

Dependency grammar and dependency parsing

Syntactic analysis (5LN455)

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Based on slides from Marco Kuhlmann



Activities - dependency parsing

- 3 lectures (December)
- I literature seminar (January 13)
- 2 assignments (DL: January 17)
 - Written assignment
 - Try and evaluate a state-of-the-art system,
 MaltParser
- Supervision on demand, by email or book a meeting



Overview

- Dependency parsing in general
- Arc-factored dependency parsing
 - Collins' algorithm
 - Eisner's algorithm
- Transition-based dependency parsing
 - The arc-standard algorithm
- Evaluation of dependency parsers



Dependency grammar



Dependency grammar

- The term 'dependency grammar' does not refer to a specific grammar formalism.
- Rather, it refers to a specific way to describe the syntactic structure of a sentence.





The notion of dependency

 The basic observation behind constituency is that groups of words may act as one unit.

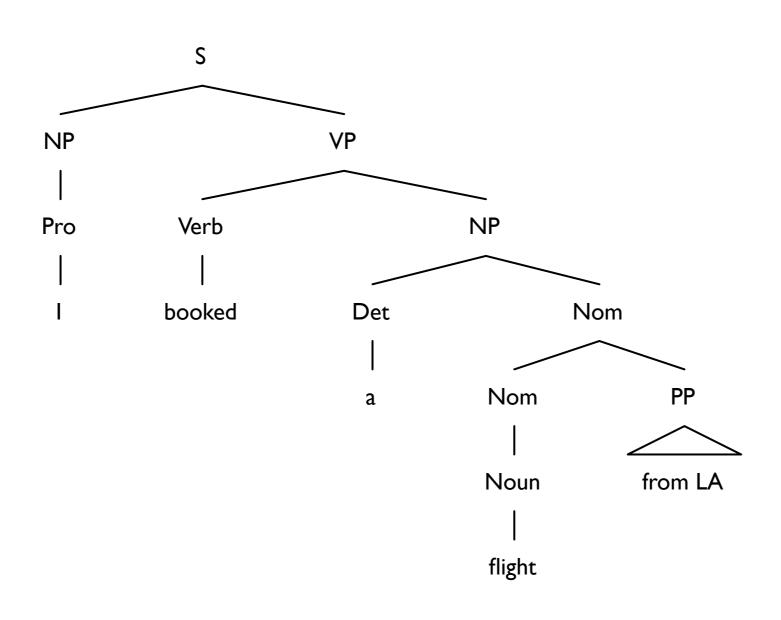
Example: noun phrase, prepositional phrase

• The basic observation behind dependency is that words have grammatical functions with respect to other words in the sentence.

Example: subject, modifier

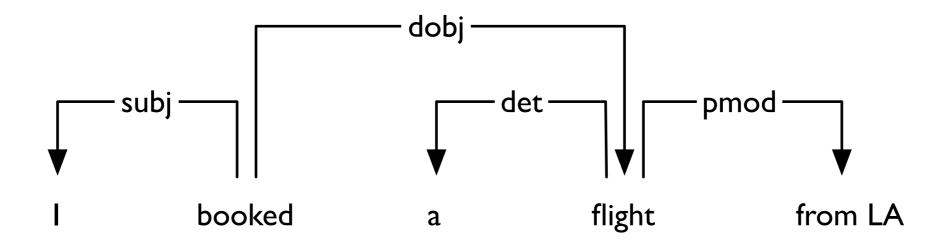
Dependency grammar

Phrase structure trees

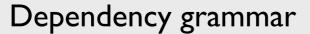




Dependency trees



- In an arc h → d, the word h is called the head, and the word d is called the dependent.
- The arcs form a rooted tree.
- Each arc has a label, I, and an arc can be described as (h, d, I)





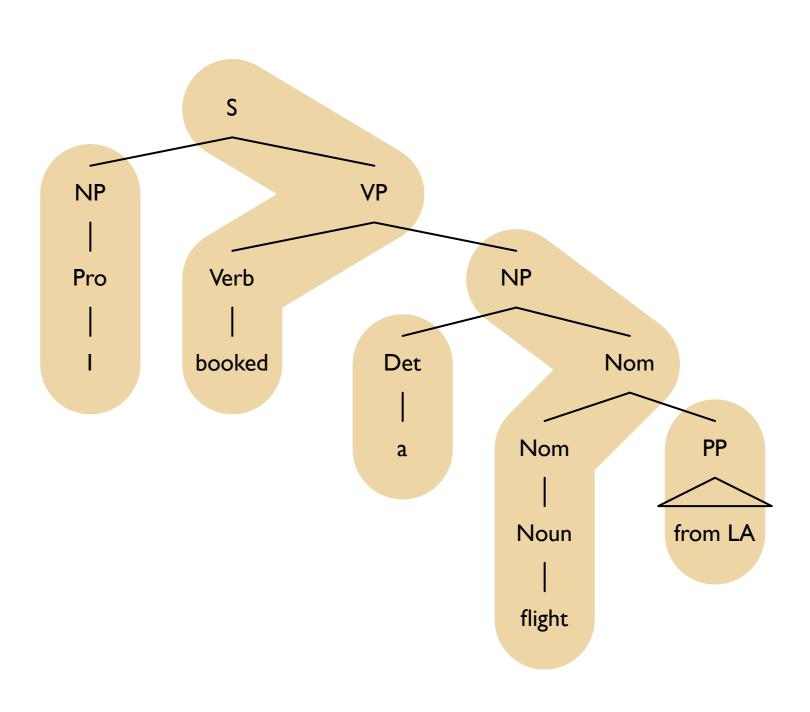
Heads in phrase structure grammar

- In phrase structure grammar, ideas from dependency grammar can be found in the notion of heads.
- Roughly speaking, the head of a phrase
 is the most important word of the phrase:
 the word that determines the phrase function.

Examples: noun in a noun phrase, preposition in a prepositional phrase

Dependency grammar

Heads in phrase structure grammar





The history of dependency grammar

- The notion of dependency can be found in some of the earliest formal grammars.
- Modern dependency grammar is attributed to Lucien Tesnière (1893–1954).



Recent years have seen

 a revived interest in dependency-based
 description of natural language syntax.





Linguistic resources

- Descriptive dependency grammars exist for some natural languages.
- Dependency treebanks exist for a wide range of natural languages.
- These treebanks can be used to train accurate and efficient dependency parsers.

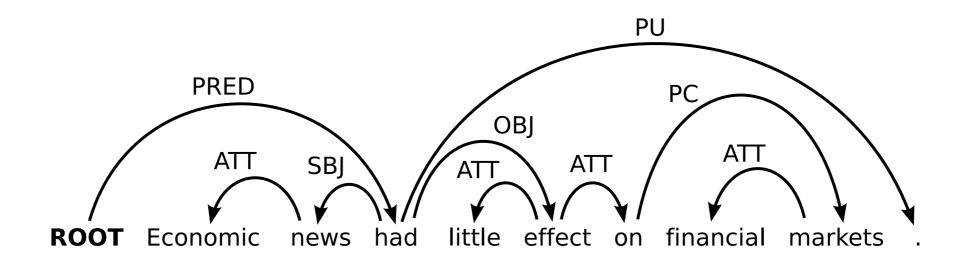


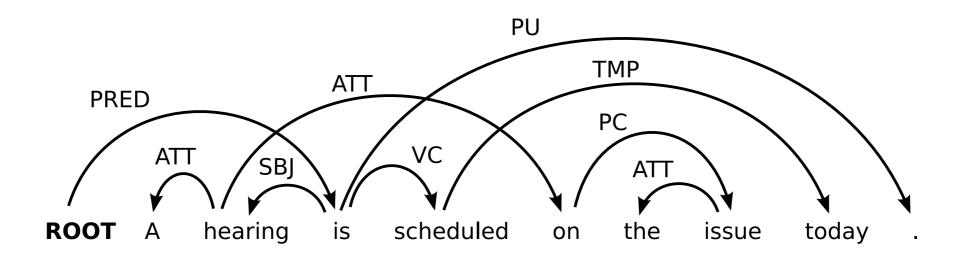
Projectivity

- An important characteristic of dependency trees is projectivity
- A dependency tree is projective if:
 - For every arc in the tree, there is a directed path from the head of the arc to all words occurring between the head and the dependent (that is, the arc (i,l,j) implies that i →* k for every k such that min(i, j) < k < max(i, j))



Projective and non-projective trees







Projectivity and dependency parsing

- Many dependency parsing algorithms can only handle projective trees
- Non-projective trees do occur in natural language
 - How often depends on the language (and treebank)



Projectivity in the course

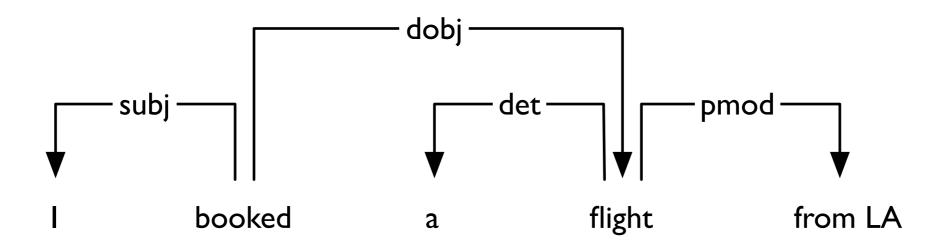
- The algorithms we will discuss in detail during the lectures will only concern projective parsing
- Non-projective parsing:
 - Seminar 2: Pseudo-projective parsing
 - Other variants mentioned briefly during the lectures
 - You can read more about it in the course book!





Ambiguity

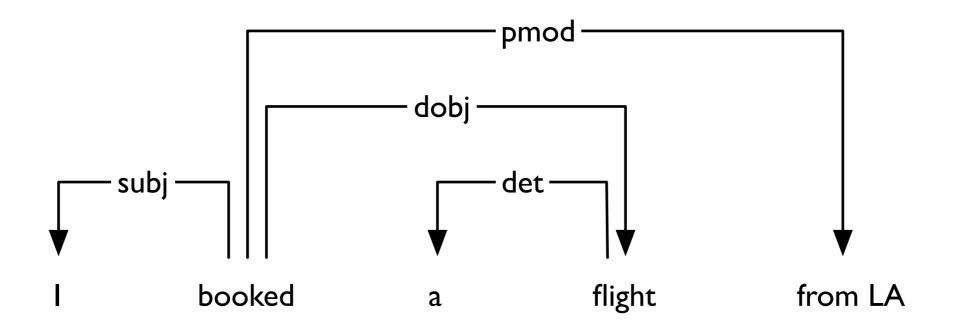
Just like phrase structure parsing, dependency parsing has to deal with ambiguity.





Ambiguity

Just like phrase structure parsing, dependency parsing has to deal with ambiguity.





Disambiguation

- We need to disambiguate between alternative analyses.
- We develop mechanisms for scoring dependency trees, and disambiguate by choosing a dependency tree with the highest score.



Scoring models and parsing algorithms

Distinguish two aspects:

- Scoring model:
 How do we want to score dependency trees?
- Parsing algorithm:
 How do we compute a highest-scoring
 dependency tree under the given scoring model?

The arc-factored model

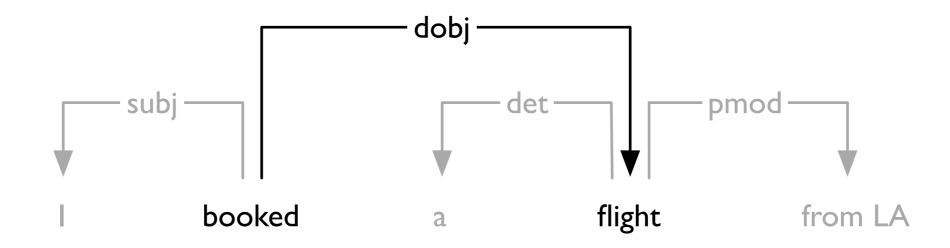
• Split the dependency tree t into parts $p_1, ..., p_n$, score each of the parts individually, and combine the score into a simple sum.

```
score(t) = score(p_1) + ... + score(p_n)
```

 The simplest scoring model is the arc-factored model, where the scored parts are the arcs of the tree.



Features



- To score an arc, we define features that are likely to be relevant in the context of parsing.
- We represent an arc by its feature vector.





Examples of features

• 'The head is a verb.'



- 'The head is a verb.'
- 'The dependent is a noun.'



- 'The head is a verb.'
- 'The dependent is a noun.'
- 'The head is a verb
 and the dependent is a noun.'



- 'The head is a verb.'
- 'The dependent is a noun.'
- 'The head is a verb

 and the dependent is a noun.'
- 'The head is a verb and the predecessor of the head is a pronoun.'



- 'The head is a verb.'
- 'The dependent is a noun.'
- 'The head is a verb

 and the dependent is a noun.'
- 'The head is a verb and the predecessor of the head is a pronoun.'
- 'The arc goes from left to right.'

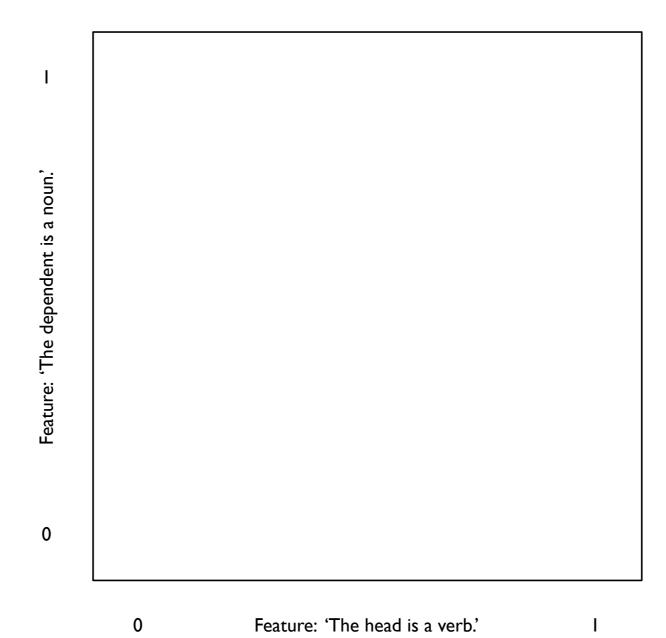


- 'The head is a verb.'
- 'The dependent is a noun.'
- 'The head is a verb

 and the dependent is a noun.'
- 'The head is a verb and the predecessor of the head is a pronoun.'
- 'The arc goes from left to right.'
- 'The arc has length 2.'

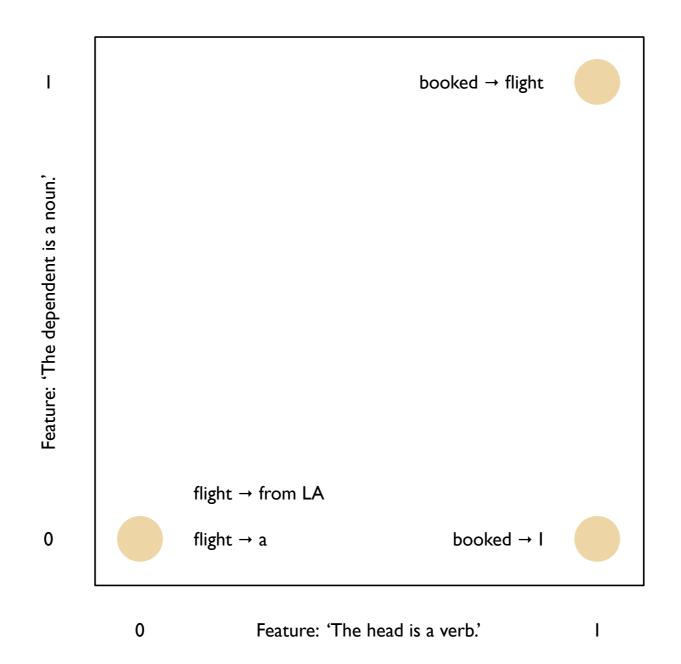


Feature vectors





Feature vectors







Implementation of feature vectors

- We assign each feature a unique number.
- For each arc, we collect the numbers
 of those features that apply to that arc.
- The feature vector of the arc is the list of those numbers.

Example: [1, 2, 42, 313, 1977, 2008, 2010]





Feature weights

- Arc-factored dependency parsers require a training phase.
- During training, our goal is to assign, to each feature f_i , a feature weight w_i .
- Intuitively, the weight w_i quantifies the effect of the feature f_i on the likelihood of the arc.

How likely is it that we will see an arc with this feature in a useful dependency tree?



Feature weights

We define the score of an arc $h \rightarrow d$ as the weighted sum of all features of that arc:

$$score(h \rightarrow d) = f_1w_1 + ... + f_nw_n$$



Training using structured prediction

- Take a sentence w and a gold-standard dependency tree g for w.
- Compute the highest-scoring dependency tree under the current weights; call it p.
- Increase the weights of all features that are in g but not in p.
- Decrease the weights of all features that are in p but not in g.





Training using structured prediction

- Training involves repeatedly parsing (treebank) sentences and refining the weights.
- Hence, training presupposes an efficient parsing algorithm.



Higher order models

- The arc-factored model is a first-order model, because scored subgraphs consist of a single arc.
- An nth-order model scores subgraphs consisting of (at most) n arcs.
- Second-order: siblings, grand-parents
- Third-order: tri-siblings, grand-siblings
- Higher-order models capture more linguistic structure and give higher parsing accuracy, but are less efficient



Parsing algorithms

- Projective parsing
 - Inspired by the CKY algorithm
 - Collins' algorithm
 - Eisner's algorithm
- Non-projective parsing:
 - Minimum spanning tree (MST) algorithms





Graph-based parsing

- Arc-factored parsing is an instance of graph-based dependency parsing
- Because it scores the dependency graph (tree)
- Graph-based models are often contrasted with transition-based models (next Wednesday)
- There are also grammar-based methods, which we will not discuss





Summary

- The term 'arc-factored dependency parsing' refers to dependency parsers that score a dependency tree by scoring its arcs.
- Arcs are scored by defining features and assigning weights to these features.
- The resulting parsers can be trained using structured prediction.
- More powerful scoring models exist.



Overview

Arc-factored dependency parsing

Collins' algorithm

Eisner's algorithm

Transition-based dependency parsing
 The arc-standard algorithm

Dependency treebanks

Evaluation of dependency parsers

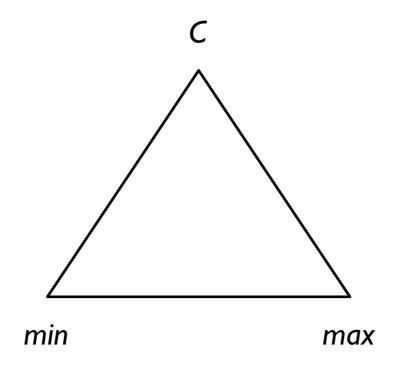




- Collin's algorithm is a simple algorithm for computing the highest-scoring dependency tree under an arc-factored scoring model.
- It can be understood as an extension
 of the CKY algorithm to dependency parsing.
- Like the CKY algorithm, it can be characterized as a bottom-up algorithm
 based on dynamic programming.



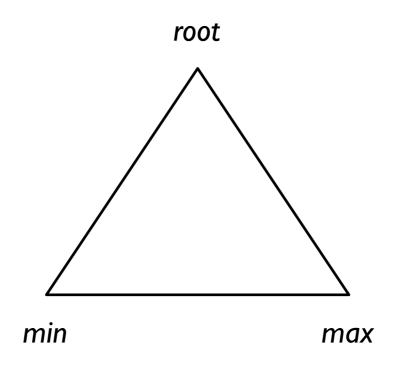
Signatures, CKY



[min, max, C]



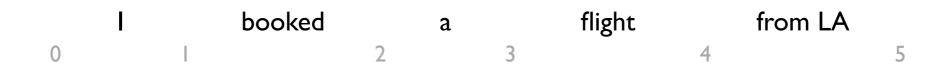
Signatures, Collins'



[min, max, root]

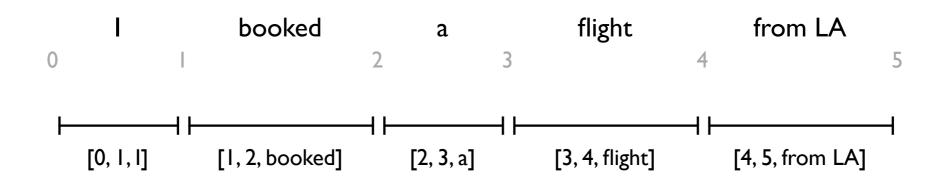


Initialization





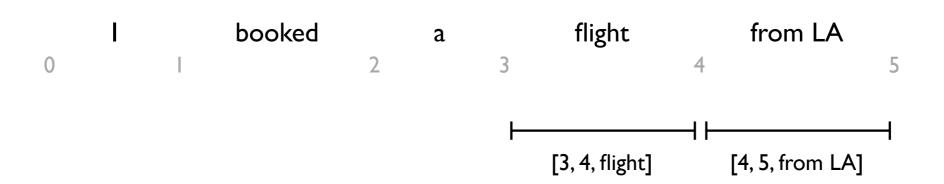
Initialization



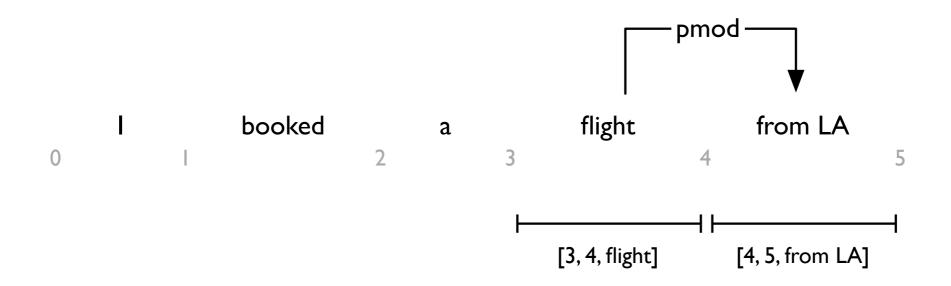




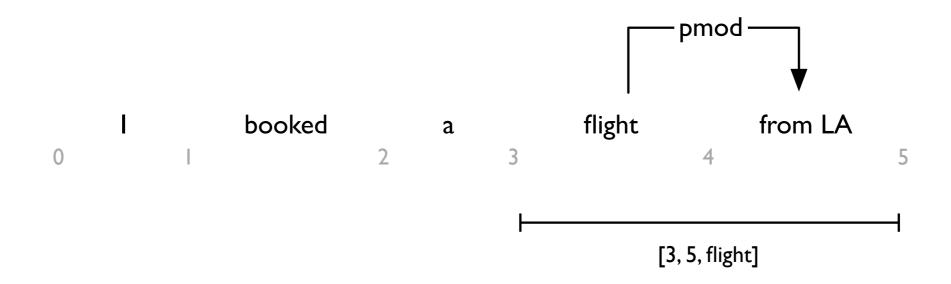






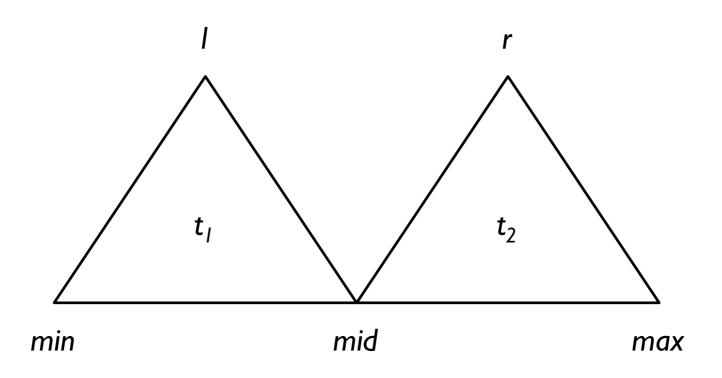




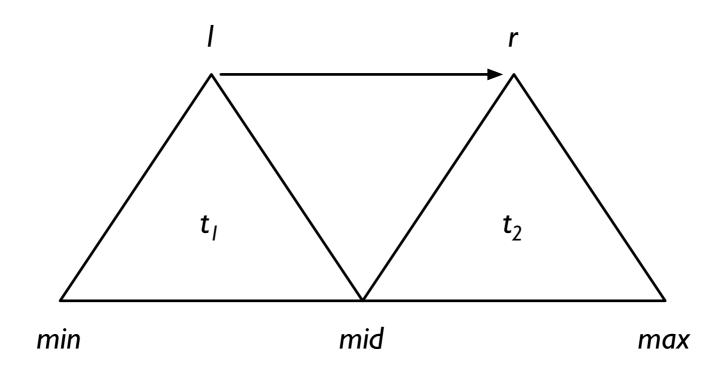




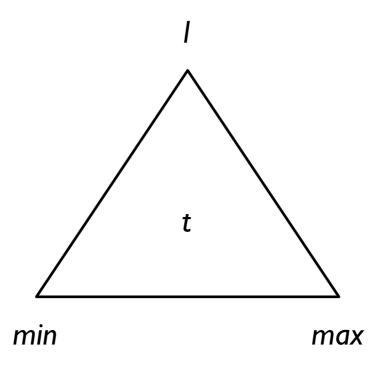




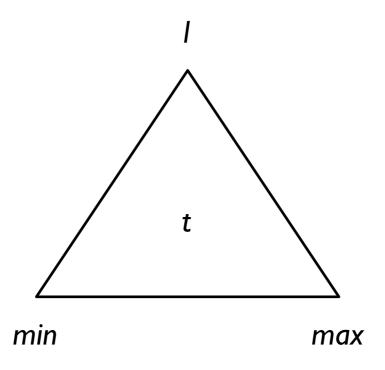








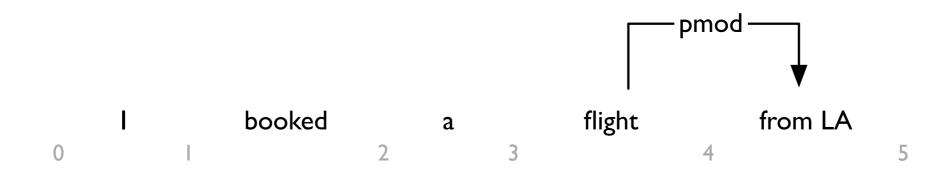




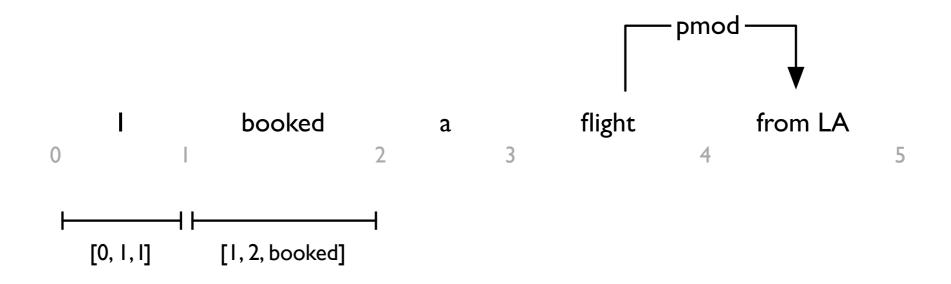
$$score(t) = score(t_1) + score(t_2) + score(l \rightarrow r)$$

```
for each [min, max] with max - min > 1 do
  for each 1 from min to max - 2 do
    double best = score[min][max][1]
    for each r from 1 + 1 to max - 1 do
      for each mid from l + 1 to r do
        t<sub>1</sub> = score[min][mid][1]
         t<sub>2</sub> = score[mid][max][r]
         double current = t_1 + t_2 + score(1 \rightarrow r)
         if current > best then
           best = current
    score[min][max][l] = best
```

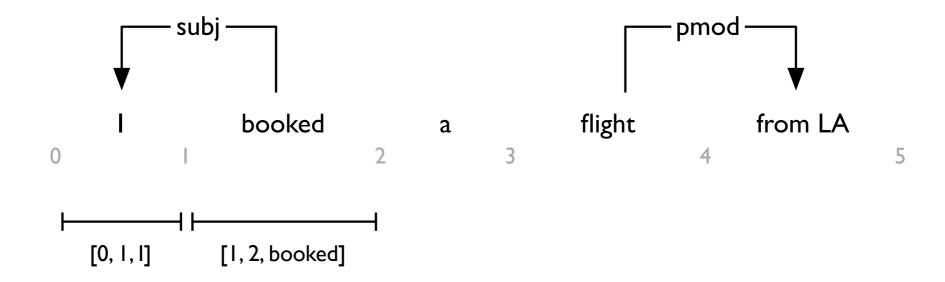




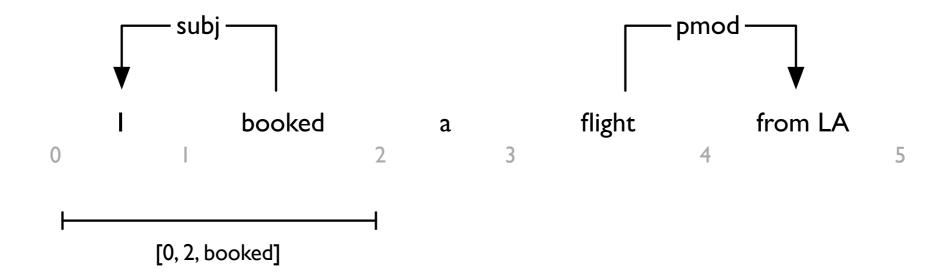






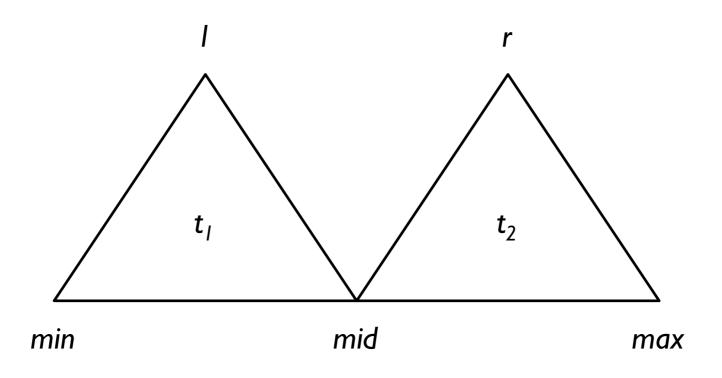




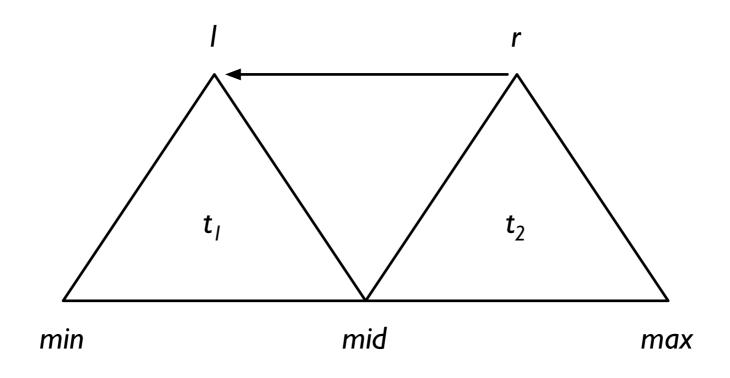




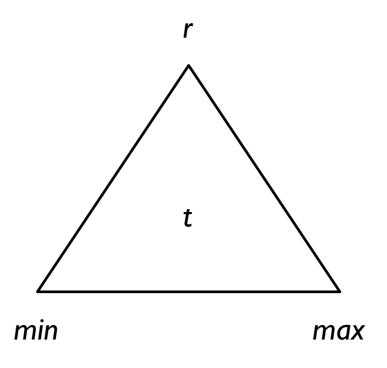


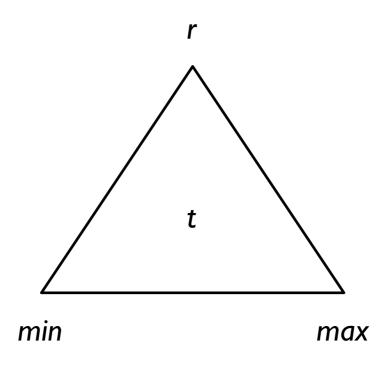








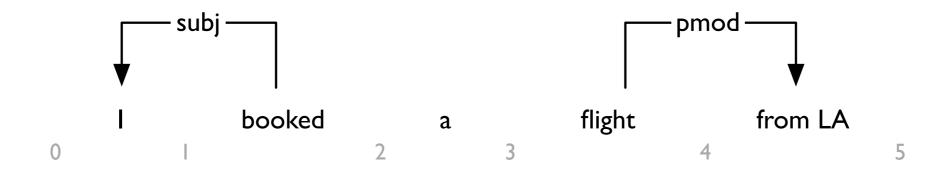




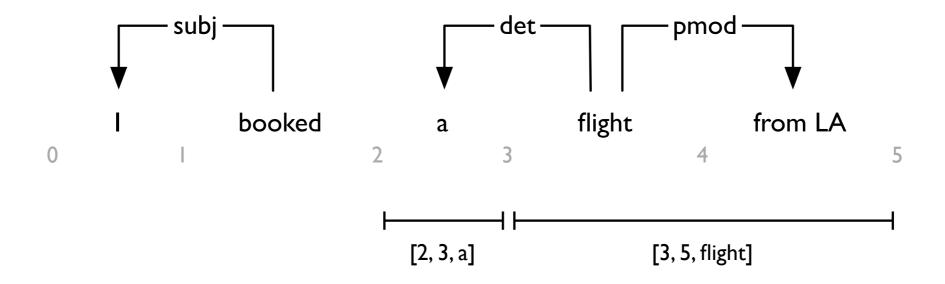
$$score(t) = score(t_1) + score(t_2) + score(r \rightarrow l)$$

```
for each [min, max] with max - min > 1 do
  for each r from min + 1 to max - 1 do
    double best = score[min][max][r]
    for each 1 from min to r - 1 do
      for each mid from 1 + 1 to r do
        t<sub>1</sub> = score[min][mid][1]
         t<sub>2</sub> = score[mid][max][r]
         double current = t_1 + t_2 + score(r \rightarrow 1)
         if current > best then
           best = current
    score[min][max][r] = best
```

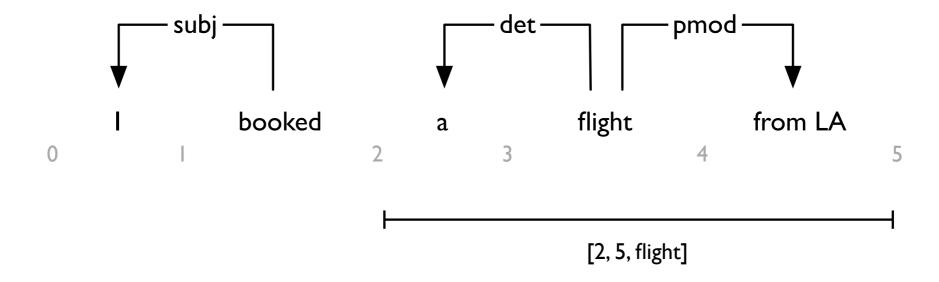




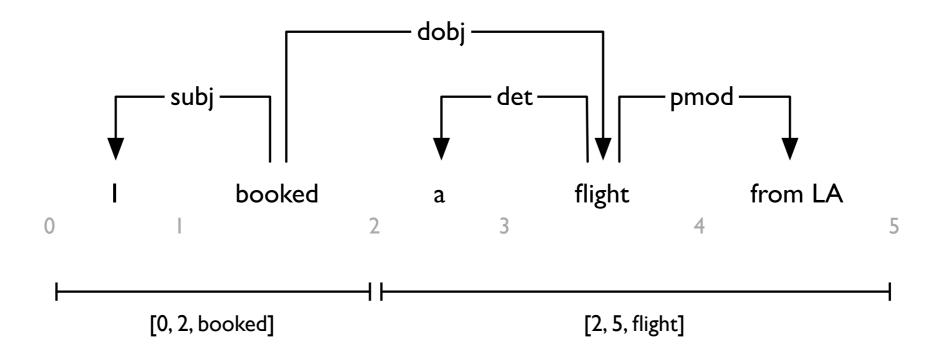




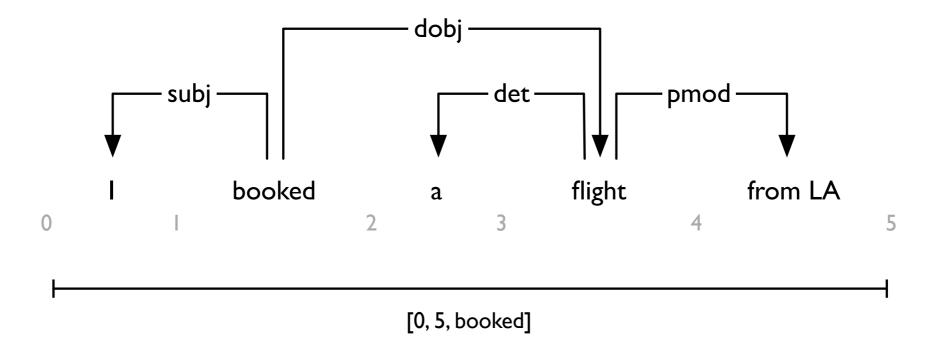














- Runtime?
- Space?

```
for each [min, max] with max - min > 1 do

for each r from min + 1 to max - 1 do

double best = score[min][max][r]

for each l from min to r - 1 do

for each mid from l + 1 to r do

t₁ = score[min][mid][l]

t₂ = score[mid][max][r]

double current = t₁ + t₂ + score(r → 1)

if current > best then

best = current

score[min][max][r] = best
```



- Runtime?
- Space?

```
for each [min, max] with max - min > 1 do
  for each r from min + 1 to max - 1 do
    double best = score[min][max][r]
    for each 1 from min to r - 1 do
      for each mid from 1 + 1 to r do
        t<sub>1</sub> = score[min][mid][l]
                                             min
        t<sub>2</sub> = score[mid][max][r]
        double current = t_1 + t_2 + score(r \rightarrow 1)
        if current > best then
           best = current
    score[min][max][r] = best
```

```
t_1 t_2 t_2 t_3 t_4 t_4 t_5
```



- Runtime?
- Space?

```
for each [min, max] with max - min > 1 do
  for each r from min + 1 to max - 1 do
    double best = score[min][max][r]
    for each 1 from min to r - 1 do
      for each mid from 1 + 1 to r do
        t<sub>1</sub> = score[min][mid][l]
                                             min
        t<sub>2</sub> = score[mid][max][r]
        double current = t_1 + t_2 + score(r \rightarrow 1)
        if current > best then
           best = current
    score[min][max][r] = best
```

```
t_1 t_2 t_2
```

- Space requirement: $O(|w|^3)$
- Runtime requirement: $O(|w|^5)$



Summary

- Collins' algorithm is a CKY-style algorithm for computing the highest-scoring dependency tree under an arc-factored scoring model.
- It runs in time $O(|w|^5)$. This may not be practical for long sentences.
- We have not discussed labels yet we will do that next lecture