## ANLP Lecture 15 Dependency Syntax and Parsing

Shay Cohen (based on slides by Sharon Goldwater and Nathan Schneider)

18 October, 2019

### A warm-up question

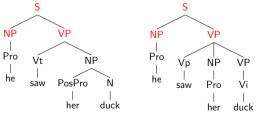
We described the generative story for PCFGs - pick a rule at random and terminate when choosing a terminal symbol. Does this process have to terminate?

### Last class

- ► Probabilistic context-free grammars
- ► Probabilistic CYK
- ► Best-first parsing
- Problems with PCFGs (model makes too strong independence assumptions)

### Evaluating parse accuracy

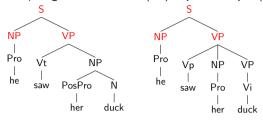
Compare gold standard tree (left) to parser output (right):



- Output constituent is counted correct if there is a gold constituent that spans the same sentence positions.
- ► Harsher measure: also require the constituent labels to match.
- Pre-terminals don't count as constituents.

### Evaluating parse accuracy

### Compare gold standard tree (left) to parser output (right):



- ▶ **Precision**: (# correct constituents)/(# in parser output) =
- Recall: (# correct constituents)/(# in gold standard) = 3/4F-score: balances precision/recall: 2pr/(p+r)

### Parsing: where are we now?

Parsing is not just WSJ. Lots of situations are much harder!

- ▶ Other languages, esp with free word order (up next) or little annotated data.
- Other domains, esp with jargon (e.g., biomedical) or non-standard language (e.g., social media text).

In fact, due to increasing focus on multilingual NLP, constituency syntax/parsing (English-centric) is losing ground to dependency parsing...

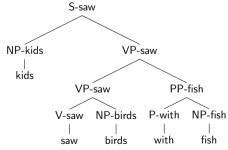
### Parsing: where are we now?

- ▶ We discussed the basics of probabilistic parsing and you should now have a good idea of the issues involved.
- ▶ State-of-the-art parsers address these issues in other ways. For comparison, parsing F-scores on WSJ corpus are:

  - vanilla PCFG:  $<80\%^1$  lexicalizing + cat-splitting: 89.5% (Charniak, 2000) Best current parsers get about 94%
- ▶ We'll say a little bit about recent methods later, but most details in sem 2.

### Lexicalization, again

We saw that adding lexical head of the phrase can help choose the right parse:



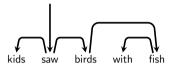
Dependency syntax focuses on the head-dependent relationships.

<sup>&</sup>lt;sup>1</sup>Charniak (1996) reports 81% but using gold POS tags as input.

### Dependency syntax

An alternative approach to sentence structure.

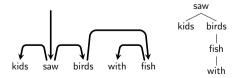
- ▶ A fully lexicalized formalism: no phrasal categories.
- Assumes binary, asymmetric grammatical relations between words: head-dependent relations, shown as directed edges:



▶ Here, edges point from heads to their dependents.

### It really is a tree!

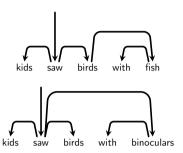
- The usual way to show dependency trees is with edges over ordered sentences.
- But the edge structure (without word order) can also be shown as a more obvious tree:



### Dependency trees

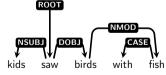
A valid dependency tree for a sentence requires:

- ► A single distinguished **root** word.
- ▶ All other words have exactly one incoming edge.
- ▶ A unique path from the root to each other word.



### Labelled dependencies

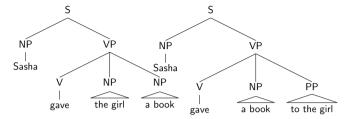
It is often useful to distinguish different kinds of head  $\rightarrow$  modifier relations, by labelling edges:



- ► Historically, different treebanks/languages used different labels
- Now, the Universal Dependencies project aims to standardize labels and annotation conventions, bringing together annotated corpora from over 50 languages.
- Labels in this example (and in textbook) are from UD.

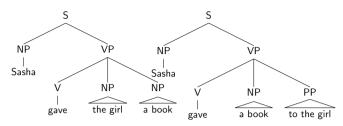
### Why dependencies??

Consider these sentences. Two ways to say the same thing:



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Consider these sentences. Two ways to say the same thing:



 $\blacktriangleright$  We only need a few phrase structure rules:  $\mathtt{S} \to \mathtt{NP} \ \mathtt{VP}$ 

 $\ensuremath{\mathsf{VP}} \to \ensuremath{\mathsf{V}} \ensuremath{\mathsf{NP}} \ensuremath{\mathsf{NP}} \ensuremath{\mathsf{NP}} \ensuremath{\mathsf{NP}} \ensuremath{\mathsf{PP}}$  NP PP plus rules for NP and PP.

### Equivalent sentences in Russian

- ▶ Russian uses morphology to mark relations between words:
  - knigu means book (kniga) as a direct object.
  - devochke means girl (devochka) as indirect object (to the girl).
- ▶ So we can have the same word orders as English:
  - ► Sasha dal devochke knigu
  - ► Sasha dal knigu devochke

### Equivalent sentences in Russian

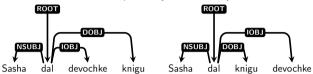
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- $\,\blacktriangleright\,$  So we can have the same word orders as English:
  - ► Sasha dal devochke knigu
  - ► Sasha dal knigu devochke
- ▶ But also many others!
  - ► Sasha devochke dal knigu
  - ► Devochke dal Sasha knigu
  - ► Knigu dal Sasha devochke

### Phrase structure vs dependencies

- ► In languages with **free word order**, phrase structure (constituency) grammars don't make as much sense.
  - ▶ E.g., we would need both S  $\rightarrow$  NP VP and S  $\rightarrow$  VP NP, etc. Not very informative about what's really going on.

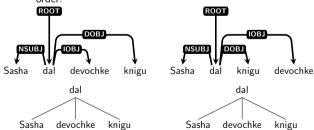
### Phrase structure vs dependencies

- ► In languages with **free word order**, phrase structure (constituency) grammars don't make as much sense.
  - ▶ E.g., we would need both  $S \to NP$  VP and  $S \to VP$  NP, etc. Not very informative about what's really going on.
- ▶ In contrast, the dependency relations stay constant:



### Phrase structure vs dependencies

Even more obvious if we just look at the trees without word order:



### Pros and cons

- ► Sensible framework for free word order languages.
- ► Identifies syntactic relations directly. (using CFG, how would you identify the subject of a sentence?)
- ▶ Dependency pairs/chains can make good features in classifiers, for information extraction, etc.
- ▶ Parsers can be very fast (coming up...)

### $\mathsf{But}$

► The assumption of asymmetric binary relations isn't always right... e.g., how to parse dogs and cats?

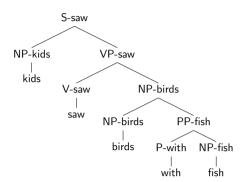
### How do we annotate dependencies?

### Two options:

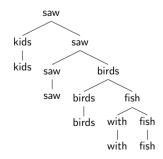
- 1. Annotate dependencies directly.
- 2. Convert phrase structure annotations to dependencies. (Convenient if we already have a phrase structure treebank.)

Next slides show how to convert, assuming we have head-finding rules for our phrase structure trees.

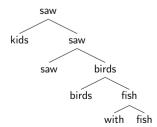
### Lexicalized Constituency Parse



### ... remove the phrasal categories...

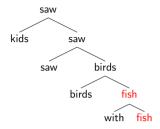


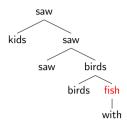
### ... remove the (duplicated) terminals...



...and collapse chains of duplicates...

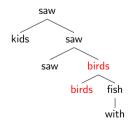
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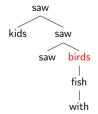




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### ...and collapse chains of duplicates...

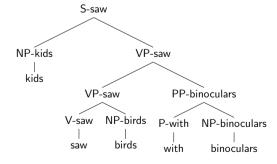
# saw birds saw birds |

### ...done!



### Constituency Tree $\rightarrow$ Dependency Tree

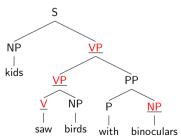
We saw how the **lexical head** of the phrase can be used to collapse down to a dependency tree:



▶ But how can we find each phrase's head in the first place?

### Head Rules

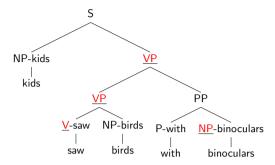
The standard solution is to use **head rules**: for every non-unary (P)CFG production, designate one RHS nonterminal as containing the head. S  $\rightarrow$  NP  $\underline{\text{VP}}$ , VP  $\rightarrow$   $\underline{\text{VP}}$  PP, PP  $\rightarrow$  P  $\underline{\text{NP}}$  (content head), etc.



► Heuristics to scale this to large grammars: e.g., within an NP, last immediate N child is the head.

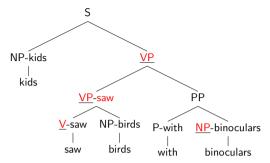
### Head Rules

Then, propagate heads up the tree:



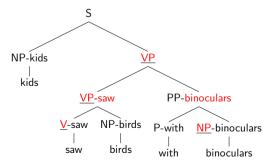
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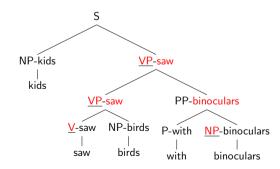
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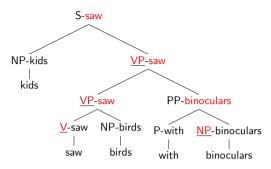
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### Head Rules

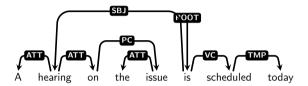
Then, propagate heads up the tree:



### **Projectivity**

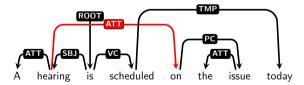
If we convert constituency parses to dependencies, all the resulting trees will be **projective**.

- Every subtree (node and all its descendants) occupies a contiguous span of the sentence.
- = the parse can be drawn over the sentence w/ no crossing edges.



### Nonprojectivity

But some sentences are nonprojective.



- ▶ We'll only get these annotations right if we directly annotate the sentences (or correct the converted parses).
- Nonprojectivity is rare in English, but common in many languages.
- Nonprojectivity presents problems for parsing algorithms.

### **Dependency Parsing**

Some of the algorithms you have seen for PCFGs can be adapted to dependency parsing.

- **CKY** can be adapted, though efficiency is a concern: obvious approach is  $O(Gn^5)$ ; Eisner algorithm brings it down to  $O(Gn^3)$ 
  - N. Smith's slides explaining the Eisner algorithm: http://courses.cs.washington.edu/courses/cse517/ 16wi/slides/an-dep-slides.pdf
- ▶ **Shift-reduce**: more efficient, doesn't even require a grammar!

### Recall: shift-reduce parser with CFG

Step 0	Op.	Stack	Input the dog bit
1	S	the	dog bit
2	R	DT	dog bit
3	S	DT dog	bit
4	R	DT V	bit
5	R	DT VP	bit
6	S	DT VP bit	
7	R	DT VP V	
8	R	DT VP VP	
9	B6	DT VP bit	
10	R	DT VP NN	
11	B4	DT V	bit
12	S	DT V bit	
13	R	DT V V	
14	R	DT V VP	
15	B3	DT dog	bit
16	R	DT NN	bit
17	R	NP	bit
	0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16	0 1 S 2 R S S 4 R S S R 6 S 7 R S R 8 R 9 B 6 10 R 11 B 4 12 S 13 R 14 R 15 B 3 16 R 17 R	0 1 S the 2 R DT 3 S DT dog 4 R DT V 5 R DT VP 6 S DT VP bit 7 R DT VP V 8 R DT VP VP 9 B6 DT VP bit 10 R DT VP NN 11 B4 DT V 12 S DT V bit 13 R DT V V 14 R DT V VP 15 B3 DT dog 16 R DT NN 17 R NP

### Transition-based Dependency Parsing

The **arc-standard** approach parses input sentence  $w_1 \dots w_N$  using two types of **reduce** actions (three actions altogether):

- **Shift:** Read next word  $w_i$  from input and push onto the stack.
- ▶ **LeftArc:** Assign head-dependent relation  $s_2 \leftarrow s_1$ ; pop  $s_2$
- **RightArc:** Assign head-dependent relation  $s_2 \rightarrow s_1$ ; pop  $s_1$

where  $s_1$  and  $s_2$  are the top and second item on the stack, respectively. (So,  $s_2$  preceded  $s_1$  in the input sentence.)

### Example

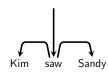
### Parsing Kim saw Sandy:

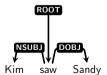
Step	$\leftarrow$ bot. $Stacktop \rightarrow$	Word List	Action	Relations
0	[root]	[Kim,saw,Sandy]	Shift	
1	[root,Kim]	[saw,Sandy]	Shift	
2	[root,Kim,saw]	[Sandy]	LeftArc	Kim←saw
3	[root,saw]	[Sandy]	Shift	
4	[root,saw,Sandy]		RightArc	saw→Sandy
5	[root,saw]		RightArc	root→saw
6	[root]		(done)	

► Here, top two words on stack are also always adjacent in sentence. Not true in general! (See longer example in JM3.)

### Labelled dependency parsing

- ▶ These parsing actions produce **unlabelled** dependencies (left).
- ► For **labelled** dependencies (right), just use more actions: LeftArc(NSUBJ), RightArc(NSUBJ), LeftArc(DOBJ), . . .





### Differences to constituency parsing

- Shift-reduce parser for CFG: not all sequences of actions lead to valid parses. Choose incorrect action → may need to backtrack.
- ▶ Here, all valid action sequences lead to valid parses.
  - Invalid actions: can't apply LeftArc with root as dependent; can't apply RightArc with root as head unless input is empty.
  - ▶ Other actions may lead to incorrect parses, but still valid.
- ► So, parser doesn't backtrack. Instead, tries to greedily predict the correct action at each step.
  - ► Therefore, dependency parsers can be very fast (linear time).
  - ▶ But need a good way to predict correct actions (next lecture).

### Notions of validity

- ▶ In constituency parsing, valid parse = grammatical parse.
  - ► That is, we first define a grammar, then use it for parsing.
- ▶ In dependency parsing, we don't normally define a grammar.
  - ▶ Valid parses are those with the properties on slide 4.

### Summary: Transition-based Parsing

- ▶ arc-standard approach is based on simple shift-reduce idea.
- Can do labelled or unlabelled parsing, but need to train a classifier to predict next action, as we'll see next time.
- Greedy algorithm means time complexity is linear in sentence length
- Only finds projective trees (without special extensions)
- ▶ Pioneering system: Nivre's MALTPARSER.

### Alternative: Graph-based Parsing

- ► Global algorithm: From the fully connected directed graph of all possible edges, choose the best ones that form a tree.
- ▶ Edge-factored models: Classifier assigns a nonnegative score to each possible edge; maximum spanning tree algorithm finds the spanning tree with highest total score in  $O(n^2)$  time.
- ▶ Pioneering work: McDonald's MSTPARSER
- ► Can be formulated as constraint-satisfaction with integer linear programming (Martins's TURBOPARSER)
- Details in JM3, Ch 16.5 (optional).

### Graph-based vs. Transition-based vs. Conversion-based

- ► TB: Features in scoring function can look at any part of the stack; no optimality guarantees for search; linear-time; (classically) projective only
- GB: Features in scoring function limited by factorization; optimal search within that model; quadratic-time; no projectivity constraint
- ➤ CB: In terms of accuracy, sometimes best to first constituency-parse, then convert to dependencies (e.g., STANFORD PARSER). Slower than direct methods.

### Choosing a Parser: Criteria

- ► Target representation: constituency or dependency?
- ▶ Efficiency? In practice, both runtime and memory use.
- ► Incrementality: parse the whole sentence at once, or obtain partial left-to-right analyses/expectations?
- ► Retrainable system?
- ► Accuracy?

### Summary

- Constituency syntax: hierarchically nested phrases with categories like NP.
- ► Dependency syntax: trees whose edges connect words in the sentence. Edges often labeled with relations like nsubj.
- Can convert constituency to dependency parse using head
- For projective trees, transition-based parsing is very fast and can be very accurate.
- ► Google "online dependency parser".

  Try out the Stanford parser and SEMAFOR!