Dependency Parsing



Outline

Two formalisms for syntactic structure: Phrase structure and dependencies

Two algorithms for dependency parsing

- Transition based dependency parsing
- Graph based dependency parsing

Evaluating dependencies

Dependency parsing

- Input: Sentence, tokenized + a dummy ROOT word
- Output: A dependency tree
 - Each word in the sentence is a node
 - Every word (except ROOT) should have an incoming edge indicating its head word
 - Only one word should be a dependent of ROOT
 - There are no cycles

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- Dependency theory also allows arrows to cross
 - Trees no arrows cross are called projective
 - Otherwise, they are called non-projective

Projective parse tree: No crossing dependency arcs when the words are laid out in their linear order, with all arcs above the word

Transition-based parsing

Graph based parsing

Transition-based parsing

- A generalization of the idea of shift-reduce parsing
- Greedily build attachments, using classifiers to decide which attachments to perform next
- Before neural networks: MaltParser (Nivre et al 2008)
- After neural networks: Chen and Manning (2014), Kipperwaser and Goldberg (2017)

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- Score all possible pairs of dependencies using a classifier
- Use a minimum spanning tree algorithm to find the best labeled tree
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Other algorithms exist as well. E.g. Eisner's algorithm is a dynamic programming approach

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Scoring trees: The edge factored model

Trees can be arbitrarily large because sentences can be arbitrarily large

We need a scoring scheme that can account for this

The edge factored model: The score for a tree is the sum of scores of all its edges

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

The modeling problem: Scoring edges

Any edge in the dependency tree is the tripe (head, dependent, label)

The scoring function can be any neural network.

Dozat and Manning (2017) trained two neural networks:

- 1. One computes the probability that there is an edge from word i to word j i.e., $P(i \rightarrow j)$
- 2. Another assigns a label to an edge, i.e., $P(label | i \rightarrow j)$

The inference problem

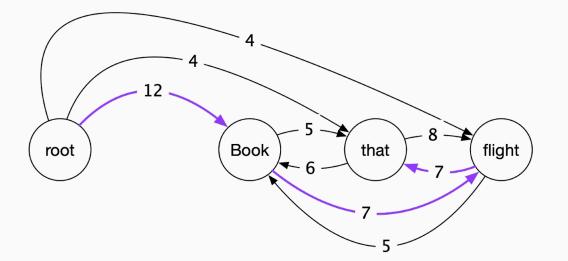
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This is the well studied problem of finding a maximum spanning tree

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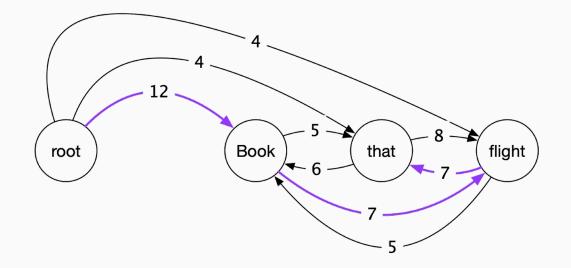
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The standard solution: The Chu-Liu Edmonds algorithm

Comparing transition- and graph-based parsing

- Computational Complexity
 - Graph based parsing is quadratic in the input length
 - Transition based parsing is linear in sentence length
- Projectivity
 - Graph based parsing can produce non-projective parse trees
 - Transition based parsing can only produce projective trees without additional cleanup
 - Tends to be a smaller issue English than for many languages
- Accuracy
 - Graph based parsers can be better on dependency arcs where the head is far from the dependent