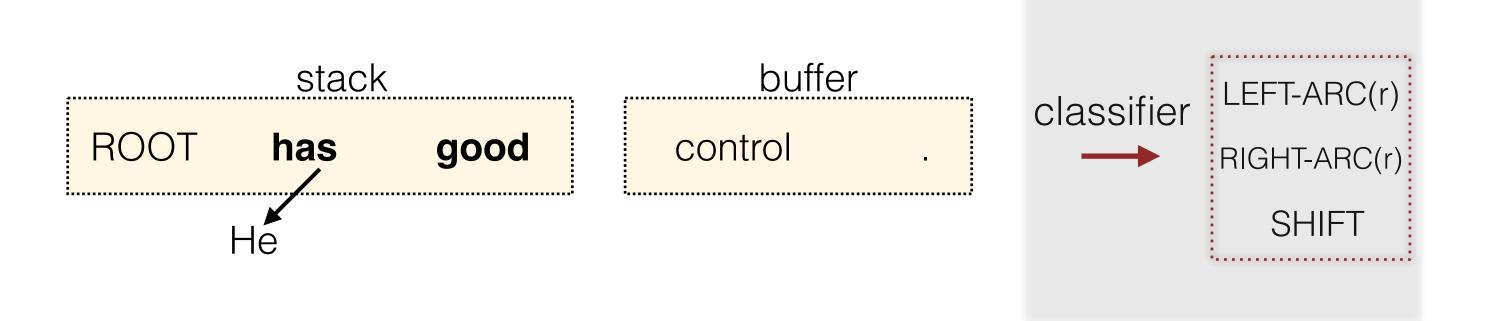
Afrikaans    1    49K    40    IE, Germanic      Akkadian    2    23K    10    Afro-Asiatic, Semitic      Akkadian    1    <1K    100    Tupian, Tupari      Albanian    1    <1K    100    Abanian      Amharic    1    10K    4700    Afro-Asiatic, Semitic      Anniaric    1    10K    4700    Afro-Asiatic, Semitic      Ancient Greek    2    416K    400    IE, Greek      Ancient Greek    2    416K    400    Arawakan      Arabic    3    1,042K    100    Arawakan      Arasyrian    1    <1K    100    Arawakan      Armenian    1    52K    100/400    IE, Armenian      Arasyrian    1    13K    100    Afro-Asiatic, Semitic      Bambara    1    13K    100    Basque    IE, Indic      Basque    1    10K    4700 500    IE, Indic    IE, Indic      Buryat    1    10K    4700    Mongolic    IE, Caltian    ISK    IE, Caltia </th <th></th> <th>100</th> <th>Abaza</th> <th>1</th> <th>&lt;1K</th> <th>P</th> <th>Northwest Caucasian</th>		100	Abaza	1	<1K	P	Northwest Caucasian
Akkadian    2    23K    23K    23K    Afro-Asiatic, Semitic      Akuntsu    1    <1K	$\rightarrow$	_		1			
Akuntsu    1    <1K	$\rightarrow$		Akkadian	2	23K		
Albanian    1    <1K			Akuntsu	1	<1K	<b>8</b> 0	Tupian, Tupari
Ancient Greek    2    416K    400    IE, Greek      Apurina    1    <1K	$\rightarrow$	_	Albanian	1	<1K	W	IE, Albanian
Image: Solution of the second seco	-		Amharic	1	10K		Afro-Asiatic, Semitic
Image: Second	-	12	Ancient Greek	2	416K	<b>4</b> 20	IE, Greek
Armenian    1    52K    52K <t< td=""><td>-</td><td><b>6</b></td><td>Apurina</td><td>1</td><td>&lt;1K</td><td><b>E0</b></td><td>Arawakan</td></t<>	-	<b>6</b>	Apurina	1	<1K	<b>E0</b>	Arawakan
Non-Assyrian    1    <1K	$\rightarrow$	ø	Arabic	3	1,042K	eiW	Afro-Asiatic, Semitic
Bambara    1    13K    13K    Mande      Basque    1    121K    Basque    Basque      Belarusian    1    275K    4<10,5    IE, Slavic      Bojpuri    2    6K    100    IE, Indic      Belarusian    1    10K    4/10,5    IE, Celtic      Belarusian    1    10K    4/10,5    Mongolic      Berton    1    10K    4/10,5    Mongolic      Bulgarian    1    156K    4/10,6    Mongolic      Buryat    1    10K    4/10,7    Mongolic      Catalan    1    531K    100    IE, Romance      Chukchi    1    6K    9    Chukotko-Kamchatkan      Chukchi    1    6K    9    Chukotko-Kamchatkan      Sioo-Tibetan    233K    6    Sino-Tibetan      Sioo-Tibetan    233K    6    Sino-Tibetan      Sioo-Tibetan    1    19K    20W    IE, Slavic      Coptic    1    48K    46    Afro-Asiatic, Egyptian      Czech    2,227K	$\rightarrow$		Armenian	1	52K	# <b>#</b> %<@6	IE, Armenian
Bambara    1    13K    13K    Mande      Basque    1    121K    Basque    Basque      Belarusian    1    275K    Amorian State    Basque      Belarusian    1    275K    Amorian State    IE, Slavic      Belarusian    1    275K    Amorian State    IE, Slavic      Belarusian    1    275K    Amorian State    IE, Slavic      Belarusian    1    10K    Amorian State    IE, Celtic      Bulgarian    1    156K    Amorian State    IE, Slavic      Buryat    1    10K    Amorian State    Mongolic      Image: Cantonese    1    13K    O    Sino-Tibetan      Image: Catalan    1    531K    Image: Catalan    IE, Romance      Image: Chukchi    1    6K    O    Sino-Tibetan      Image: Classical Chinese    1    233K    O    Sino-Tibetan      Image: Classical Chinese    1    233K    Image: Classical Chinese    1    233K      Image: Classical Chinese    1    233K    Image: Classie Classical Chinese </td <td><math>\rightarrow</math></td> <td>X</td> <td>Assyrian</td> <td>1</td> <td>&lt;1K</td> <td><b>E0</b></td> <td>Afro-Asiatic, Semitic</td>	$\rightarrow$	X	Assyrian	1	<1K	<b>E0</b>	Afro-Asiatic, Semitic
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Croatian    1    199K    IIQW    IE, Slavic      Czech    5    2,227K    IIQW    IE, Slavic      Danish    2    100K    IIII    IE, Germanic      Dutch    2    306K    IIV    IE, Germanic	-	gar.	Classical Chinese	1	233K	0	Sino-Tibetan
Czech    5    2,227K    Czech    IE, Slavic      Danish    2    100K    III (Germanic)      Dutch    2    306K    III (Germanic)	-	*	Coptic	1	48K	<b>4</b> 20	Afro-Asiatic, Egyptian
Danish    2    100K    IE, Germanic      Dutch    2    306K    IIIV    IE, Germanic	-		Croatian	1	199K	®₽₩	IE, Slavic
Dutch 2 306K 💷 V IE, Germanic	$\rightarrow$		Czech	5	2,227K	<b>₽&lt;⊅⊡0</b> ∆W	IE, Slavic
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#### https://universaldependencies.org/

# Universal Dependencies

### 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 to learn a classifier that predicts  $t_k$  from  $c_k$  as input



 $(2|\mathbf{R}| + 1)$  -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

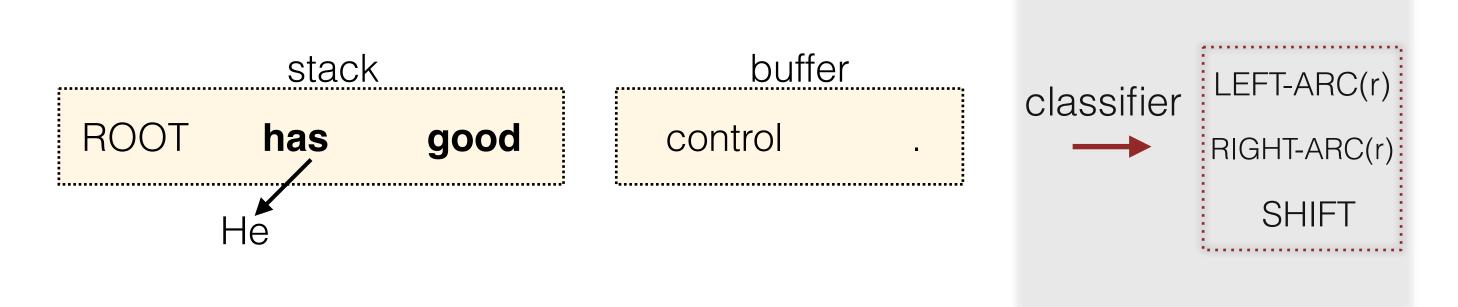
**function** DEPENDENCYPARSE(*words*) **returns** dependency tree

state  $\leftarrow$  {[root], [words], [] }; initial configuration while *state* not final

 $t \leftarrow Classifier (state)$ ; choose a transition operator to apply state  $\leftarrow$  APPLY(*t*, *state*); apply it, creating a new state

return *state* 

# Feature extraction



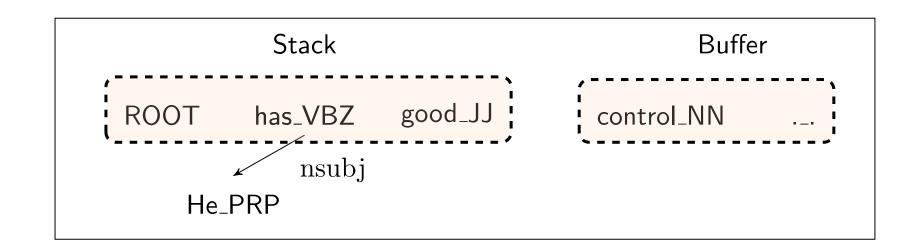
- Extract features from the configuration

Source	Feature templates		
One word	$s_1.w$	<i>s</i> <sub>1</sub> . <i>t</i>	$s_1.wt$
	$s_2.w$	<i>s</i> <sub>2</sub> . <i>t</i>	$s_2.wt$
	$b_1.w$	$b_1.w$	$b_0.wt$
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

• Use your favorite classifier: logistic regression, SVM, FFNNs, ...

#### Feature extraction



#### **Feature templates**

$$s_2 \cdot w \circ s_2 \cdot t$$
$$s_1 \cdot w \circ s_1 \cdot t \circ b_1 \cdot w$$

(Nivre 2008): Algorithms for Deterministic Incremental Dependency Parsing

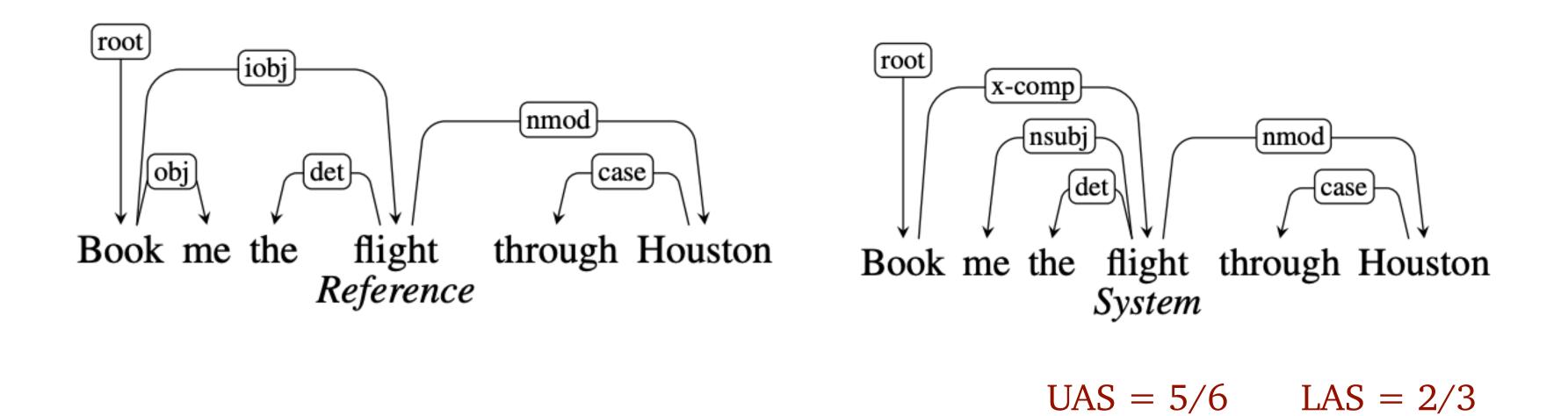
w: words, t: part-of-speech tags

#### Features $s_2 \cdot w = has \circ s_2 \cdot t = VBZ$ $s_1 \cdot w = \text{good} \circ s_1 \cdot t = JJ \circ b_1 \cdot w = \text{control}$

These days, we can use neural networks to automatically extract features!

# Evaluating dependency parsing

- Unlabeled attachment score (UAS)
- Labeled attachment score (LAS)



= percentage of words that have been assigned the correct head

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

# Evaluating dependency parsing

#### Parser

(Chen and Manning, 2014) (Dyer et al., 2015) (Ballesteros et al., 2016) (Weiss et al., 2015) (Andor et al., 2016) (Ma et al., 2018) §

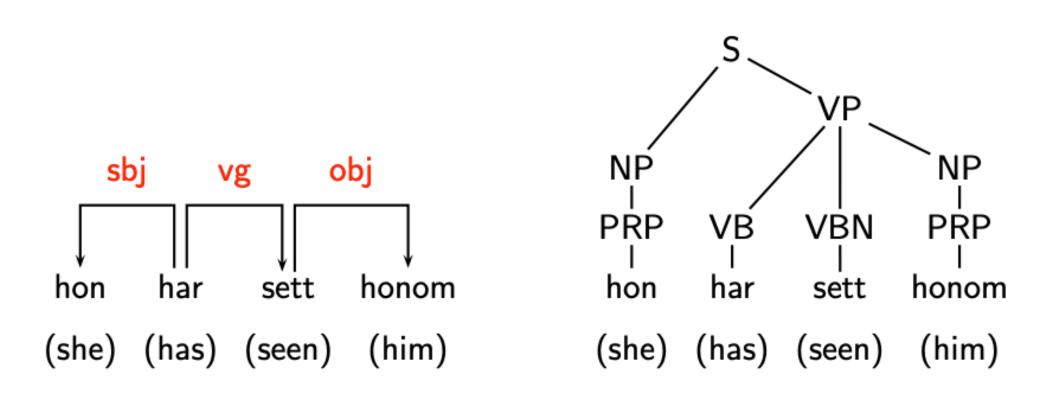
(Kiperwasser and Goldberg (Kiperwasser and Goldberg (Wang and Chang, 2016) (Cheng et al., 2016) (Kuncoro et al., 2016) (Zheng, 2017) § (Dozat and Manning, 2017)

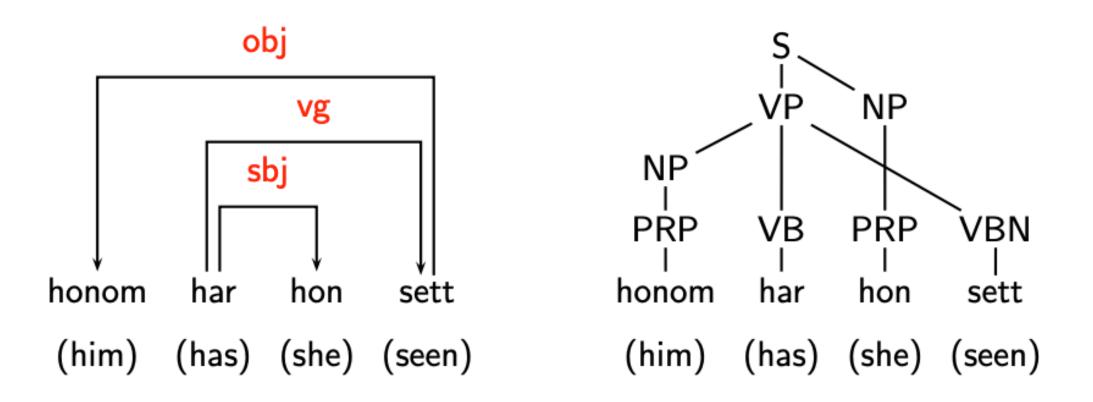
T: transition-based / G: graph-based

		Test		
		UAS	LAS	
)	T	91.8 93.1 93.56 94.26 94.61 95.87	89.6 90.9 92.41 91.42 92.79 94.19	
rg, 2016a) § rg, 2016b)	G	93.0 93.1 94.08 94.10 94.26 95.53 95.74	90.9 91.0 91.82 91.49 92.06 93.94 94.08	

## Advantages of dependency structure

• More suitable for free word order languages





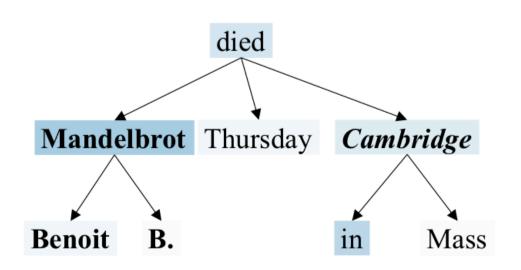
# Advantages of dependency structure

#### • More suitable for free word order languages

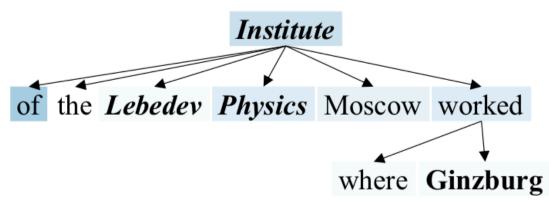
#### • The predicate-argument structure is more useful for some applications

#### Relation: *per:city\_of\_death*

Benoit B. Mandelbrot, a maverick mathematician who developed an innovative theory of roughness and applied it to physics, biology, finance and many other fields, died Thursday in *Cambridge*, Mass.



Relation: *per:employee\_of* In a career that spanned seven decades, Ginzburg authored several groundbreaking studies in various fields -- such as quantum theory, astrophysics, radio-astronomy and diffusion of cosmic radiation in the Earth's atmosphere -- that were of "Nobel Prize caliber," said Gennady Mesyats, the director of the Lebedev Physics Institute in Moscow, where Ginzburg worked.



#### Relation: *org:founded\_by*

Anil Kumar, a former director at the consulting firm McKinsey & Co, pleaded guilty on Thursday to providing inside information to *Raj* **Rajaratnam**, the founder of the Galleon Group, in exchange for payments of at least \$ 175 million from 2004 through 2009.

