



Escuela Politécnica Superior

Master course

Deep learning for natural language processing

Unit 2 – Natural language tasks (part III)

Dependency parsing

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Contents

1. The dependency parsing problem
2. Dependency parsing algorithms
3. Evaluation of dependency parsers
4. Resources and references

Disclaimer: some materials of this presentation come from or is based on the slides and chapters written by Dan Jurafsky and James H. Martin for their book “Speech and Language Processing,” and the slide written by Christopher Manning at Stanford University.

Contents

1. The dependency parsing problem

- **Dependency relations**
- Dependency trees
- Extraction of dependency trees
- Projectivity in dependency trees

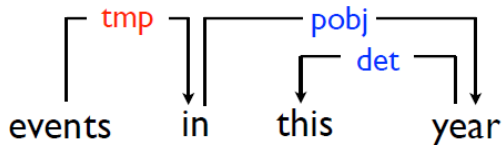
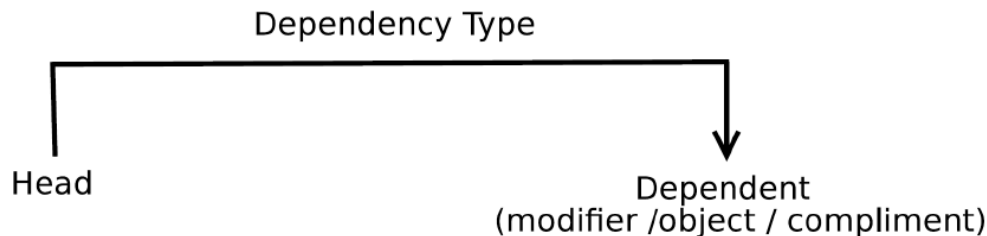
2. Dependency parsing algorithms

3. Evaluation of dependency parsers

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Dependency relations

- A **dependency** is an asymmetric **syntactic** or **semantic** relation between two lexical tokens
 - Its two tokens are called **head** and **dependent**
 - It may be labelled with a **type**, e.g., *tmp* (temporal), *pobj* (object of a preposition), and *det* (determiner)



2. Dependency parsing

2.1. The dependency parsing problem

Dependency relations

- The **Universal Dependency (UD) set** – 37 relations, ~200 treebanks, >100 languages
 - **Examples of relations**

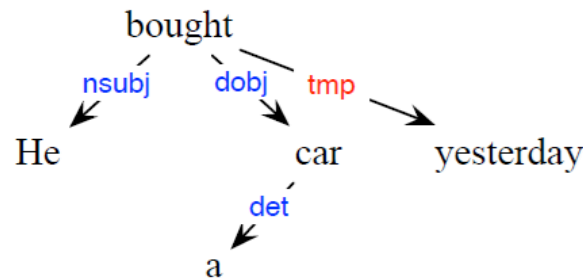
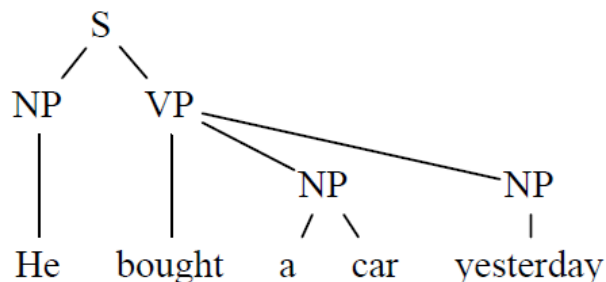
Clausal Argument Relations	Description
NSUBJ	Nominal subject
DOBJ	Direct object
IOBJ	Indirect object
CCOMP	Clausal complement
XCOMP	Open clausal complement
Nominal Modifier Relations	Description
NMOD	Nominal modifier
AMOD	Adjectival modifier
NUMMOD	Numeric modifier
APPOS	Appositional modifier
DET	Determiner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

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

<https://universaldependencies.org/u/dep/index.html>

Dependency relations

- **Dependency relations** do not correspond to **constituent relations**
 - **Constituent structure**
 - Starts with the bottom level constituents (tokens)
 - Groups smaller constituents into bigger constituents (phrases)
 - **Dependency structure**
 - Builds an acyclic graph (tree) by adding edges between tokens



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- **Projectivity in dependency trees**

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Dependency trees

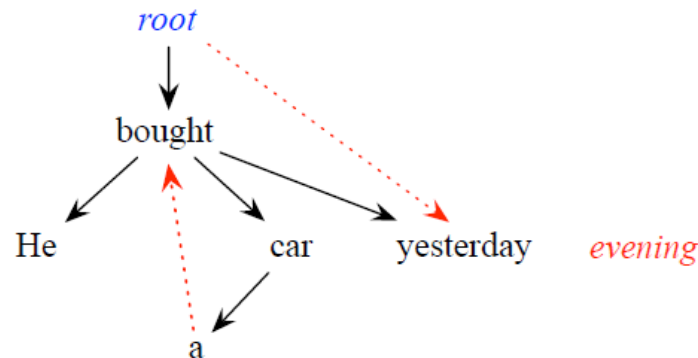
- **Dependency tree**

- For a **sentence** $s = w_1 \dots w_n$, a dependency tree is a **graph** $G_s = (V_s, A_s)$ so that

- $V_s = \{w_0 = \text{root}, w_1, \dots, w_n\}$
- $A_s = \{(w_i, r, w_j) : i \neq j, w_i \in V_s, w_j \in V_s - \{w_0\}, r \in R_s\}$
- R_s = a subset of dependency relations in s

- It has the following **properties**:

- **single-head**: each word (vertex) has only one head (incoming arc), except for the root
- **connected**: contains all the words in the sentence (i.e., there is a path from the root to each word)
- **acyclic**

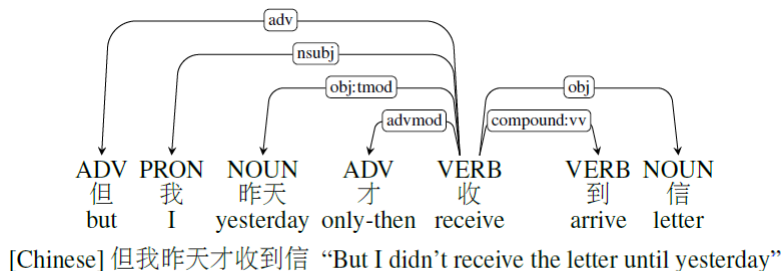
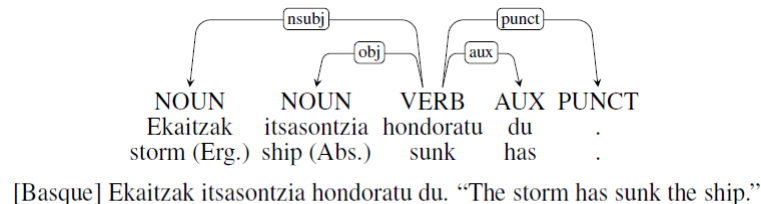
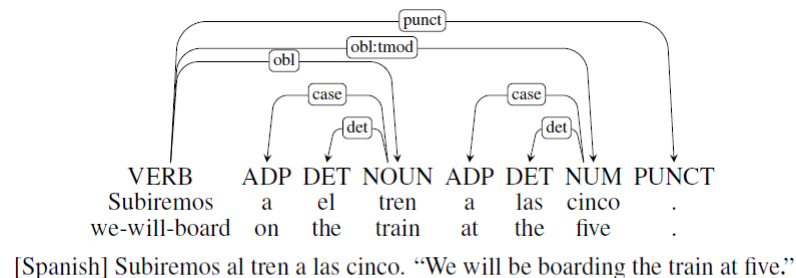
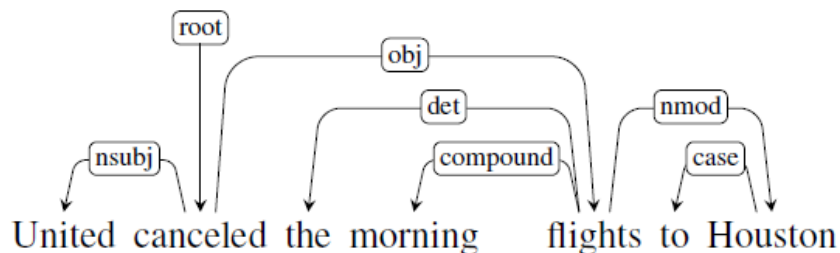


2. Dependency parsing

2.1. The dependency parsing problem

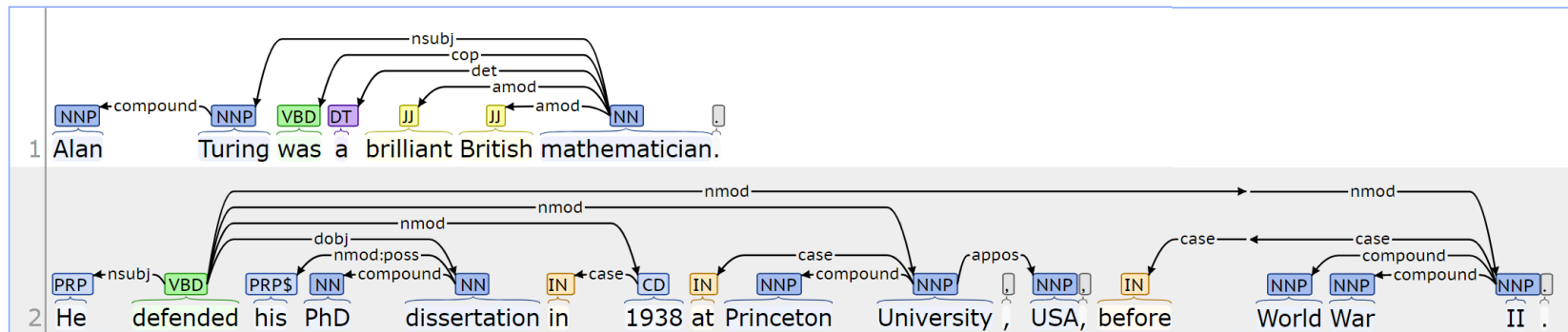
Dependency trees

- **Treebanks** - labeled dependency trees



Extraction of dependency trees

- **Dependency parsing** is the task of extracting the dependency tree of a sentence, defining the relationships between “head” and “dependent” words
- **Example:** “Alan Turing was a brilliant British mathematician. He took a leading role in breaking Nazi ciphers during World War II.”



Extraction of dependency trees

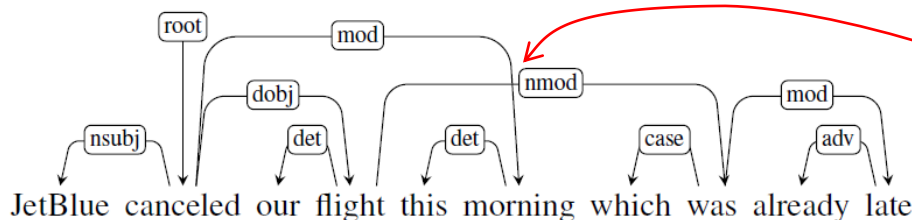
- **Dependency parsing**

- Provides useful information for many **NLP applications**: machine translation, information extraction, question answering, sentiment analysis, etc.
- Is **faster** (about 1 millisecond per sentence) and more **language-independent** than most other parsing tasks

Projective trees make computation easier, but most theoretical frameworks do not assume projectivity; there is need to capture long-distance dependencies and free word order in some languages.

Projectivity in dependency trees

- **Projectivity** is an additional property of a dependency tree; if it is satisfied, the tree is *well-formed*
 - An **arc** from a head to a dependent is said to be **projective** if there is a path from the head to every word that lies between the head and the dependent in the sentence
 - If word A depends on word B, then all words between A and B are also subordinate to B (i.e., dominated by B)
 - A **dependency tree** is said to be **projective** if all its arcs are projective
 - Example: the following tree is non-projective since there is no path from “flight” to the intervening words “this” and “morning” (which are before “was”)



Trick

A **projective dependency tree** has no “crossing” arc.

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 - **Types of dependency parsers**
 - Transition-based dependency parsing
 - Graph-based dependency parsing
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Types of dependency parsers

- **Transition-based parsers**

- Perform a **local, greedy parsing**
- Have problems when the heads are very far from the dependents
- Tend to produce non-projective trees, which is not a significant issue in English, but it is a problem for many other languages

- **Graph-based parsers**

- Perform a **global, exhaustive parsing**
- Are more accurate, especially on long sentences, since they score entire trees
- Can produce non-projective trees

Types of dependency parsers

- **Transition-based parsers**

- **Transition**: an operation (e.g., *shift*, *reduce*) that searches for a dependency relation between each pair of words
- Greedy search that finds *local optima* (locally optimized transitions) → do better for **local dependencies**
- Projective: $O(n)$, non-projective: $O(n^2)$

- **Graph-based parsers**

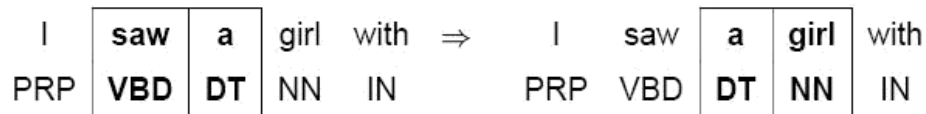
- Build a **complete graph** with **directed/weighted edges** and find on it a spanning tree with the highest score (sum of all weighted edges)
- Exhaustive search that finds for the *global optimum* (maximum spanning tree) → do better for **long-distance dependencies**
- $O(n^3)$

Contents

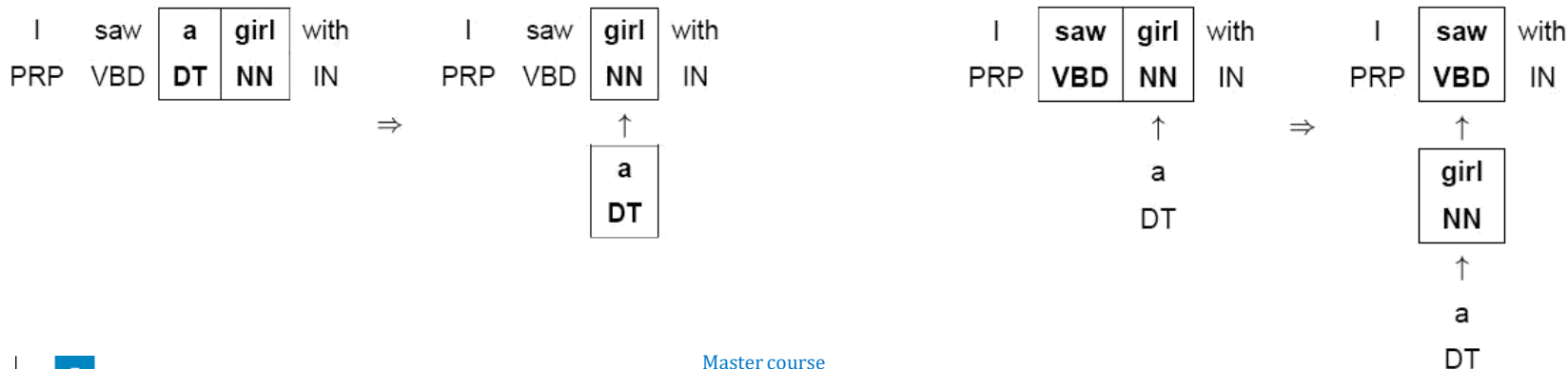
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Transition-based dependency parsing

- Local, greedy methods that focus on **pairs of words** and are based on 3 main **actions**: shift, left, right
 - Shift**: moves the focus to the next word pair

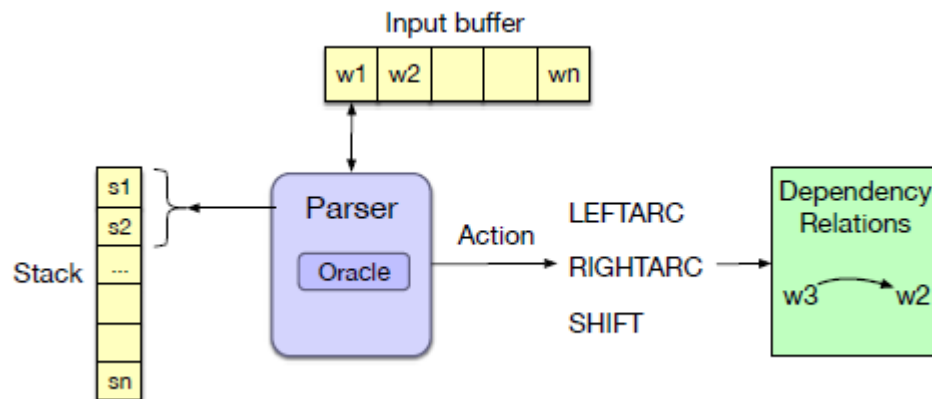


- Left/Right**: decides if the left/right word depends on the right/left word



Transition-based dependency parsing

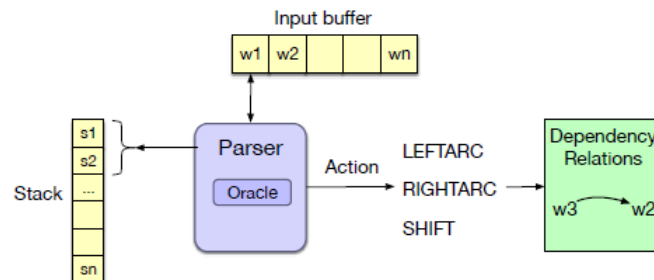
- Builds on a stack-based approach called **shift-reduce parsing** originally developed for analyzing programming languages (Aho & Ullman, 1972)
- **Configuration**
 - **Stack**
 - **Input: buffer (queue) of words**
 - **Output: set of dependency relations**
- **Goal**
 - Finding a final configuration where all words accounted for relations form dependency tree



The parser examines the top two elements s_1 and s_2 of the stack, and selects an action based on consulting an **oracle** that examines the current configuration.

Transition-based dependency parsing

- **Transitions** produce a new configuration given the current configuration
- **Parsing** is the task of finding a sequence of transitions that leads from the start state to the desired end state
 - **Start state**
 - **Stack**: initialized with **ROOT** node
 - **Buffer**: initialized with words in sentence
 - **Dependency relation set**: empty
 - **End state**
 - **Stack**: empty
 - **Buffer**: empty
 - **Dependency relations set**: final parse



Transition-based dependency parsing

- **A generic transition-based dependency parser**

- Assumes the existence of an **oracle**
- Follows a greedy algorithm
- Has linear complexity

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

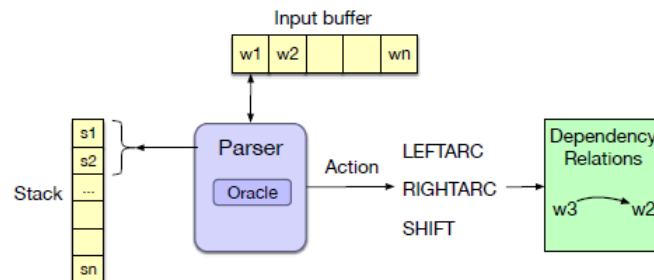
state \leftarrow { [root], [*words*], [] } ; initial configuration

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



Transition-based dependency parsing

- **A generic transition-based dependency parser**

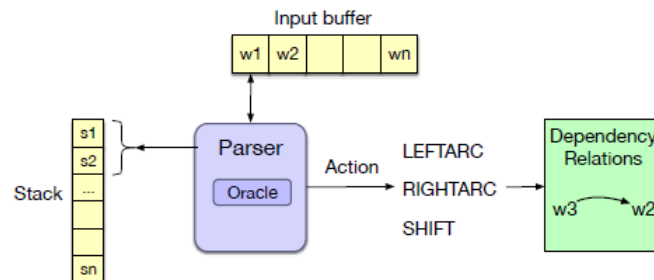
- Given a current configuration with stack S , dependency relations R_c , and **reference parse** R_p , **the oracle** chooses transitions as follows:

LEFTARC(r): **if** $(S_1 \ r \ S_2) \in R_p$

RIGHTARC(r): **if** $(S_2 \ r \ S_1) \in R_p$ **and** $\forall r', w \text{ s.t. } (S_1 \ r' \ w) \in R_p$ **then** $(S_1 \ r' \ w) \in R_c$

SHIFT: **otherwise**

where S_1 and S_2 are the 1st (top) the 2nd words in the stack respectively



Transition-based dependency parsing

- **Transition operators**

- **LEFT-ARC**

- creating a head-dependent relation $s_2 \leftarrow s_1$ between the word s_1 at the top of the stack and the word s_2 under top
 - removing s_2 from stack

- **RIGHT-ARC**

- creating head-dependent relation $s_2 \rightarrow s_1$ between s_2 and s_1
 - removing s_1 from stack

- **SHIFT**

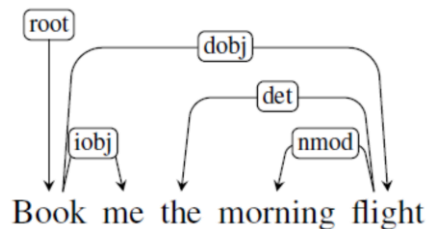
- removing the word w_1 at the head of the buffer
 - pushing w_1 on the stack

Preconditions

- ROOT cannot have incoming arcs
- LEFT-ARC cannot be applied when ROOT is the 2nd element in the stack
- LEFT-ARC and RIGHT-ARC require two elements in the stack to be applied

Transition-based dependency parsing

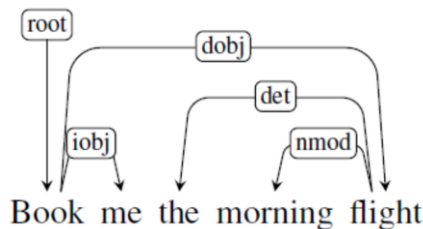
- Trace of an example transition-based parse



Step	Stack	Word List	Action	Relation Added
0	[root]	[book, me, the, morning, flight]		
1				
2				
3				
4				
5				
6				
7				
8				
9				
10				

Transition-based dependency parsing

- Trace of an example transition-based parse



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	

Transition-based dependency parsing

- **Comments**

- Due to **ambiguity**, there may be several transition sequences that lead to **different valid parses**
- Given the **greedy nature** of the algorithm, the oracle may provide a **wrong operator** at some point in the parse
 - There are techniques that allow transition-based techniques to explore the search space more fully
- To produce labeled trees, LEFT-ARC and RIGHT-ARC should be **parametrize operators** with **dependency labels**, as in LEFT-ARC(nsubj) or RIGHT-ARC(dobj)
 - The job of the oracle is more difficult

Transition-based dependency parsing

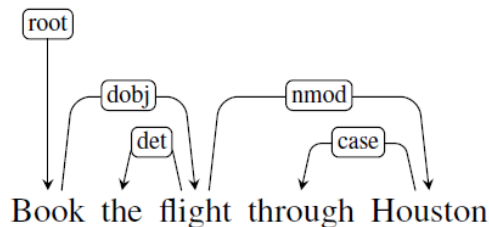
- **Creating the oracle**

- State-of-the-art transition-based parsers use **supervised machine learning** methods to train a classifier which plays the role of the oracle
 - Given appropriate **training data**, these methods learn a function that maps from configurations to transition operators
- The oracle takes as **input** a configuration and returns as **output** a transition operator
 - To train its classifier, **configurations paired with transition operators** (i.e., LEFT-ARC, RIGHT-ARC or SHIFT) are needed
 - But treebanks consist of **entire sentences paired with their corresponding trees**

Transition-based dependency parsing

- **Creating the oracle**

- How to generate **training instances** consisting of [configuration, transition] pairs **from a treebank** composed of sentence parses?
 - By **simulating** the operations of a parser in the context of a reference dependency tree



Step	Stack	Word List	Predicted Action
0	[root]	[book, the, flight, through, houston]	SHIFT
1	[root, book]	[the, flight, through, houston]	SHIFT
2	[root, book, the]	[flight, through, houston]	SHIFT
3	[root, book, the, flight]	[through, houston]	LEFTARC
4	[root, book, flight]	[through, houston]	SHIFT
5	[root, book, flight, through]	[houston]	SHIFT
6	[root, book, flight, through, houston]	[]	LEFTARC
7	[root, book, flight, houston]	[]	RIGHTARC
8	[root, book, flight]	[]	RIGHTARC
9	[root, book]	[]	RIGHTARC
10	[root]	[]	Done

Transition-based dependency parsing

• Creating the oracle

- Having generated appropriate [configuration, transition] training instances, useful **features from the configurations** are extracted to train classifiers
 - Focus on top words of the stack, and use of word forms and PoS
 - Consideration of context: word neighbors in stack and buffer

Stack	Word buffer	Relations
[root, canceled, flights]	[to Houston]	(canceled → United) (flights → morning) (flights → the)



$\langle s_1.w = flights, op = shift \rangle$
 $\langle s_2.w = canceled, op = shift \rangle$
 $\langle s_1.t = NNS, op = shift \rangle$
 $\langle s_2.t = VBD, op = shift \rangle$
 $\langle b_1.w = to, op = shift \rangle$
 $\langle b_1.t = TO, op = shift \rangle$
 $\langle s_1.wt = flightsNNS, op = shift \rangle$
 $\langle s_1.t \circ s_2.t = NNSVBD, op = shift \rangle$

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	$s_1.w \circ s_2.w$	$s_1.t \circ s_2.t$	$s_1.t \circ b_1.w$
	$s_1.t \circ s_2.wt$	$s_1.w \circ s_2.w \circ s_2.t$	$s_1.w \circ s_1.t \circ s_2.t$
	$s_1.w \circ s_1.t \circ s_2.t$	$s_1.w \circ s_1.t$	

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Graph-based dependency parsing

- **Searching** for a tree or trees that maximize some score through the **space of possible trees for a given sentence**

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

- **Edge-factored algorithms:** the score for a tree is based on the scores of the edges that comprise the tree

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

- Employing methods drawn from graph theory to search for optimal solutions

Graph-based dependency parsing

- **Chu-Liu-Edmonds' algorithm**

- Based on **maximum spanning tree** (MST) algorithm for weighted, directed graphs
- Given an input sentence, a **fully-connected, weighted, directed graph** is created
 - The vertices are the input words
 - The directed edges represent all possible head-dependent assignments
 - An additional ROOT vertex is included with outgoing edges directed at all the other vertices
 - The **weights** in the graph reflect the score for each possible head-dependent relation as provided by a model generated from training data
- Given these weights, a maximum spanning tree of this graph emanating from the ROOT represents the preferred dependency parse for the sentence

Graph-based dependency parsing

- **Chu-Liu-Edmonds' algorithm**

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

```
 $F \leftarrow \square$ 
```

```
 $T' \leftarrow \square$ 
```

```
 $score' \leftarrow \square$ 
```

```
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  $T$ 
```

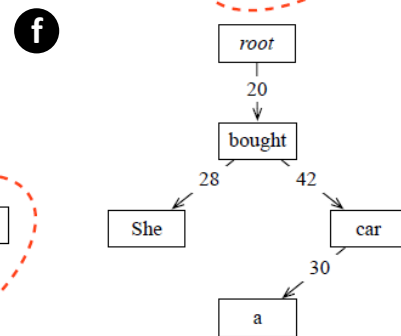
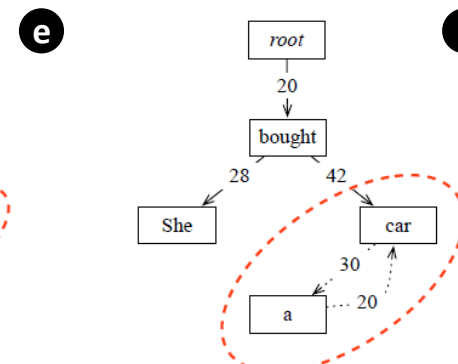
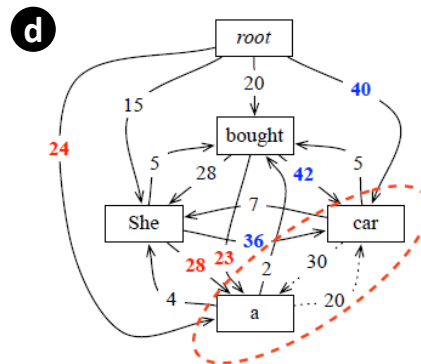
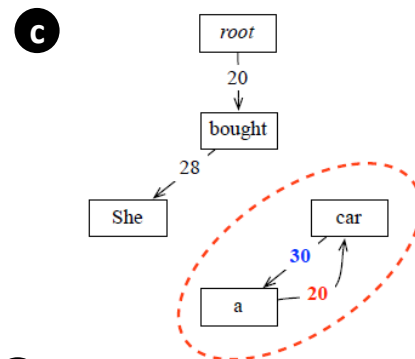
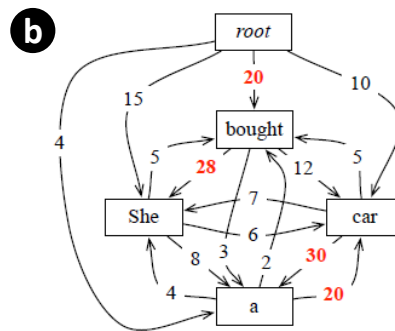
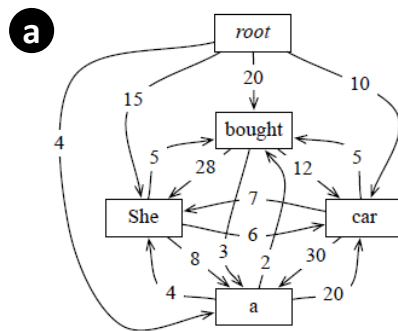
```
function CONTRACT( $G, C$ ) returns contracted graph
```

```
function EXPAND( $T, C$ ) returns expanded graph
```


Graph-based dependency parsing

• Chu-Liu-Edmonds' algorithm

1. Keep only incoming edges with the maximum scores
2. If there is a cycle:
 - Pretend vertices in the cycle as one vertex, and update scores for all incoming edges to the cycle
 - Go to #1
3. Break all cycles by removing inappropriate edges in the cycle



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Evaluation of dependency parsers

- **Corpus-scale metrics**

- Percentage of sentences with the correct root
- Percentage of correctly parsed sentences

- **Sentence-scale metrics**

- For each tree, the percentages of words with...
 - **correct heads** → **unlabeled attachment score (UAS)**
 - **correct labels** → **label accuracy score (LS)**
 - **correct heads and labels** → **labeled attachment score (LAS)**

Evaluation of dependency parsers

• Metrics – example

• **Unlabeled attachment score, UAS** (correct heads)

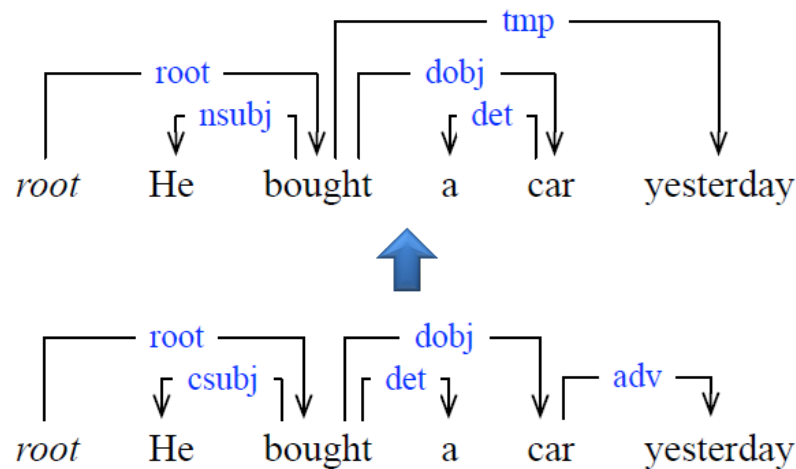
- Mismatches: bought → a, car → yesterday
- $UAS = 3/5 = 60\%$

• **Label accuracy, LS** (correct labels)

- Mismatches: He-csubj, yesterday-adv
- $LS = 3/5 = 60\%$

• **Labeled attachment score, LAS** (correct heads and labels)

- Mismatches: He-csubj, bought → a, car → yesterday-adv
- $LAS = 2/5 = 40\%$



Evaluation of dependency parsers

- **Metrics – representative performance numbers**
 - The CoNLL-X (2006) shared task provides evaluation numbers for various dependency Parsing approaches over 13 languages
 - LAS scores from 65–92%, depending greatly on language/treebank
 - Some UAS scores for English

Parser	UAS
Sagae and Lavie (2006): ensemble of dependency parsers	92.7
Charniak (2000): generative, constituency as dependencies	92.2
Collins (1999): generative, constituency as dependencies	91.7
McDonald and Pereira (2005): MST graph-based dependencies	91.5
Yamada and Matsumoto (2003): transition-based dependencies	90.4

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Resources

- **Typed dependencies manual**

- https://nlp.stanford.edu/software/dependencies_manual.pdf

- **Repository of dependency parsers, papers and evaluation results**

- http://nlpprogress.com/english/dependency_parsing.html

- **Stanford parsers**

- <https://nlp.stanford.edu/software/lex-parser.html>
- <https://stanfordnlp.github.io/CoreNLP/depparse.html>



- **NLTK parsers**

- <https://www.nltk.org/api/nltk.parse.html>
- <http://www.nltk.org/howto/dependency.html>



References

- **Jurafsky, D., Martin, J. H.** (2025) **Speech and language processing** (3rd edition – draft January 12, 2025).
 - Chapter 19
- **Eisenstein, J.** (2019). **Introduction to Natural Language Processing.** The MIT Press.
 - Chapter 11



Escuela Politécnica Superior

Master course

Deep learning for natural language processing

Unit 2 – Natural language tasks (part III)

Dependency parsing

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