

# 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 12)
- 2 assignments (DL: January 13)
  - 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.

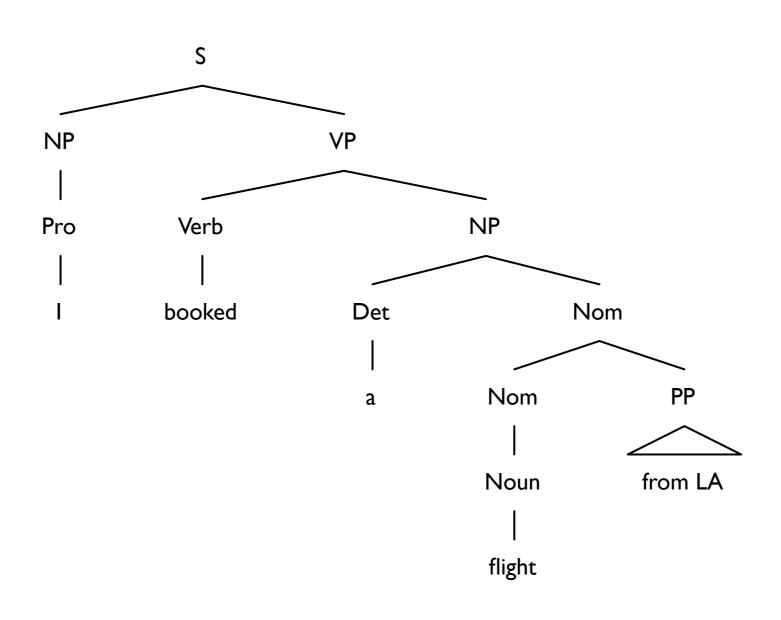
Example: noun phrase, prepositional phrase

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

Example: subject, modifier

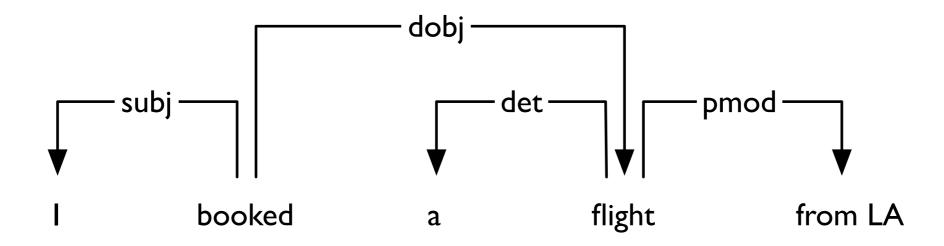
### Dependency grammar

### Phrase structure trees





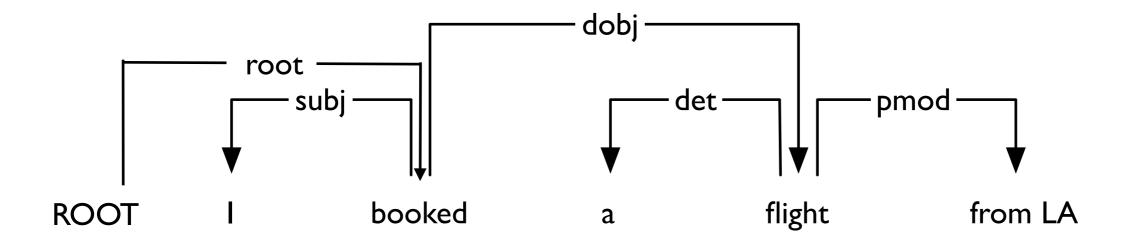
### Dependency trees



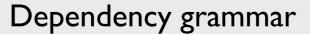
- In an arc h → d, the word h is called the head, and the word d is called the dependent.
- The arcs form a rooted tree.
- Each arc has a label, I, and an arc can be described as (h, d, I)



### Dependency trees



- In an arc h → d, the word h is called the head, and the word d is called the dependent.
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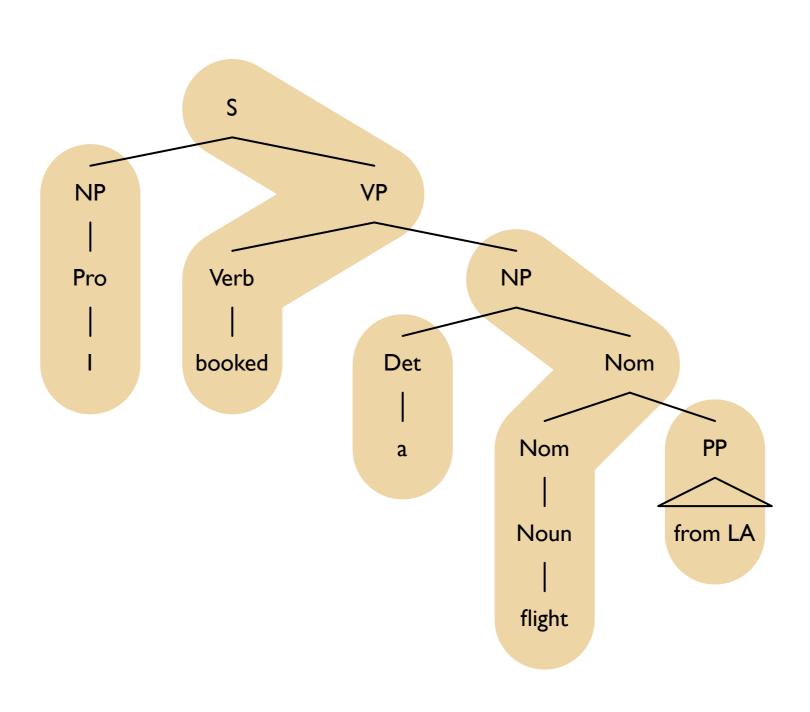
# Heads in phrase structure grammar

- 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.

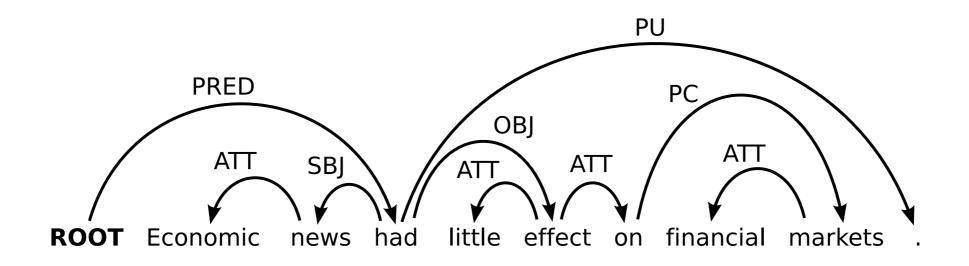


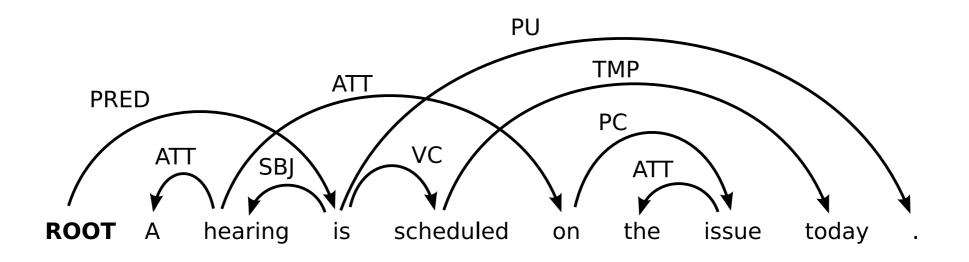
### Projectivity

- 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))</li>



### 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

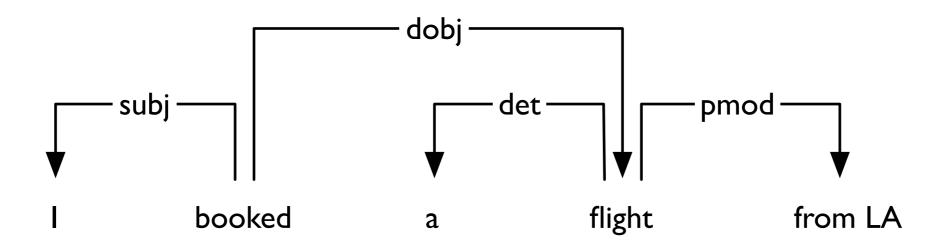
- The algorithms we will discuss in detail during the lectures will only concern projective parsing
- Non-projective parsing:
  - Seminar 2: Pseudo-projective parsing
  - Other variants mentioned briefly during the lectures
  - You can read more about it in the course book!





## **Ambiguity**

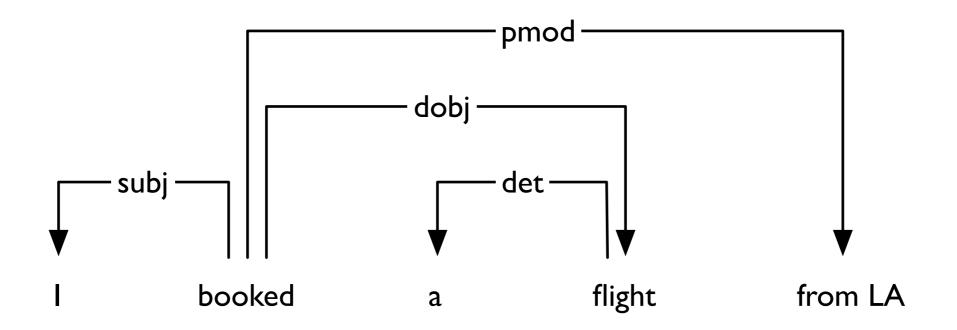
Just like phrase structure parsing, dependency parsing has to deal with ambiguity.





## **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

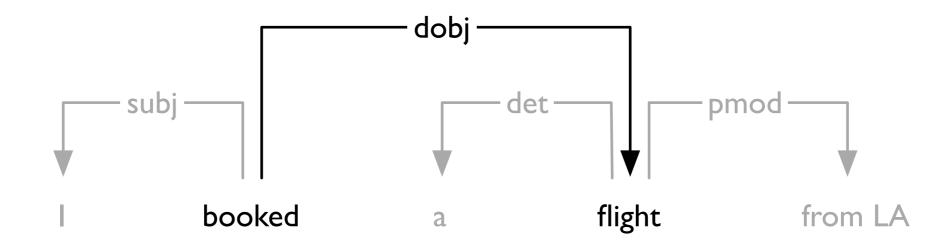
• Split the dependency tree t into parts  $p_1, ..., p_n$ , score each of the parts individually, and combine the score into a simple sum.

```
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.'

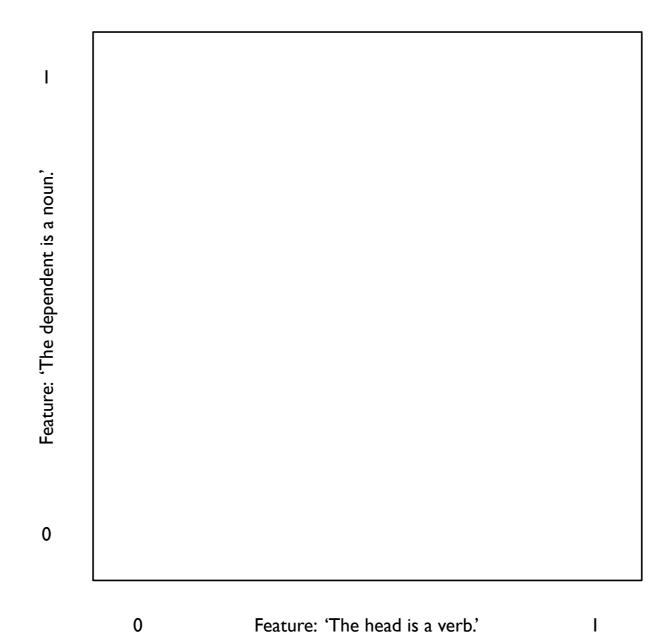


- 'The head is a verb.'
- 'The dependent is a noun.'
- 'The head is a verb

   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.'

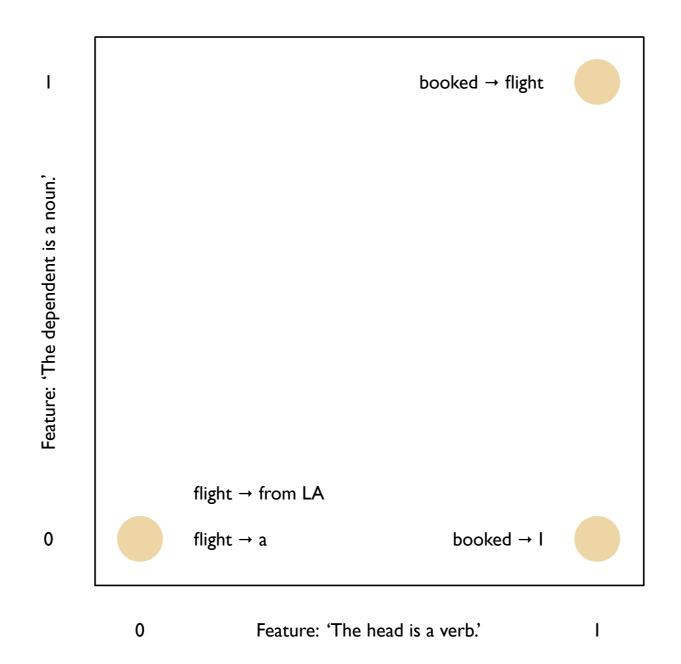


### Feature vectors





### 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 (Tuesday, Dec 13)
- 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

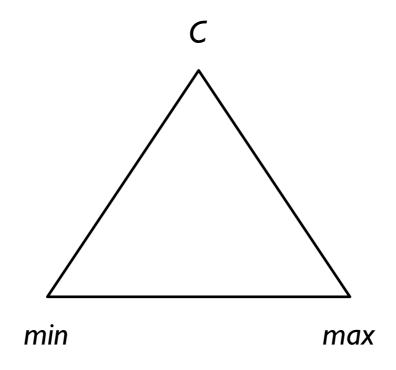




- Collin's algorithm is a simple algorithm for computing the highest-scoring dependency tree under an arc-factored scoring model.
- It can be understood as an extension
   of the CKY algorithm to dependency parsing.
- Like the CKY algorithm, it can be characterized as a bottom-up algorithm
   based on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



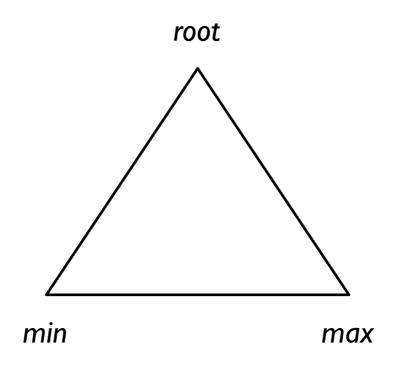
# Signatures, CKY



[min, max, C]



# Signatures, Collins'



[min, max, root]

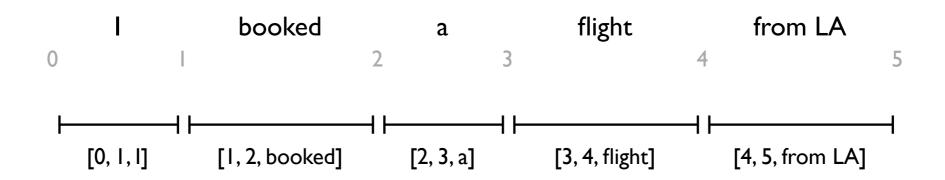


### Initialization





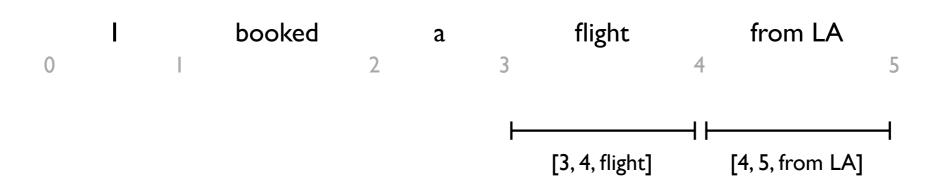
### Initialization



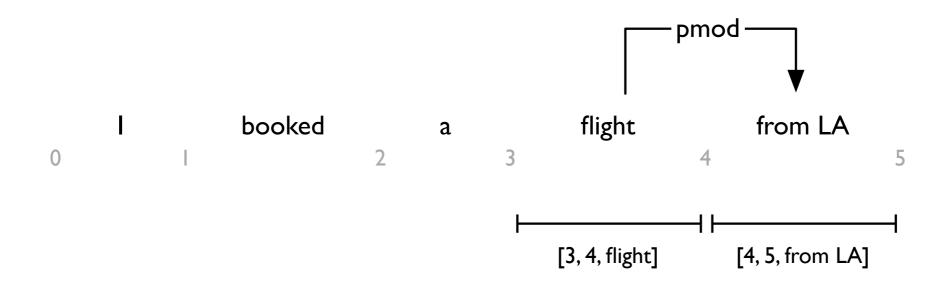




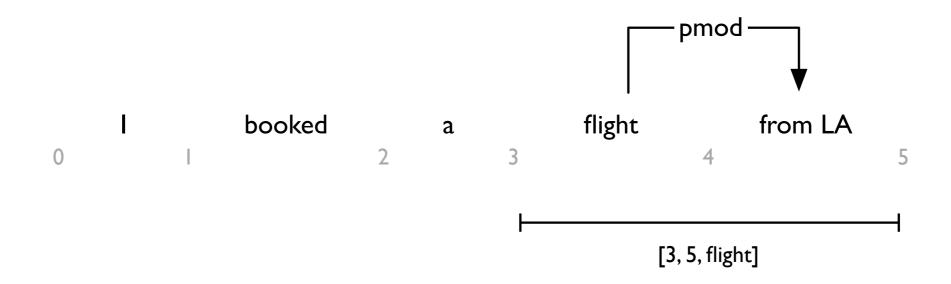






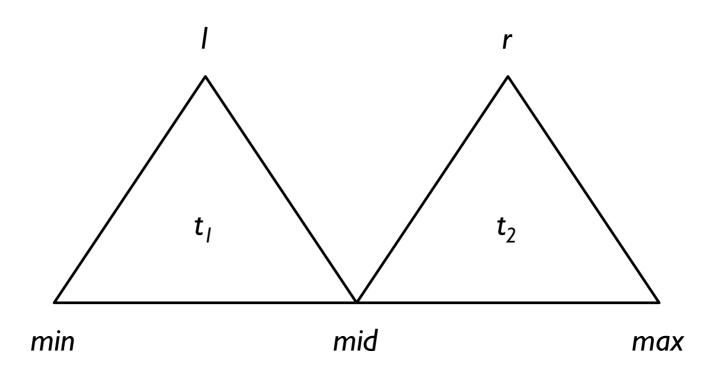




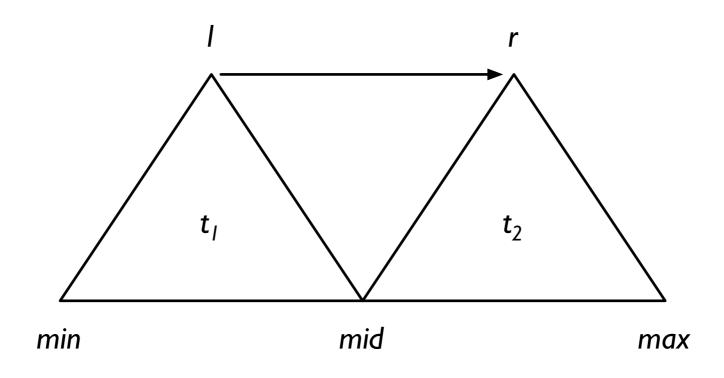




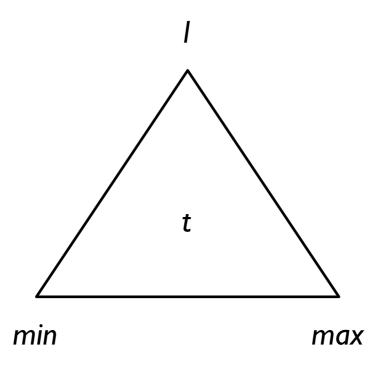




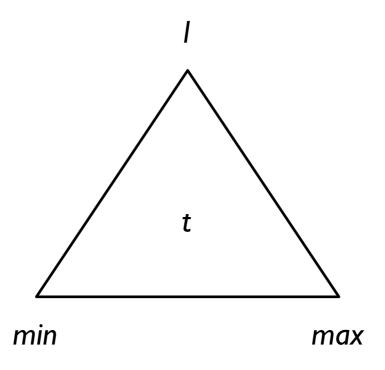








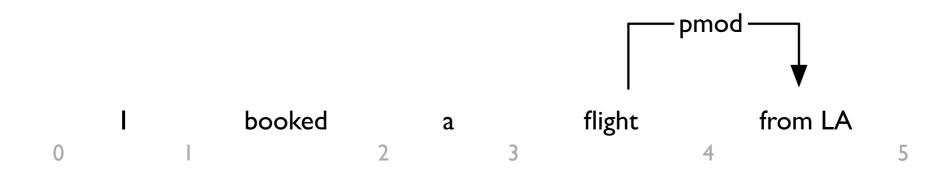




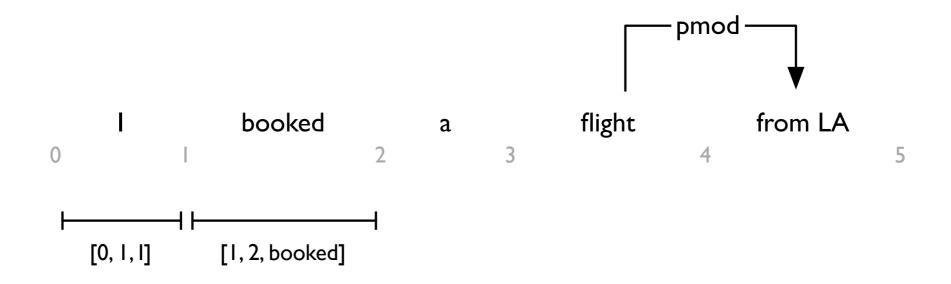
$$score(t) = score(t_1) + score(t_2) + score(l \rightarrow r)$$

```
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
```

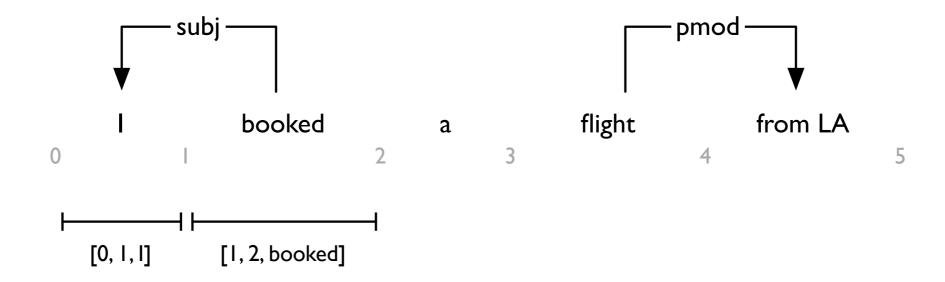




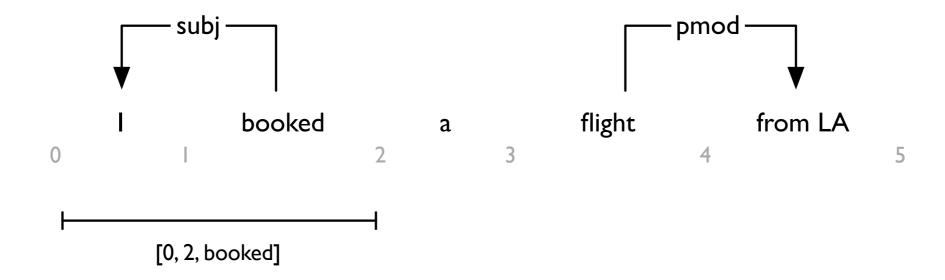






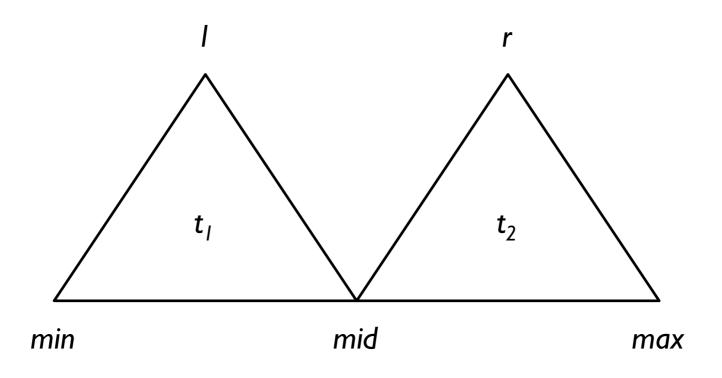




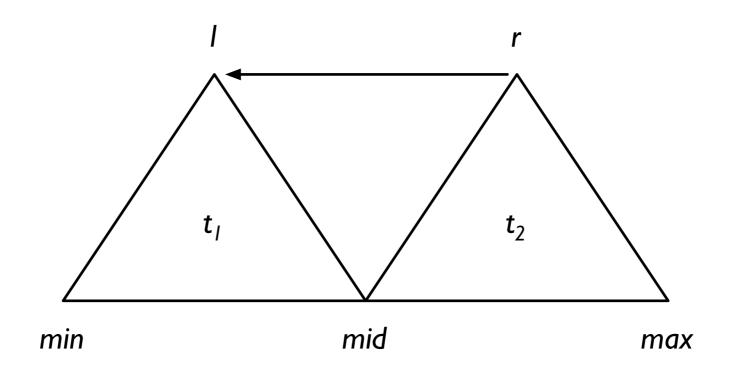




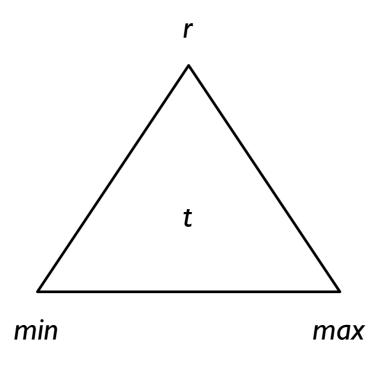


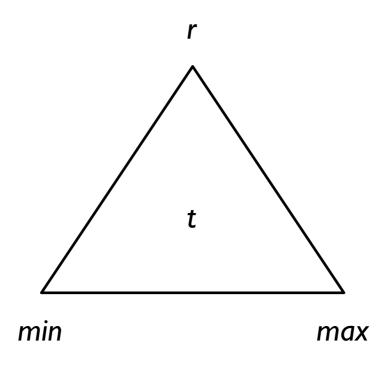








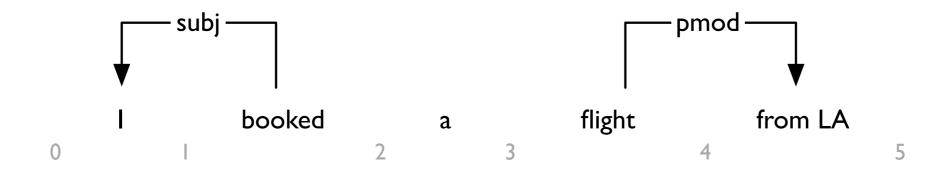




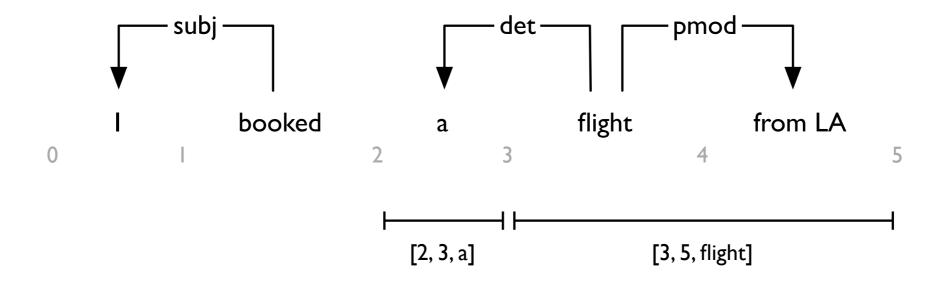
$$score(t) = score(t_1) + score(t_2) + score(r \rightarrow l)$$

```
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
```

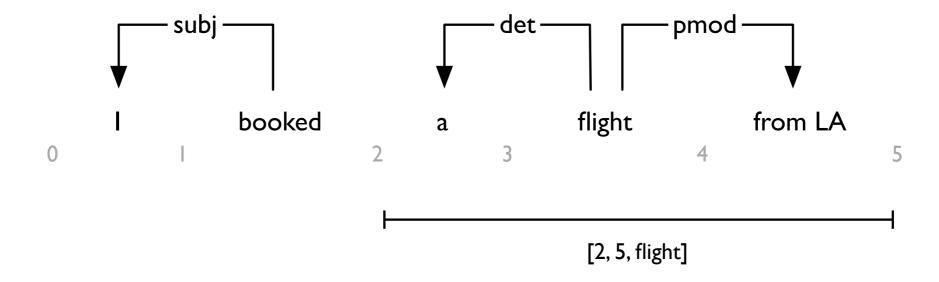




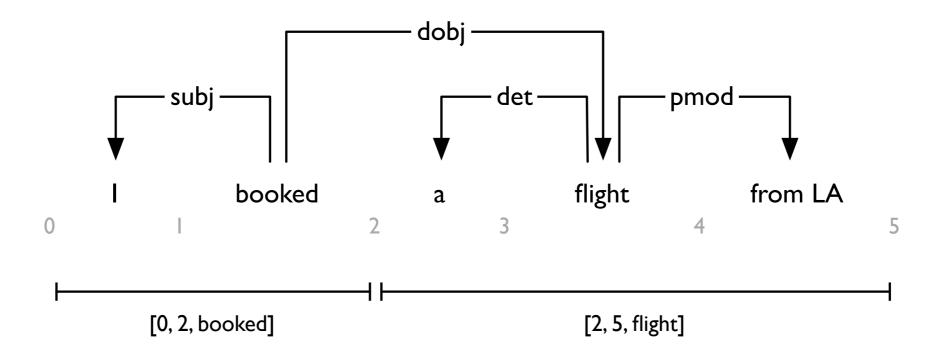




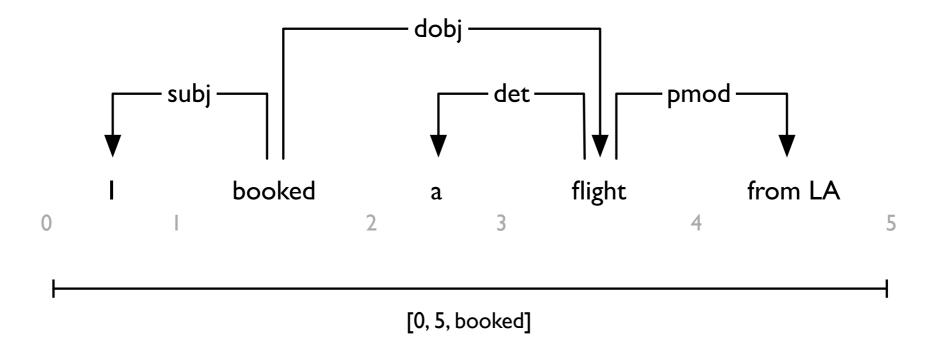














- Runtime?
- Space?

```
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][1]

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