

Welcome back to CIS 530!

PLEASE TYPE YOUR QUESTIONS IN THE CHAT

IF YOUR INTERNET IS TOO SLOW TO SEE THE
VIDEO, YOU CAN FIND THE SLIDES ON THE CLASS
WEBSITE

New course policies

1. I'm granting everyone 10 extra late days. You can now use up to 3 late days per HW, quiz or project milestone.
2. I'm offering a HW option for the term project component of the grade. You can do 4 extra HW assignments instead of a project.
3. I'm allowing everyone to drop their lowest scoring quiz.
4. Everyone can drop their lowest scoring homework. (You can't drop project milestones).
5. You can opt to do the course pass/fail. 50% and above is passing.

Homework Option

We are creating a set of 4 additional weekly homework assignments. They will have the same deadlines as the project milestones. You may do the homework assignments individually or in pairs.

HW9: Classifying Depression due – requires special data access

HW10: Neural Machine Translation

HW11: BERT

HW12: Perspectives Detection

You can do the homework individually or in pairs.

HW will be graded based on leaderboard and reports (autograders may not be available).

Project Option

The project is a team exercise, with teams of 4-6. Your project will be a self-designed multi-week team-based effort. Milestones:

1. Submit a formal project definition and a literature review. (due 4/8)
2. Collect your data, write an evaluation script and a baseline. (4/15)
3. Implement a published baseline. Prepare a draft of your final project presentation. (4/22)
4. Finish all your extensions to the public baseline, and submit your final report. (4/29)

You need to declare whether you intend to do the project or homework option by this Wednesday using the [Google form linked on Piazza](#).

<http://computational-linguistics-class.org/term-project.html>

Office hours

Office hours are going to be held via Zoom. TAs host a Zoom group meeting and post the link on Piazza.

We will use the chat to manage the queue. Just like you would write your name on the whiteboard in an in-person meeting. You should write this info to add yourself to the queue:

1. Your name
2. A short version of your question
3. Whether it should be discussed publicly and privately (code help)

For private questions, the TA will add you to a breakout room. For public ones, we'll discuss them as a group so you can hear the answers to other students' questions.

Schedule

<http://computational-linguistics-class.org/lectures.html#now>

Mon, Mar 23,
2020

Wrap-up of Constituency Parsing /
Dependency Parsing [[Zoom link](#)]

Jurafsky and Martin, [Chapter 14 "Statistical Constituency Parsing"](#)
Jurafsky and Martin, [Chapter 15 "Dependency Parsing"](#)
Dragomir Radev, [Dependency Parsing](#)
Dragomir Radev, [Statistical Parsing](#)

Wed, Mar 25,
2020

Logical Representations of Sentence
Meaning [[Zoom link](#)]

Jurafsky and Martin, [Chapter 16 "Logical Representations of Sentence Meaning"](#)

Wed, Mar 25,
2020

[HW7 "Named Entity Recognition" due](#)

Mon, Mar 30,
2020

Information Extraction [[Zoom link](#)]

Jurafsky and Martin, [Chapter 18 "Information Extraction"](#)

Mon, Mar 30,
2020

Quiz due (covers Chapters 12-14)

Jurafsky and Martin, [Chapter 12 "Constituency Grammars"](#)
Jurafsky and Martin, [Chapter 13 "Constituency Parsing"](#)
Jurafsky and Martin, [Chapter 14 "Statistical Constituency Parsing"](#)

Wed, Mar 25,
2020

Deadline to decide on term project versus
weekly homework option. Please specify
your preference by [filling out this form](#).

Fri, Mar 27, 2020

Deadline to complete the IRB training for
HW9, if you're doing the HW option.
Please follow the [instruction for obtaining
data on the HW9 page](#).

Wed, Apr 1, 2020

Semantic Role Labeling [[Zoom link](#)]

Jurafsky and Martin, [Chapter 20 "Semantic Role Labeling"](#)

Wed, Apr 1, 2020

[HW8 "Learning Hypernyms" due](#)

Fri, Apr 3, 2020

Withdraw Deadline

Reminders



HOMEWORK 7 DUE DATE IS
DUE BY MIDNIGHT ON 3/25.
HW8 WILL BE DUE 4/1.



WASH YOUR HANDS



TAKE CARE OF YOURSELF.
MENTAL HEALTH IS
IMPORTANT TOO.

Review: Constituency Parsing

JURAFSKY AND MARTIN CHAPTERS 12-14

Formal Definition of a PCFG

A probabilistic context-free grammar G is defined by four parameters:

\mathbf{N} is a set of **non-terminal symbols** (or variables)

- In NLP, we often use the Penn Treebank tag set

$\mathbf{\Sigma}$ is set of **terminal symbols**

- These are the words (also sometimes called the leaf nodes of the parse tree)

\mathbf{R} is a set of production rules, each of the form $A \rightarrow \beta$ [probability]

- $S \rightarrow NP VP$ [0.8]
- $S \rightarrow Aux NP VP$ [0.15]
- $S \rightarrow VP$ [0.05]

\mathbf{S} is the start symbol (a non-terminal)

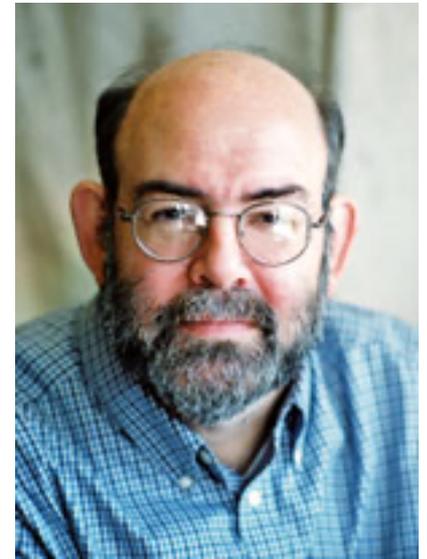
Treebanks as grammar

Treebanks == data

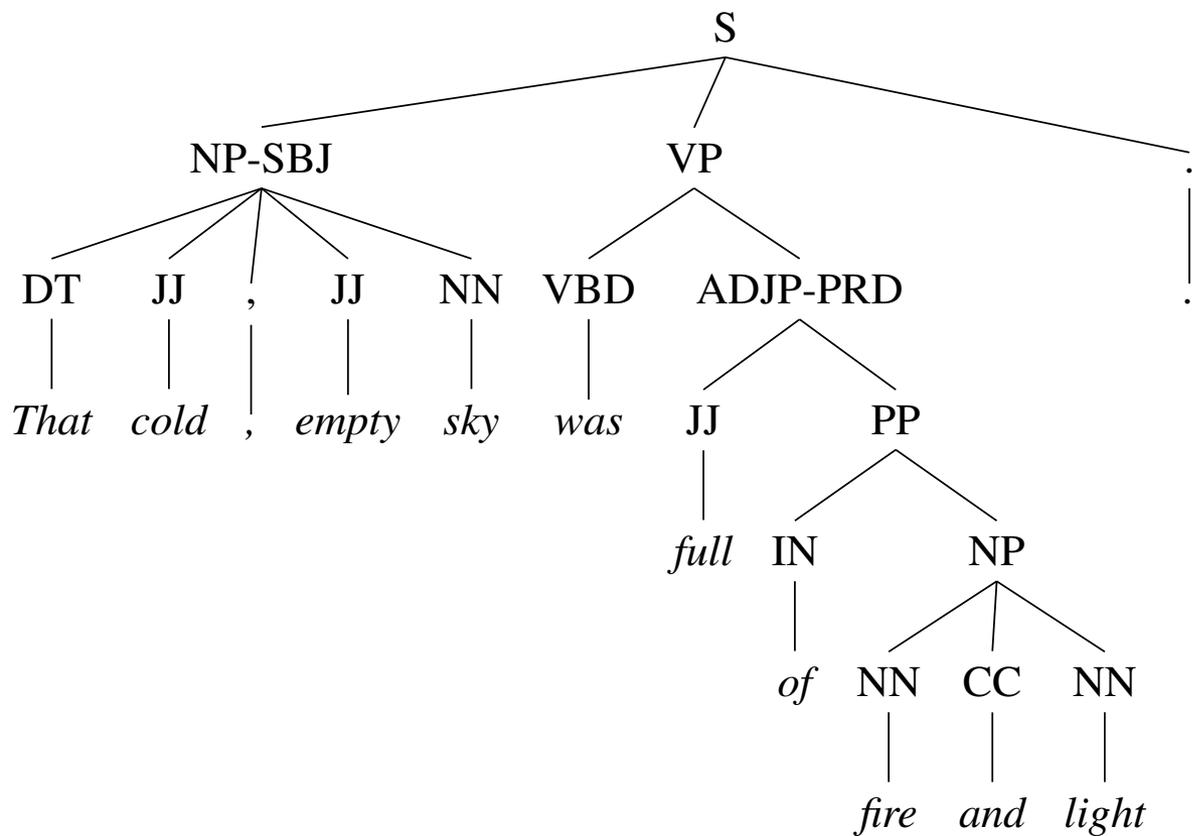
Initially, building a treebank might seem like it would be a lot slower and less useful than building a grammar.

However, a treebank gives us many things

- Reusability of the labor
 - Many parsers, POS taggers, etc.
 - Valuable resource for linguistics
- Broad coverage
- Frequencies and distributional information
- A way to evaluate systems



Mitch Marcus



Extracted rules		
$S \rightarrow NP VP .$	$DT \rightarrow \text{That}$	$JJ \rightarrow \text{full}$
$NP \rightarrow DT JJ , JJ NN$	$JJ \rightarrow \text{cold}$	$IN \rightarrow \text{of}$
$VP \rightarrow VBD ADJP$	$, \rightarrow ,$	$NN \rightarrow \text{fire}$
$ADJP \rightarrow JJ PP$	$JJ \rightarrow \text{empty}$	$CC \rightarrow \text{and}$
$PP \rightarrow IN NP$	$NN \rightarrow \text{sky}$	$NN \rightarrow \text{light}$
$NP \rightarrow NN CC NN$	$VBD \rightarrow \text{was}$	

Rules with counts

40717 PP → IN NP
33803 S → NP-SBJ VP
22513 NP-SBJ → -NONE-
21877 NP → NP PP
20740 NP → DT NN
14153 S → NP-SBJ VP .
12922 VP → TO VP
11881 PP-LOC → IN NP
11467 NP-SBJ → PRP
11378 NP → -NONE-
11291 NP → NN
...
989 VP → VBG S
985 NP-SBJ → NN
983 PP-MNR → IN NP
983 NP-SBJ → DT
969 VP → VBN VP
100 VP → VBD PP-PRD
100 PRN → : NP :
100 NP → DT JJS
100 NP-CLR → NN
99 NP-SBJ-1 → DT NNP
98 VP → VBN NP PP-DIR
98 VP → VBD PP-TMP
98 PP-TMP → VBG NP
97 VP → VBD ADVP-TMP VP
...
10 WHNP-1 → WRB JJ
10 VP → VP CC VP PP-TMP
10 VP → VP CC VP ADVP-MNR
10 VP → VBZ S , SBAR-ADV
10 VP → VBZ S ADVP-TMP

Compute
Probabilities using
MLE.

CKY Algorithm

function CKY-PARSE(*words*, *grammar*) **returns** *table*

for $j \leftarrow$ **from** 1 **to** LENGTH(*words*) **do**

for all $\{A \mid A \rightarrow \text{words}[j] \in \text{grammar}\}$
 $\text{table}[j-1, j] \leftarrow \text{table}[j-1, j] \cup A$

for $i \leftarrow$ **from** $j-2$ **downto** 0 **do**

for $k \leftarrow i+1$ **to** $j-1$ **do**

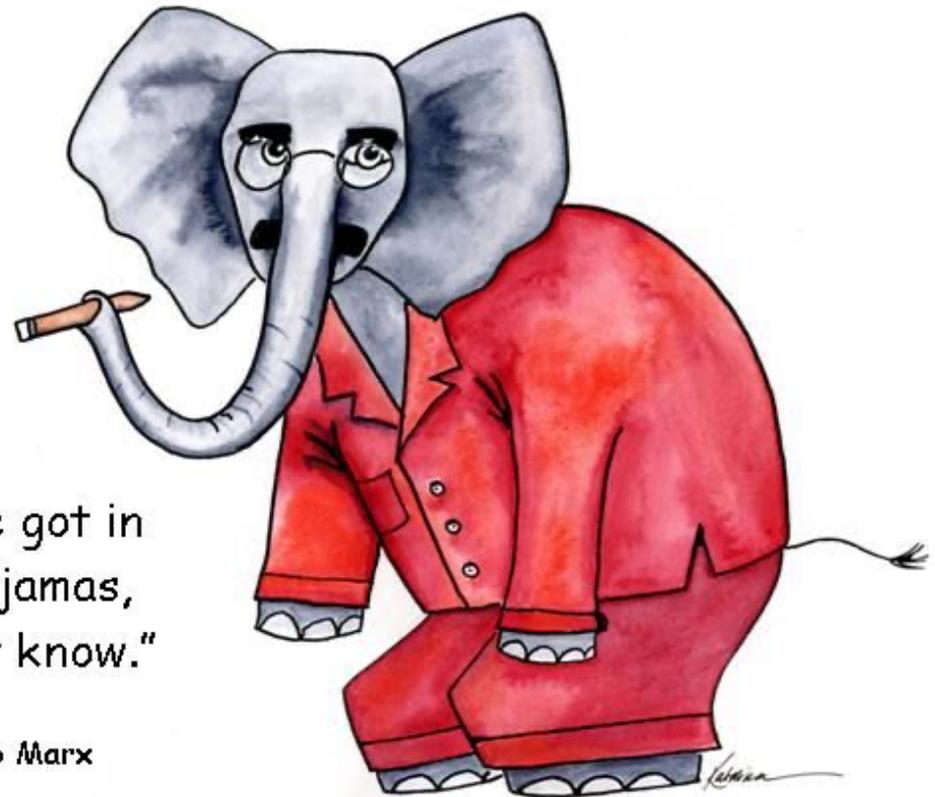
for all $\{A \mid A \rightarrow BC \in \text{grammar} \text{ and } B \in \text{table}[i, k] \text{ and } C \in \text{table}[k, j]\}$
 $\text{table}[i, j] \leftarrow \text{table}[i, j] \cup A$

CKY Demo at <http://lxmls.it.pt/2015/cky.html>

Ambiguity

Ambiguity can arise because of words with **multiple senses** or **POS tags**. Many kinds of ambiguity are also structural.

"One morning I shot an elephant in my pajamas.

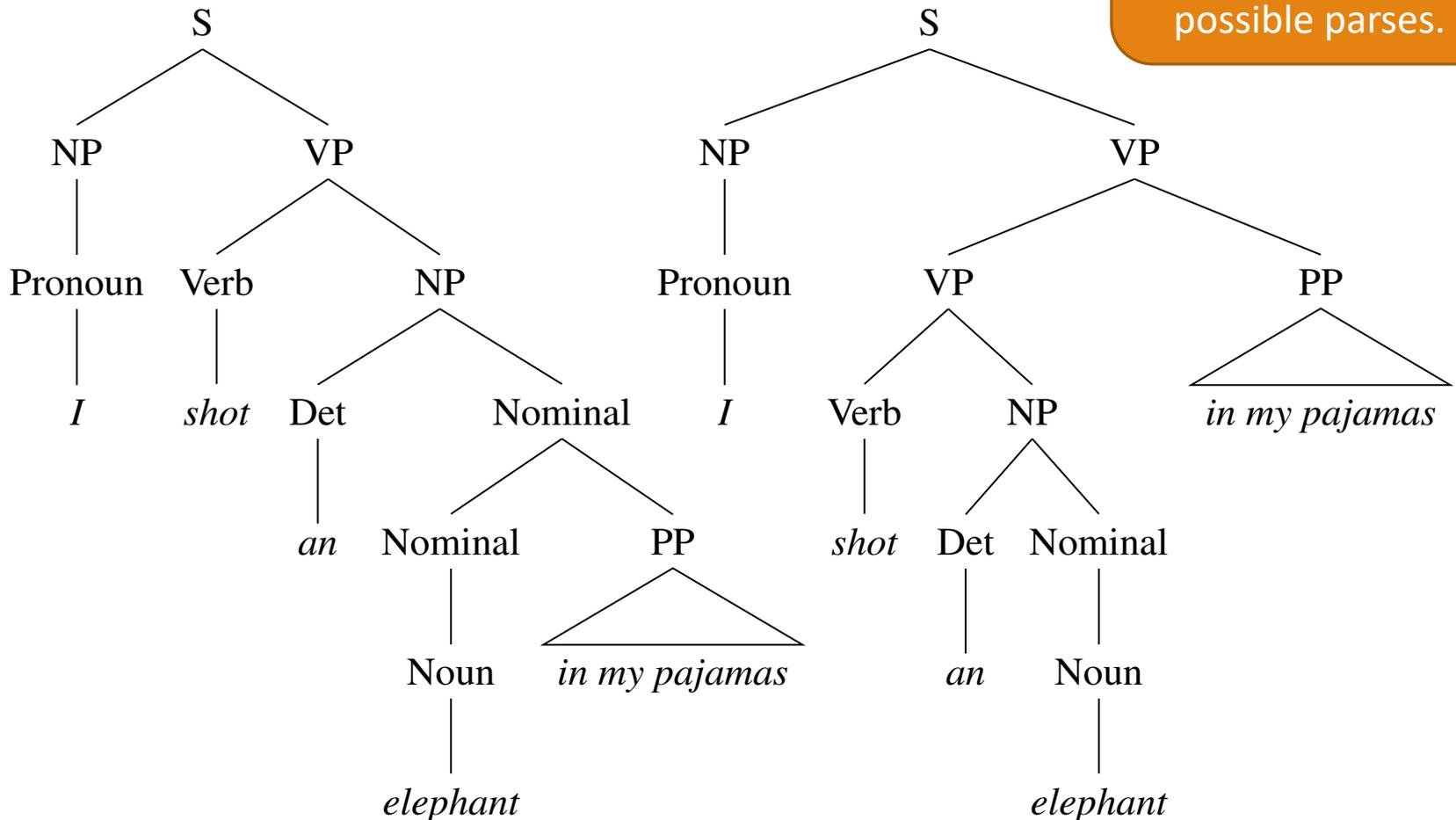


How he got in
my pajamas,
I don't know."

Groucho Marx

Attachment Ambiguity

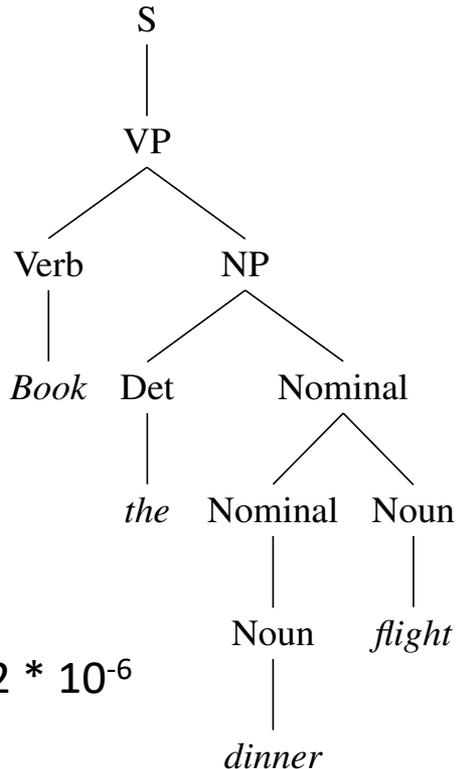
Probabilities give us a way of choosing between possible parses.



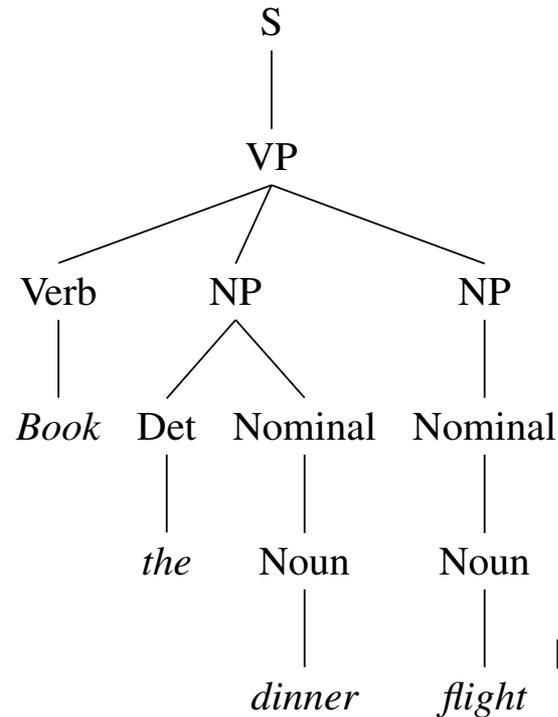
Finding best parse

Pick the parse with the highest probability.

$$\hat{T}(S) = \operatorname{argmax}_{T \text{ s.t. } S = \text{yield}(T)} P(T|S) = P(T, S) = \prod_{i=1}^n P(\text{RHS}_i | \text{LHS}_i)$$

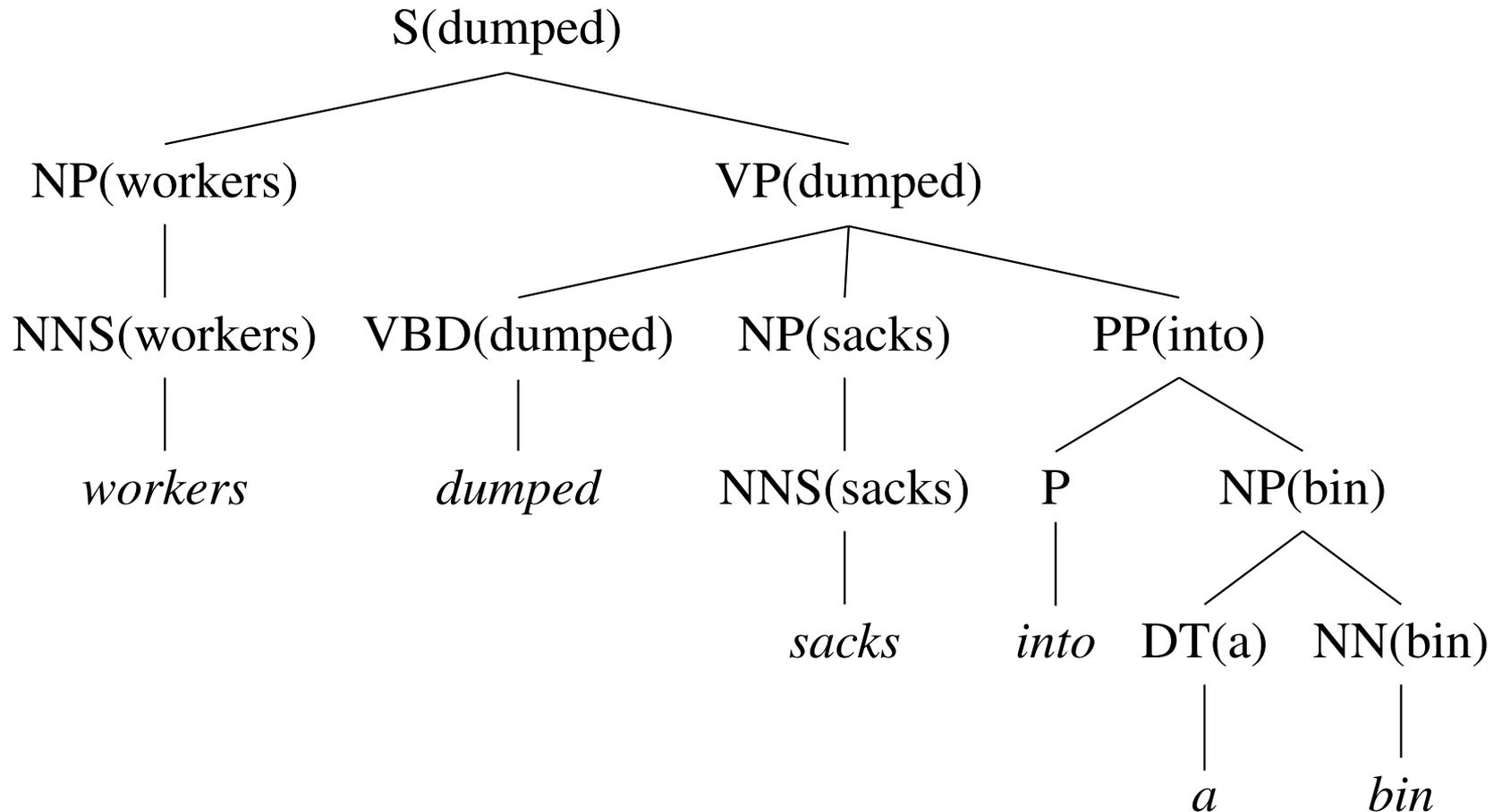


$$P(T, S) = 2.2 * 10^{-6}$$



$$P(T, S) = 6.1 * 10^{-7}$$

Constituents have heads

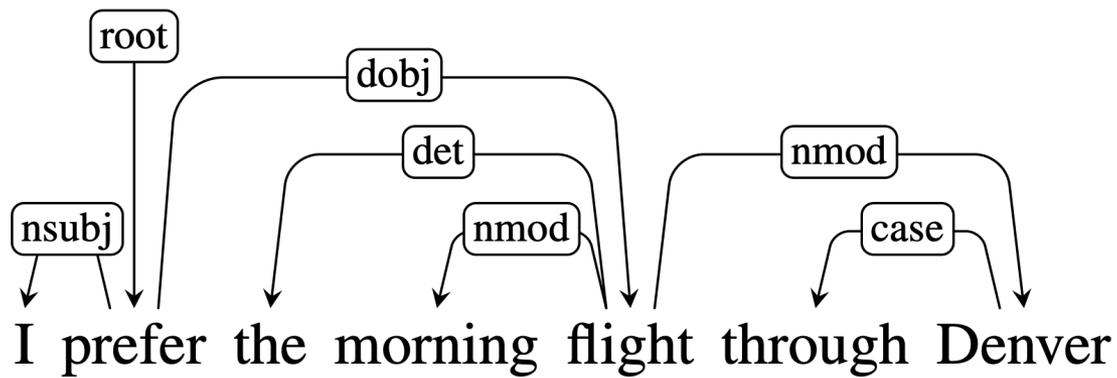


Dependency Parsing

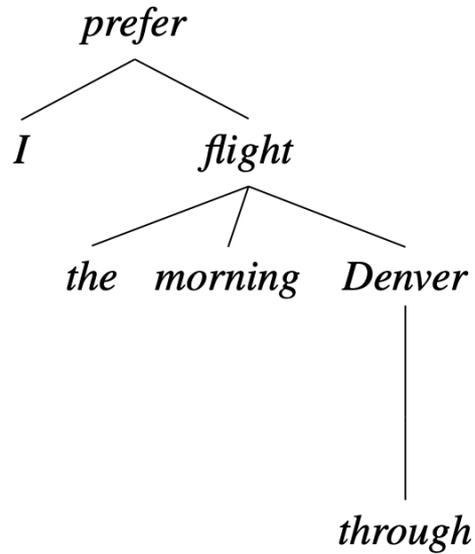
JURAFSKY AND MARTIN CHAPTER 15

Dependency Grammars

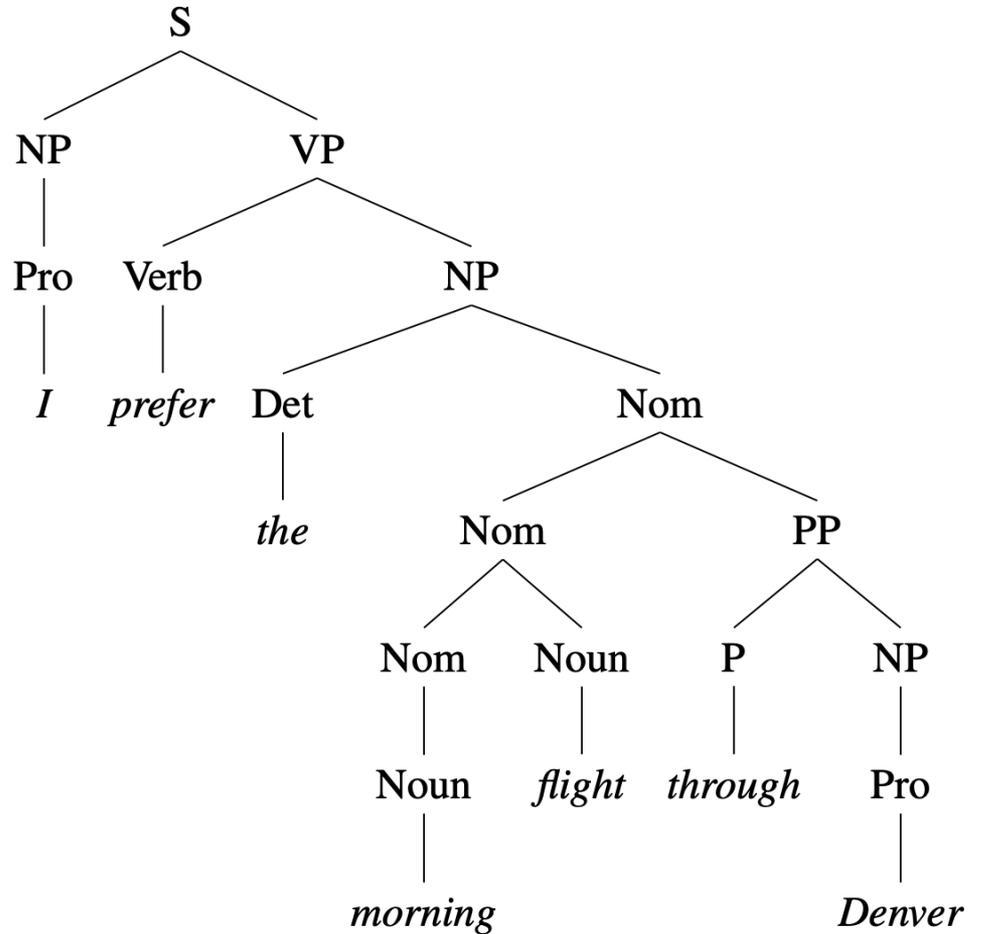
Dependency grammars depict the syntactic structure of sentences solely in terms of the **words in a sentence** and an **associated set of directed head-dependent grammatical relations** that hold among these words.



Dependency – based



Constituent– based



Advantages of dependencies

- Dependencies don't have nodes corresponding to phrasal constituents. Instead they **directly encode information** that is often buried in phrase structure parses.
- Dependency grammars are better able deal with languages that have a relatively **free word order**.
- Dependency relations **approximate semantic relationships** between words and arguments, which is useful for many applications
 - coreference resolution
 - question answering
 - information extraction.

Dependency Formalism

The dependency structures are directed graphs.

$$G = (V, A)$$

where **V** is a **set of vertices** and **A** is a set of **ordered pairs of vertices** (or **directed arcs**). Each arc points from the **head** to a **dependent**



Directed arcs can also be **labeled** with the **grammatical relation** that holds between the head and a dependent.

Dependency Trees

Other common constraints are that dependency structure must be **connected**, have a **designated root node**, and be acyclic or planar. These result in a **rooted tree** called a **dependency tree**.

A dependency tree is a digraph where:

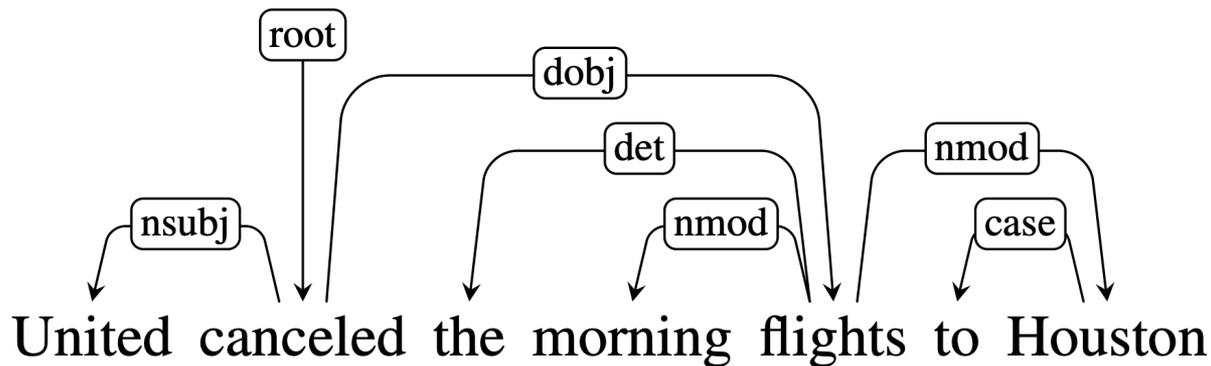
1. There is a **single designated root node** that has no incoming arcs
2. Each vertex has **exactly one incoming arc** (except the root node)
3. There is a **unique path** from the root node to each vertex in V

This mean that each word in the sentence has exactly one head.

Head  Dependent

Dependency Relations

In addition having directed arcs point from the head to the dependent, arc can be labeled with the **type of grammatical function** involved between the words



- **nsubj** and **dobj** identify the subject and direct object of the verb *cancelled*
- **nmod**, **det** and **case** relations denote modifiers of the nouns *flights* and *Houston*.

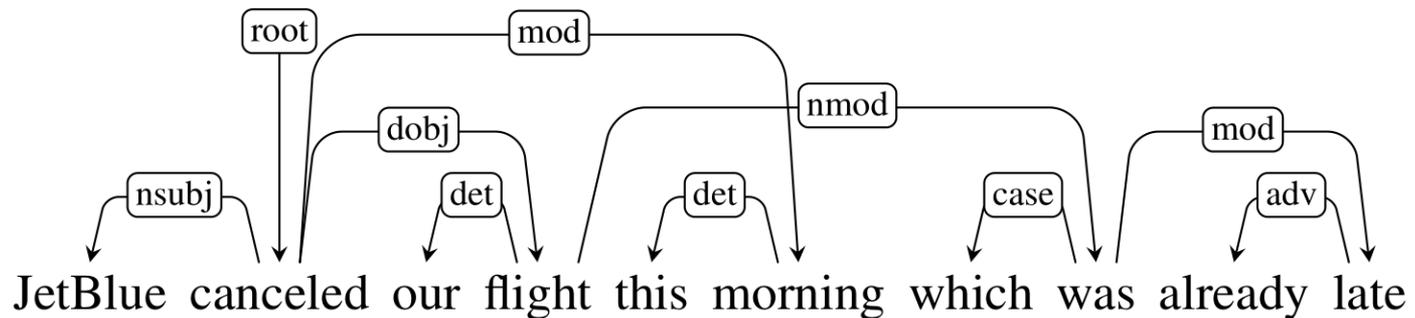
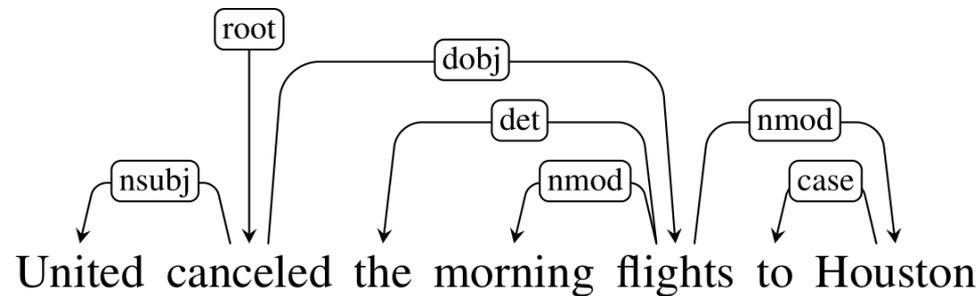
Dependency Relations

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

Dependency Relations

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

Projective vs Non-projective

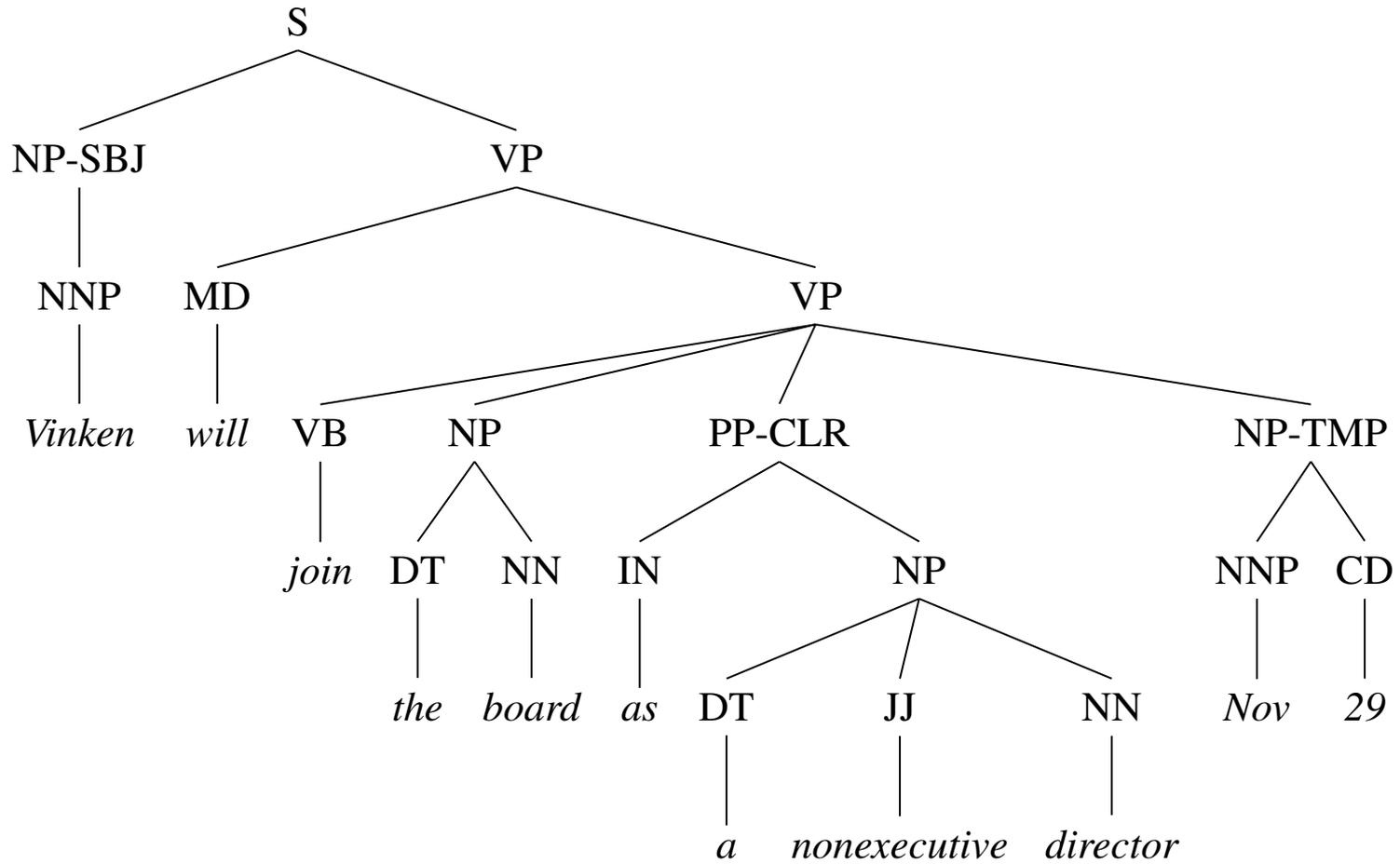


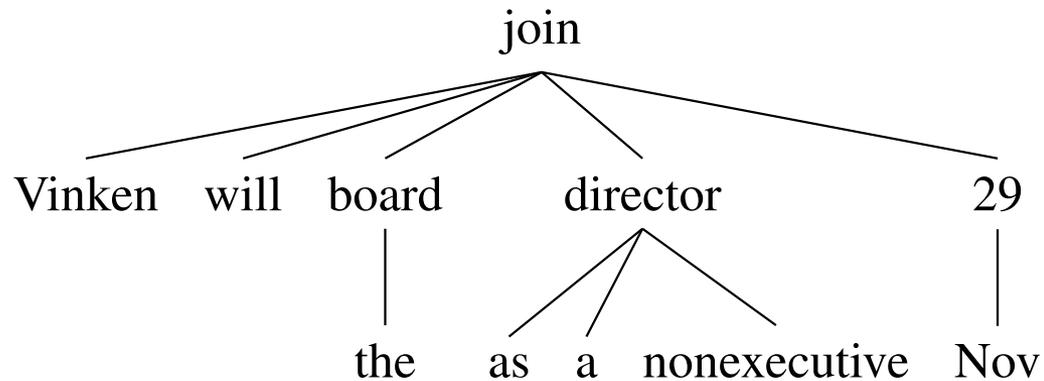
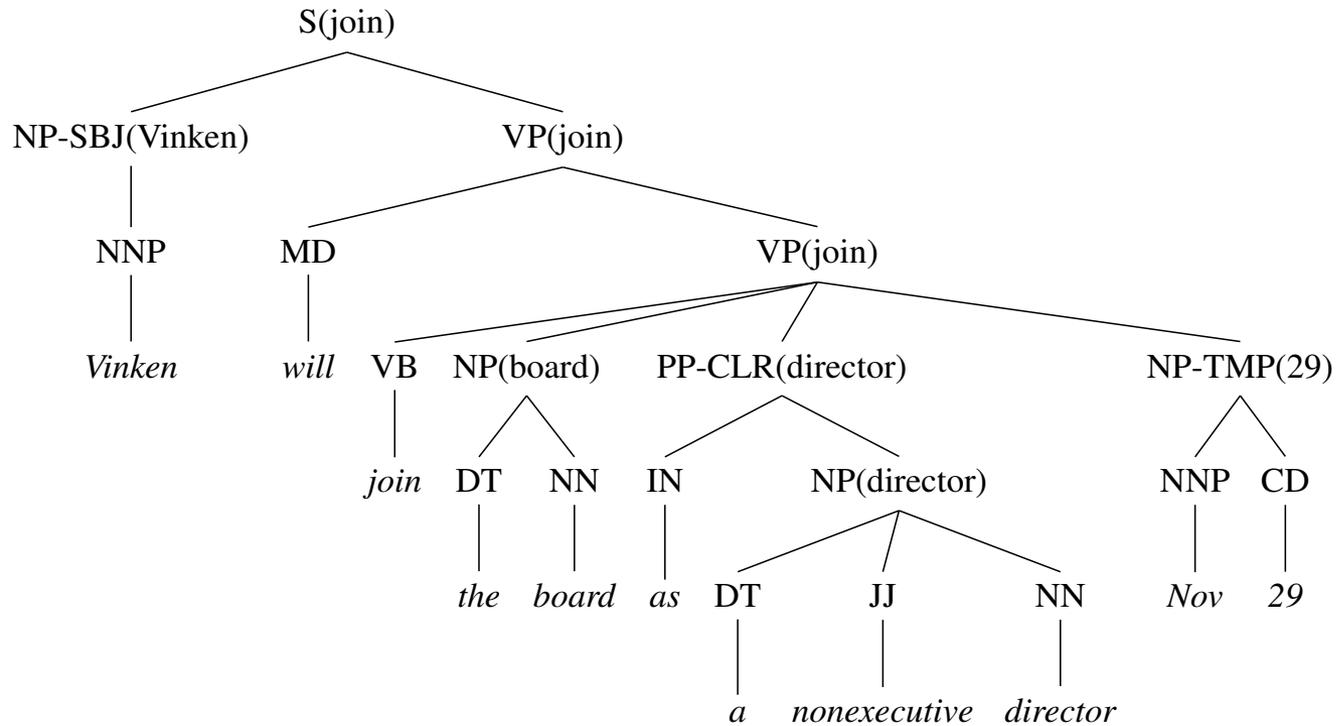
Dependency Treebanks

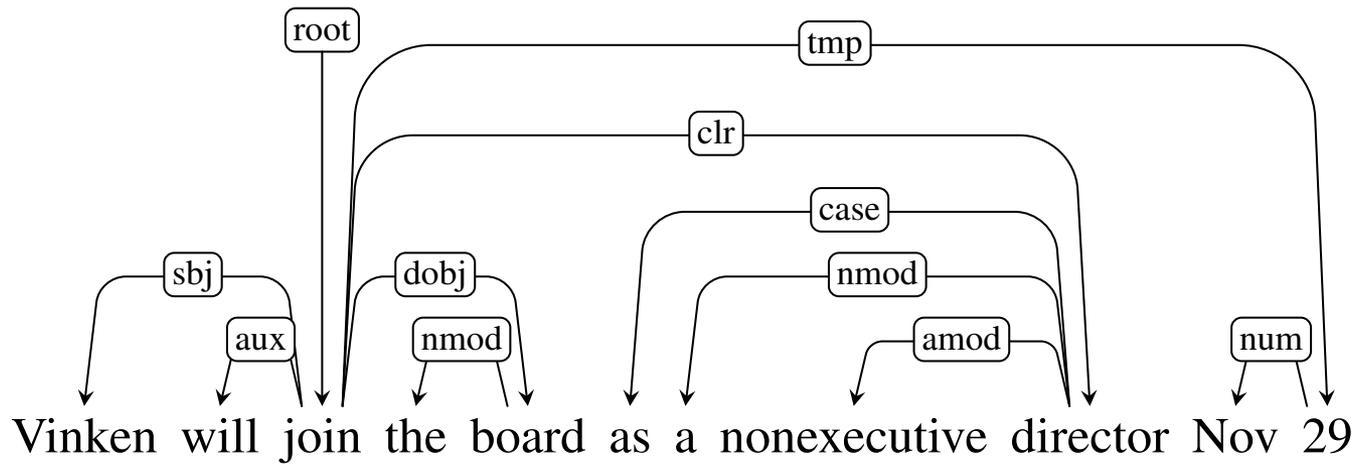
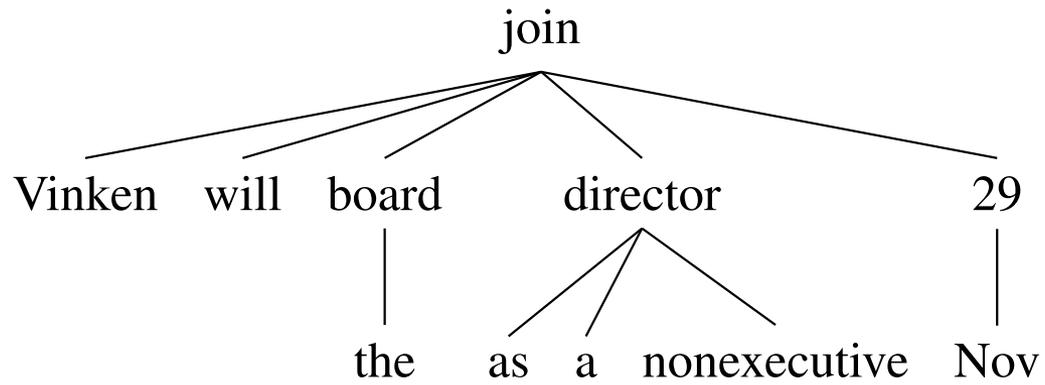
Dependency Treebanks are typically created by the following methods:

1. Having human annotators build dependency structures **directly**
2. Using an **automatic parser** and then employing human annotators to correct the output
3. Automatically **transforming phrase-structure treebanks** into dependency structure treebanks

Directly annotated dependency treebanks have been often created for **morphologically rich languages** such as Czech (Prague Dependency Treebank), Hindi and Finnish.







Parsing Methods

There are two main approaches used in dependency parsers:

1. **Transition-Based**
2. **Graph-Based**

Transition-based approaches can only produce projective trees. Therefore any sentences with non-projective structures will contain errors.

In contrast, graph-based parsing approaches can handle non-projectivity but are more computationally expensive.

Transition-based Parsing

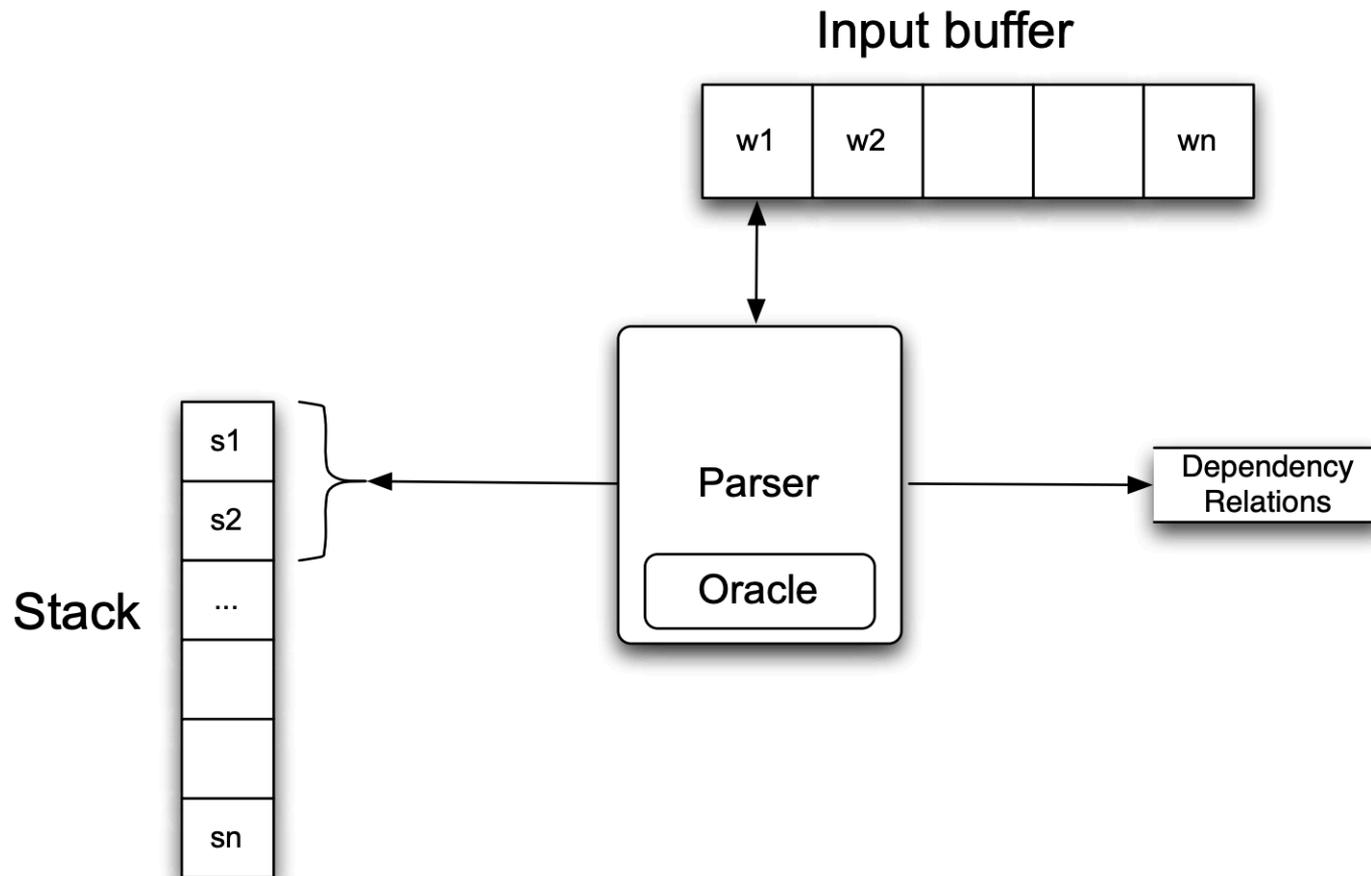
Transition-based parsing systems employ a **greedy stack-based** algorithm to create dependency structures.

A key element in transition-based parsing is the notion of a **configuration** which consists of a **stack**, an **input buffer of words** and a **set of relations representing the dependency tree**.

Parsing consists of a **sequence of “shift-reduce” transitions**. Once all the words have been moved off the stack, they have each and been assigned a head (and an appropriate relation).

The resulting configuration is a **dependency tree**.

Transition-based Parser



The parser examines the top two elements of the stack and selects an action based on consulting an **oracle** that examines the current configuration.

Transition-based Parser

Intuition: create a dependency tree by examining the words in a single pass over the input, moving from left to right:

- Assign the current word as the head of some previously seen word,
- Assign some previously seen word as the head of the current word,
- Or postpone doing anything with the current word, adding it to the stack so that it can be processed later.

Transition-based Parser

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

state \leftarrow { [root], [*words*], [] } ; initial configuration

while *state* **not final**

 t \leftarrow ORACLE(*state*) ; choose a transition operator to apply

 state \leftarrow APPLY(*t*, *state*) ; apply it, creating a new state

return *state*

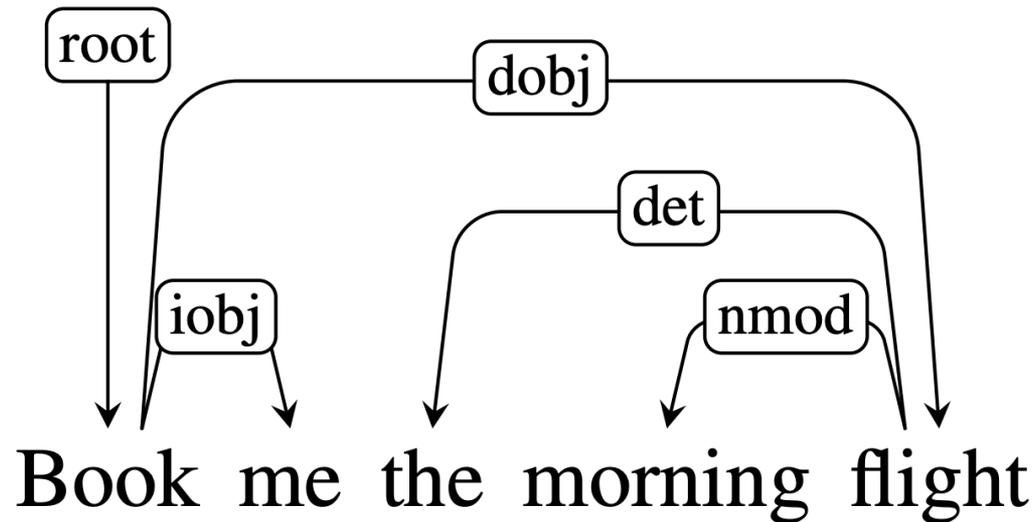
Complexity is **linear in the length of the sentence** $O(V)$ since it is based on a single left to right pass through the words in the sentence \rightarrow each word must be first shifted onto the stack and then reduced

Operators

There are three **transition operators** that will operate on the top two elements of the stack:

1. **LEFTARC**: Assert a head-dependent relation between the word at the top of the stack and the word directly beneath it; remove the lower word from the stack.
2. **RIGHTARC**: Assert a head-dependent relation between the second word on the stack and the word at the top; remove the word at the top of the stack;
3. **SHIFT**: Remove the word from the front of the input buffer and push it onto the stack.

Worked example:



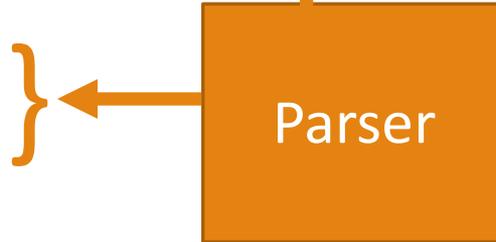
Step	Stack	Word List	Action	Relation Added
0	[root]	[book, me, the, morning, flight]	SHIFT	
1	[root, book]	[me, the, morning, flight]	SHIFT	
2	[root, book, me]	[the, morning, flight]	RIGHTARC	(book → me)
3	[root, book]	[the, morning, flight]	SHIFT	
4	[root, book, the]	[morning, flight]	SHIFT	
5	[root, book, the, morning]	[flight]	SHIFT	
6	[root, book, the, morning, flight]	[]	LEFTARC	(morning ← flight)
7	[root, book, the, flight]	[]	LEFTARC	(the ← flight)
8	[root, book, flight]	[]	RIGHTARC	(book → flight)
9	[root, book]	[]	RIGHTARC	(root → book)
10	[root]	[]	Done	

Figure 15.7 Trace of a transition-based parse.

input buffer:

Book me a morning flight

stack: Root



Action: **Shift**

Root Book me a morning flight

input buffer:

me a morning flight

stack: Book
Root



Action: **Shift**

Root Book me a morning flight

input buffer:

a morning flight

stack: me
Book
Root



Action: **RightArc**

iobj



Root Book me a morning flight

input buffer:

a morning flight

stack: Book
Root



Action: **Shift**

iobj

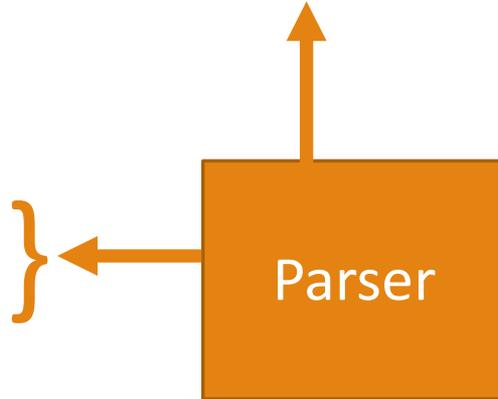


Root Book me a morning flight

input buffer:

morning flight

stack: a
Book
Root



Action: **Shift**



Root Book me a morning flight

input buffer:

flight

stack: morning

a

Book

Root



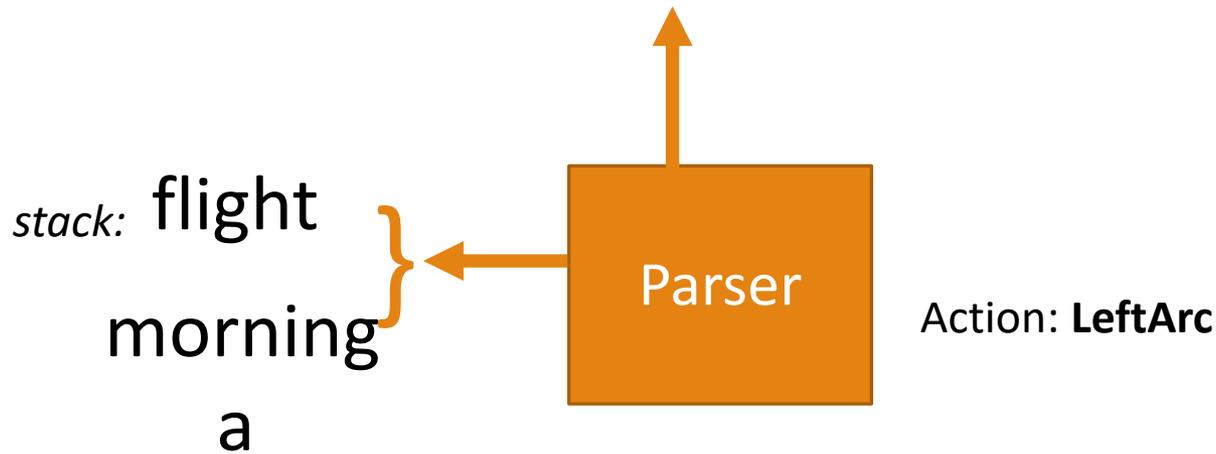
Action: **Shift**

iobj



Root Book me a morning flight

input buffer:



Book

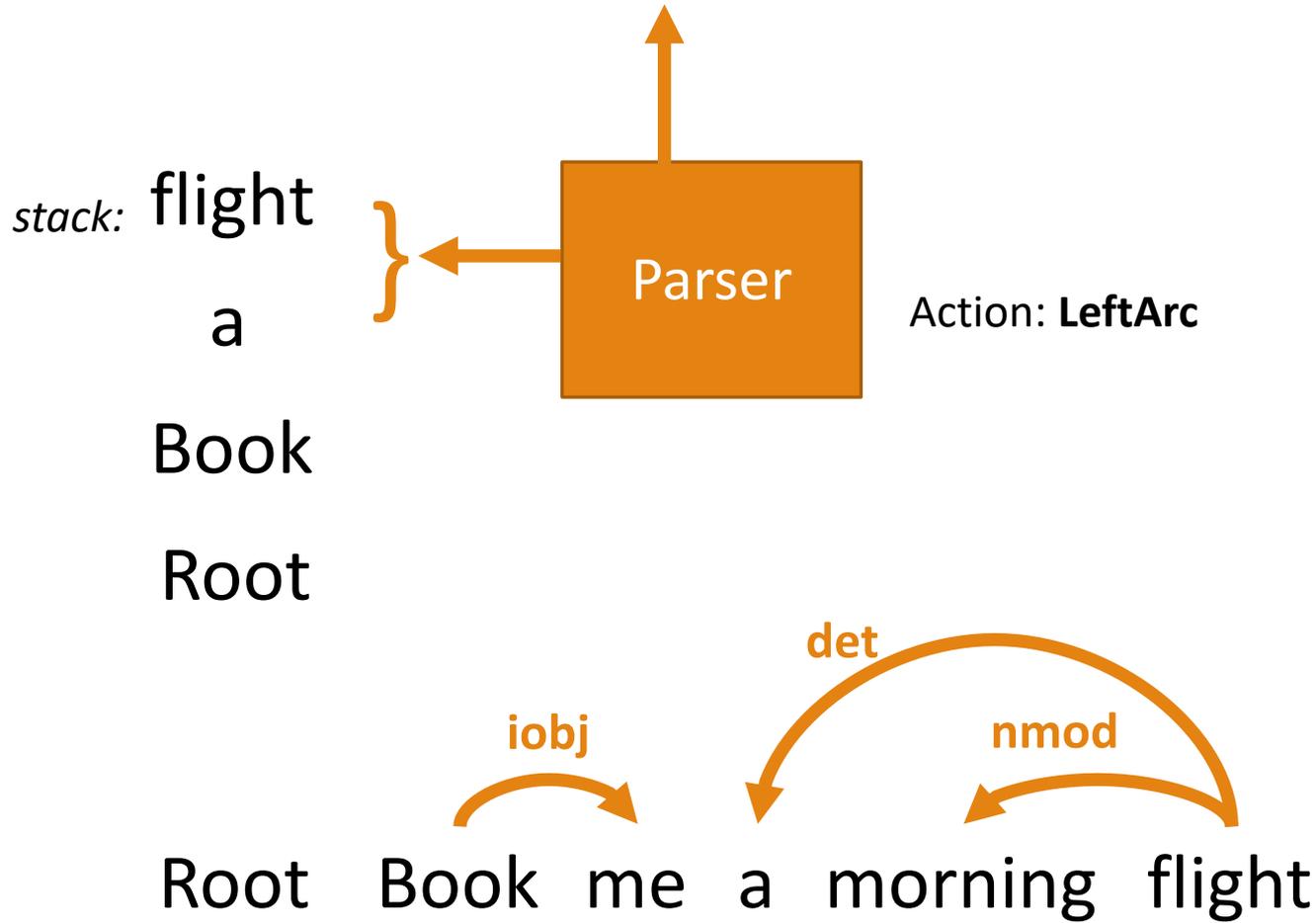
Root

iobj

nmod

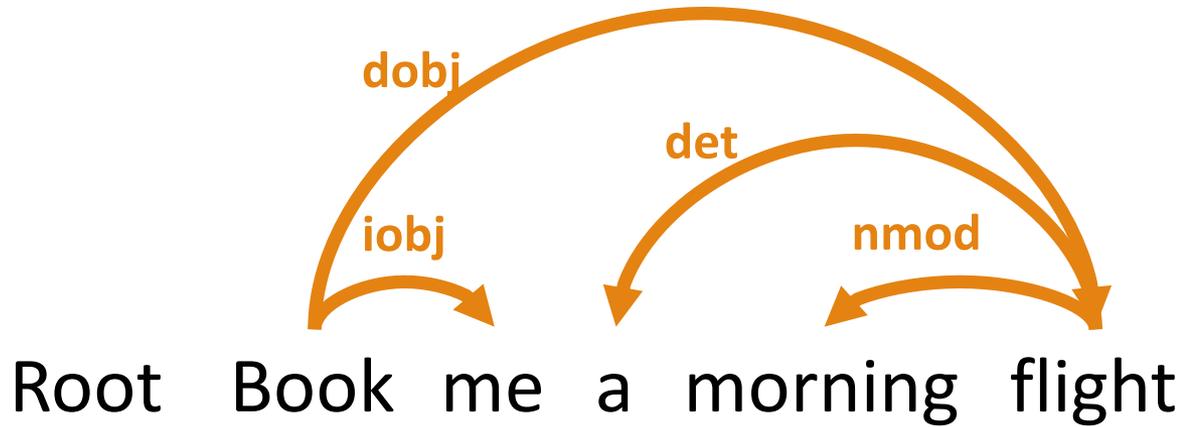
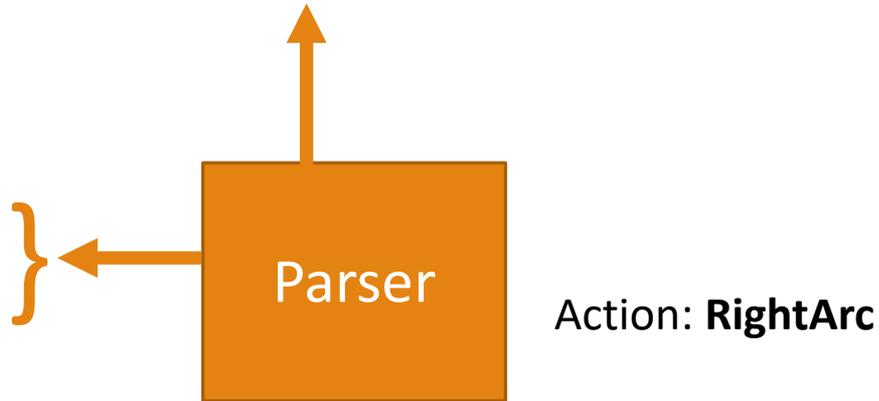
Root Book me a morning flight

input buffer:

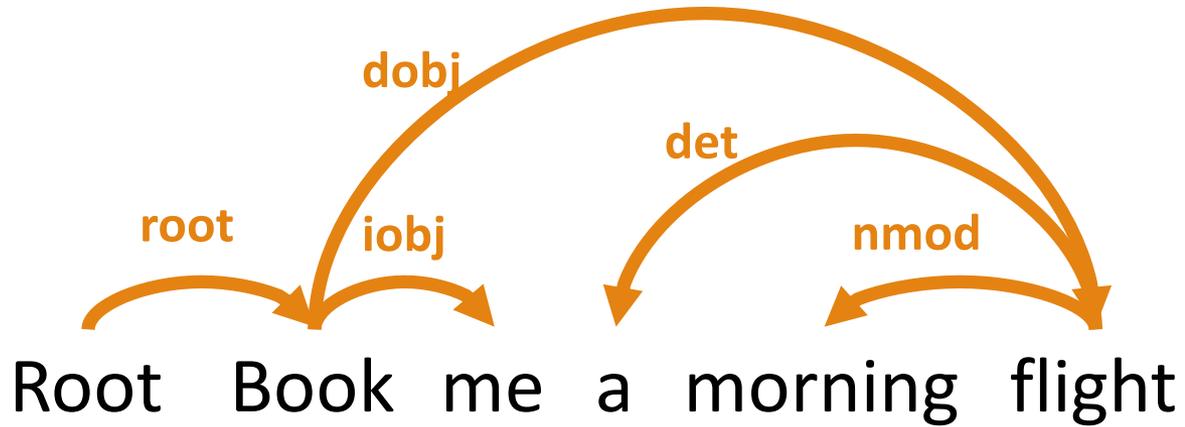
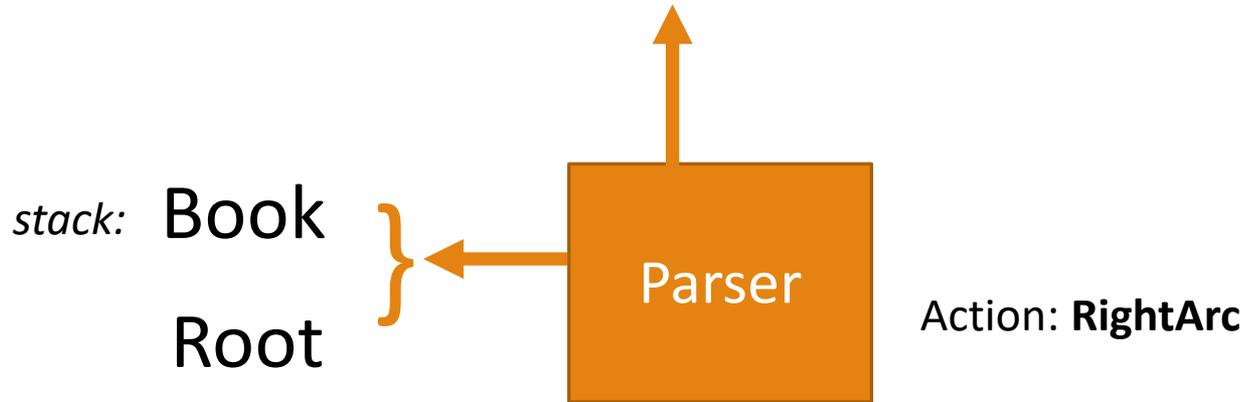


input buffer:

stack: flight
Book
Root

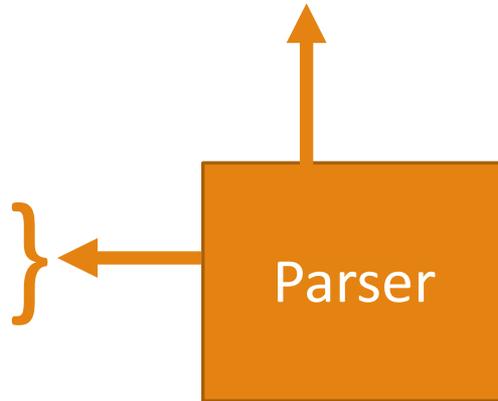


input buffer:

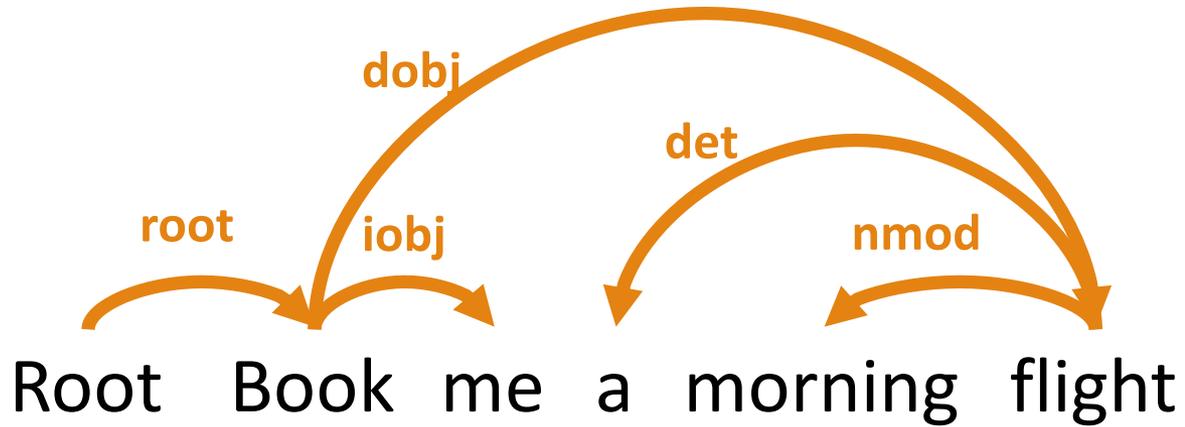


input buffer:

stack: Root



Action: **Done**



Creating the Oracle

SOTA transition-based systems use supervised machine learning methods to train classifiers that play the role of the **oracle**, which takes in as input a configuration and returns as output a transition operator.

Problem: What about the training data? To train the oracle, we need configurations paired with transition operators, which aren't provided by the Treebanks...

Solution: simulate the operation of the parser by running the algorithm and relying on a new training oracle to give correct transition operators for each successive operation.

Graph-based Parsing

Graph-based methods for creating dependency structures search through the space of possible dependency trees for a tree that maximizes some score function:

$$\hat{T}(S) = \operatorname{argmax}_{t \in G_S} \operatorname{score}(t, S)$$

where, the score for a tree is based on the scores of the edges that comprise the tree:

$$\operatorname{score}(t, S) = \sum_{e \in t} \operatorname{score}(e)$$

A common approach involves the use of **maximum spanning trees (MST)**

function MAXSPANNINGTREE($G=(V,E)$, $root$, $score$) **returns** *spanning tree*

$F \leftarrow []$

$T' \leftarrow []$

$score' \leftarrow []$

for each $v \in V$ **do**

$bestInEdge \leftarrow \operatorname{argmax}_{e=(u,v) \in E} score[e]$

$F \leftarrow F \cup bestInEdge$

for each $e=(u,v) \in E$ **do**

$score'[e] \leftarrow score[e] - score[bestInEdge]$

if $T=(V,F)$ is a spanning tree **then return** it

else

$C \leftarrow$ a cycle in F

$G' \leftarrow \text{CONTRACT}(G, C)$

$T' \leftarrow \text{MAXSPANNINGTREE}(G', root, score')$

$T \leftarrow \text{EXPAND}(T', C)$

return T

function CONTRACT(G, C) **returns** *contracted graph*

function EXPAND(T, C) **returns** *expanded graph*

Figure 15.13 The Chu-Liu Edmonds algorithm for finding a maximum spanning tree in a weighted directed graph.

Training

While we can reduce the score of tree to a sum of the scores of the edges that comprise it, each edge score can also be reduced to a **weighted sum of features extracted from it.**

$$\text{score}(S, e) = \sum_{i=1}^N w_i f_i(S, e) = w \cdot f$$

Commonly used features include:

- **Wordforms, lemmas and POS of the headword and dependent**
- **Corresponding features of contexts before, after and between words**
- **Word embeddings**
- **Dependency relation type**
- **Direction of the relation (to the right or to the left)**
- **Distance from the head to the dependent**

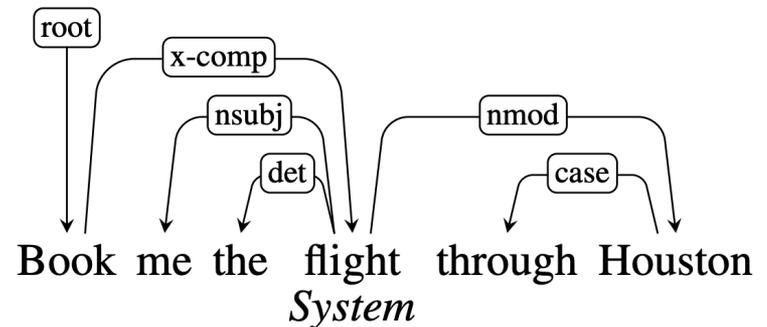
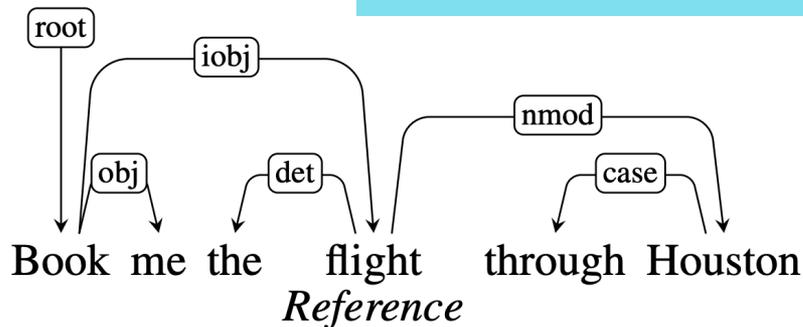
Evaluation

The common method for evaluating dependency parsers are **labeled attachment accuracy (LAS)** and **unlabeled attachment accuracy**

Labeled attachment refers to the proper assignment of a word to its head with the correct dependency relation.

Unlabeled attachment refers to the proper assignment of a word to its head ONLY (ignores dependency relation)

LAS = 2/3, UAS = 5/6





Next time: Logical
Representations
of Sentence
Meaning
