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Dependency grammar and dependency parsing

Syntactic analysis (5LN455)

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Based on slides from Marco Kuhlmann

Overview

- Arc-factored dependency parsing
  - Collins' algorithm
  - Eisner's algorithm
- Evaluation of dependency parsers
- Transition-based dependency parsing
  - The arc-standard algorithm
- Projectivity
- Advanced dependency parsing

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Dependency grammar

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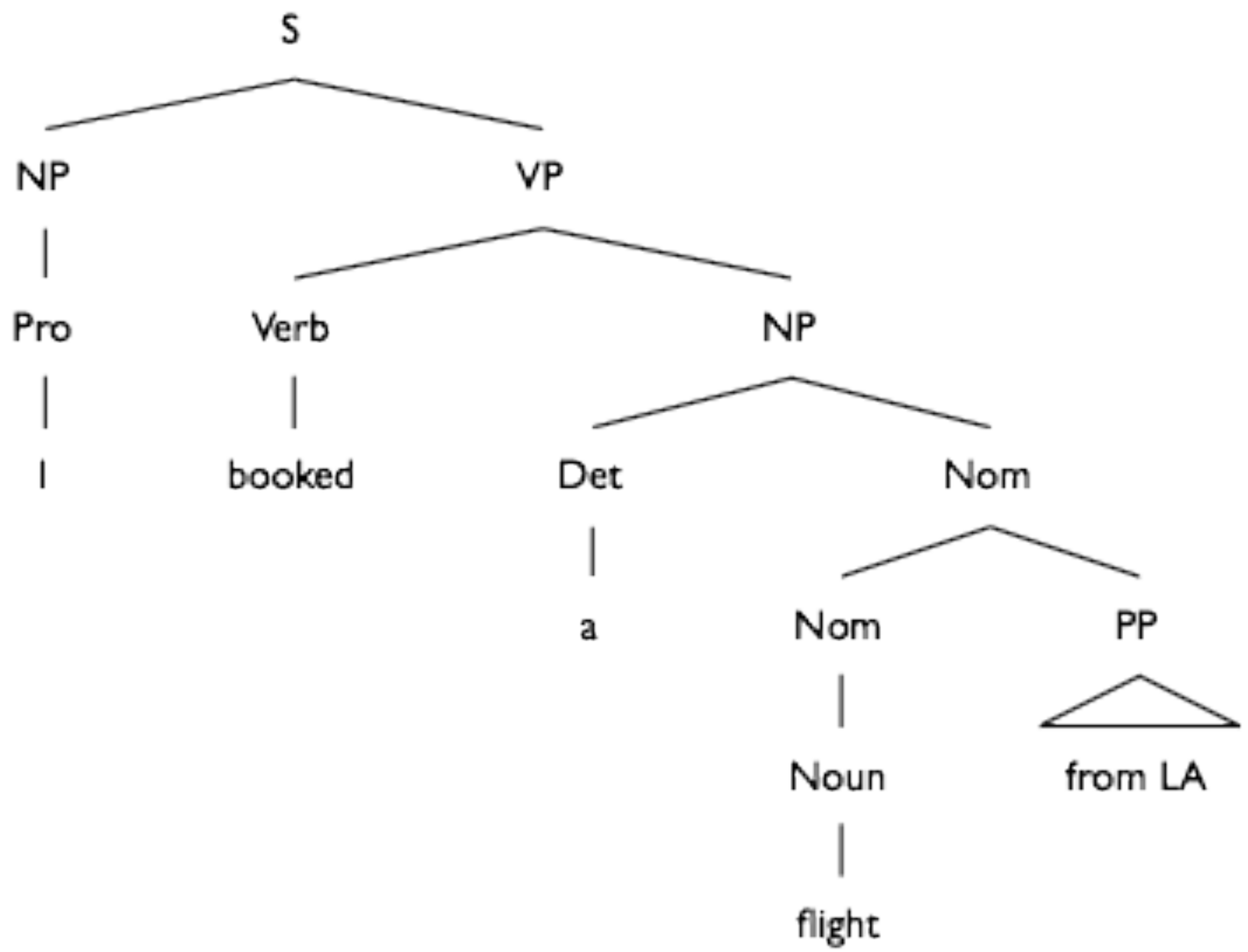
Dependency grammar

- 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.

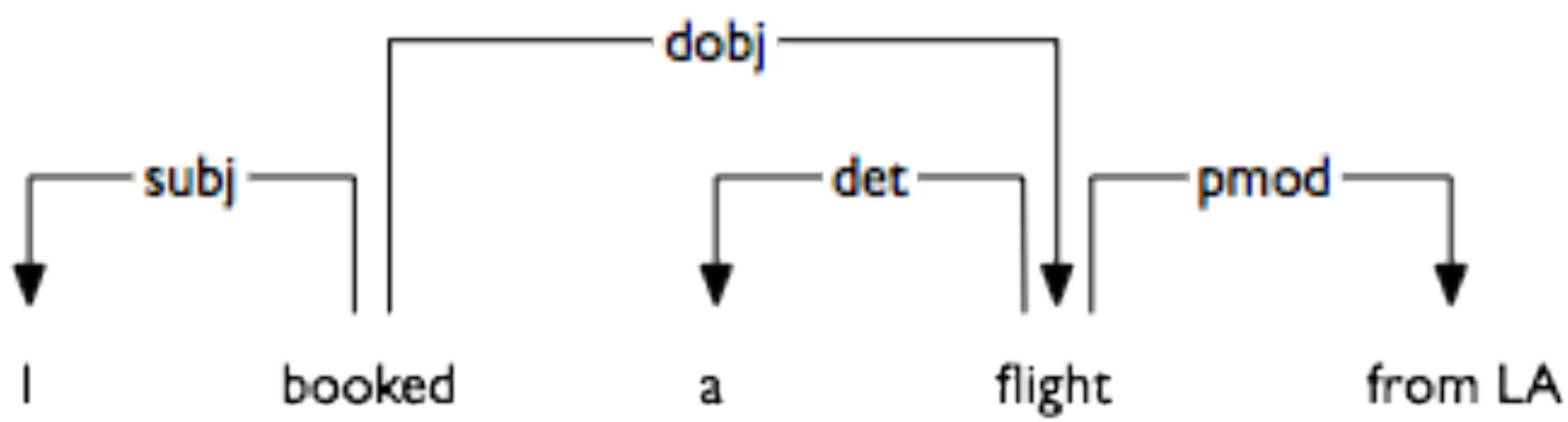
The notion of dependency

- 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

Phrase structure trees

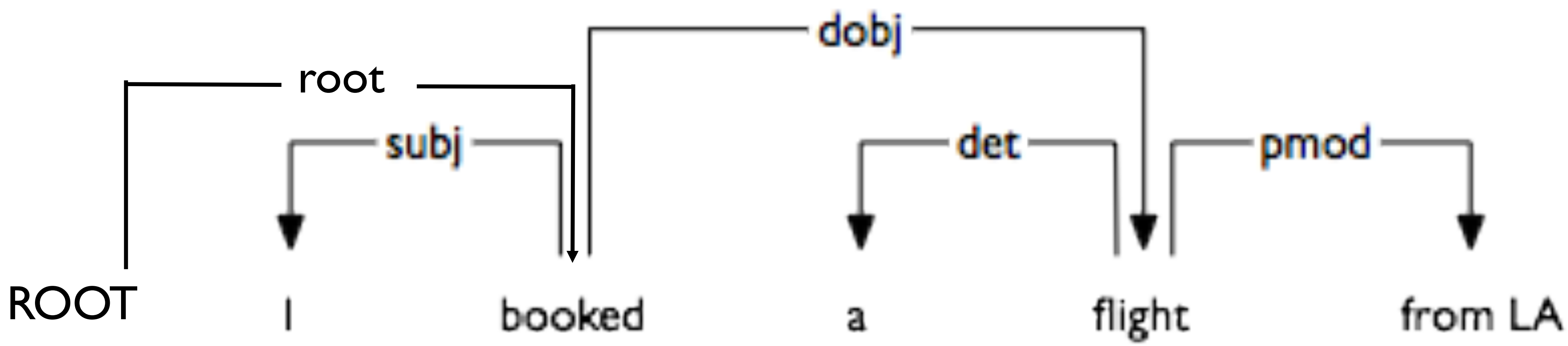


Dependency trees



- In an arc $h \rightarrow d$, 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, *l*, and an arc can be described as (*h*, *d*, *l*)

Dependency trees



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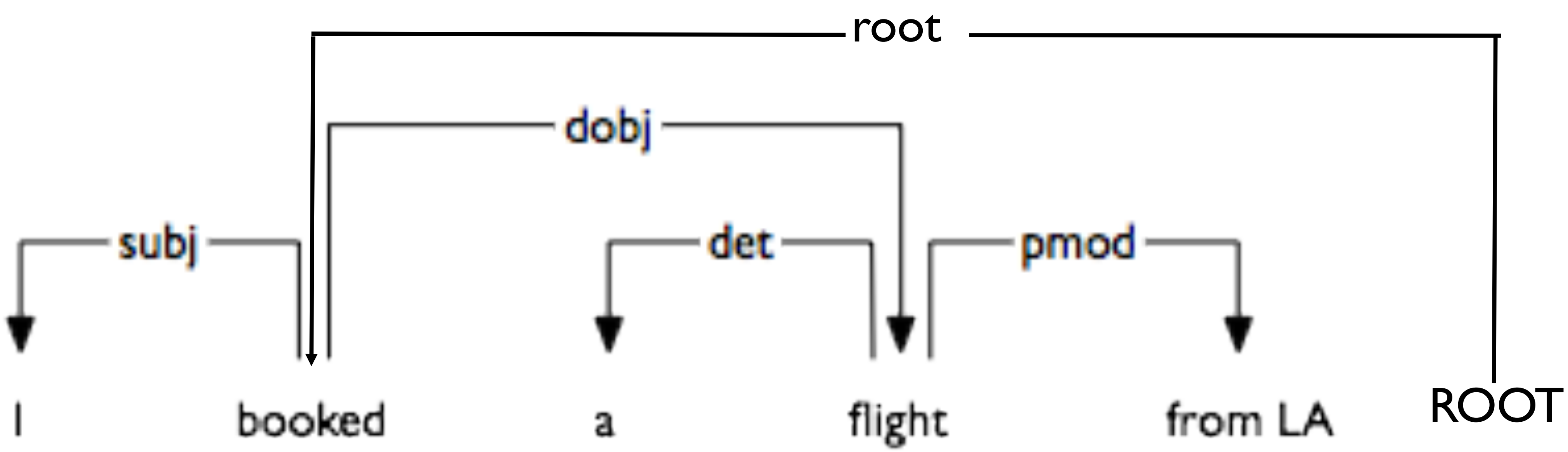

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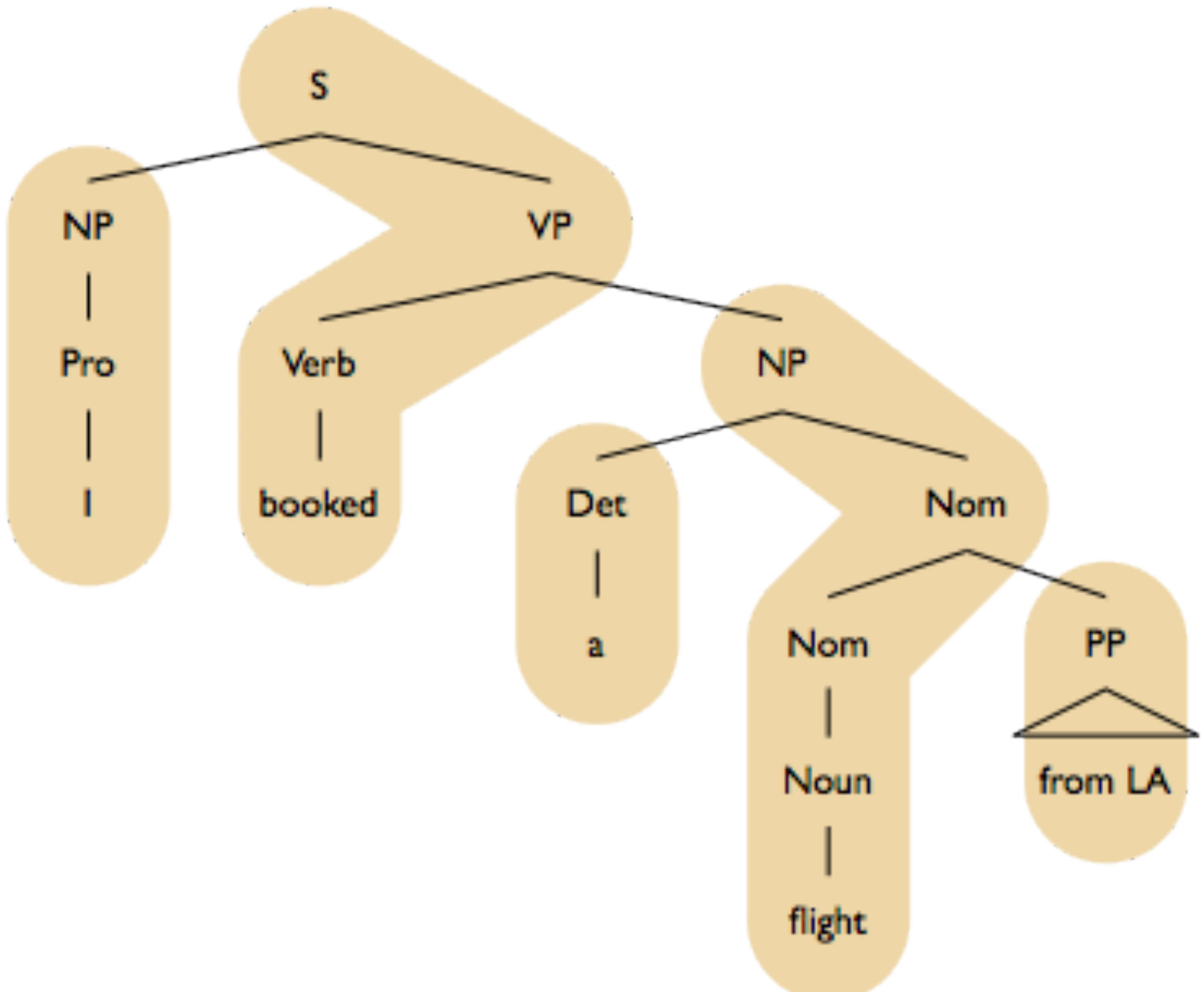
Heads in phrase structure grammar

- 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

Heads in phrase structure grammar



Linguistic resources

- Dependency treebanks exist
  for a wide range of natural languages.
- These treebanks can be used to train
  accurate and efficient dependency parsers.
- We will not use grammars in the parsing
  algorithms we discuss in the course

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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 $i \rightarrow^* k$ for every k such that $\min(i, j) < k < \max(i, j)$)

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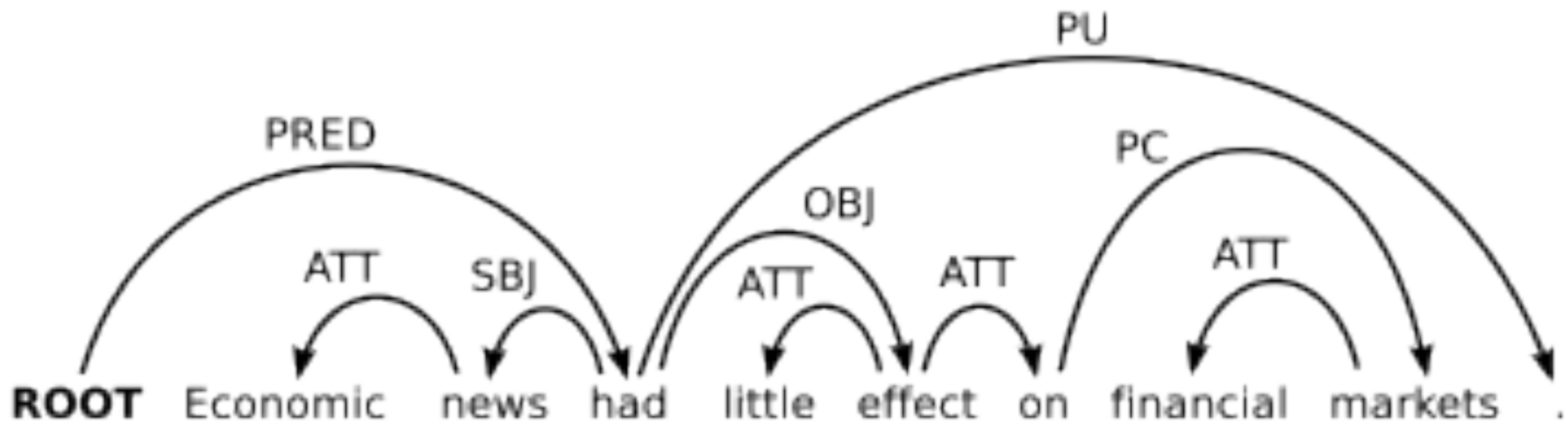
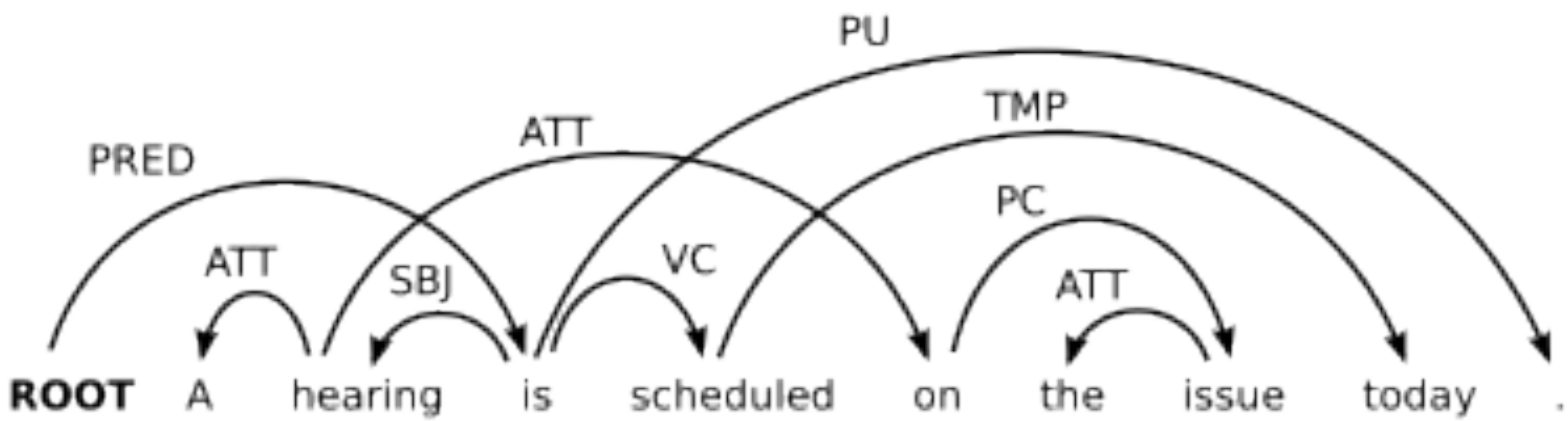
Projective and non-projective trees





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)

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Projectivity in the course

- The algorithms we will discuss in detail during the lectures will only concern projective parsing
- Non-projective parsing:
  - You can read more about it in the course book!

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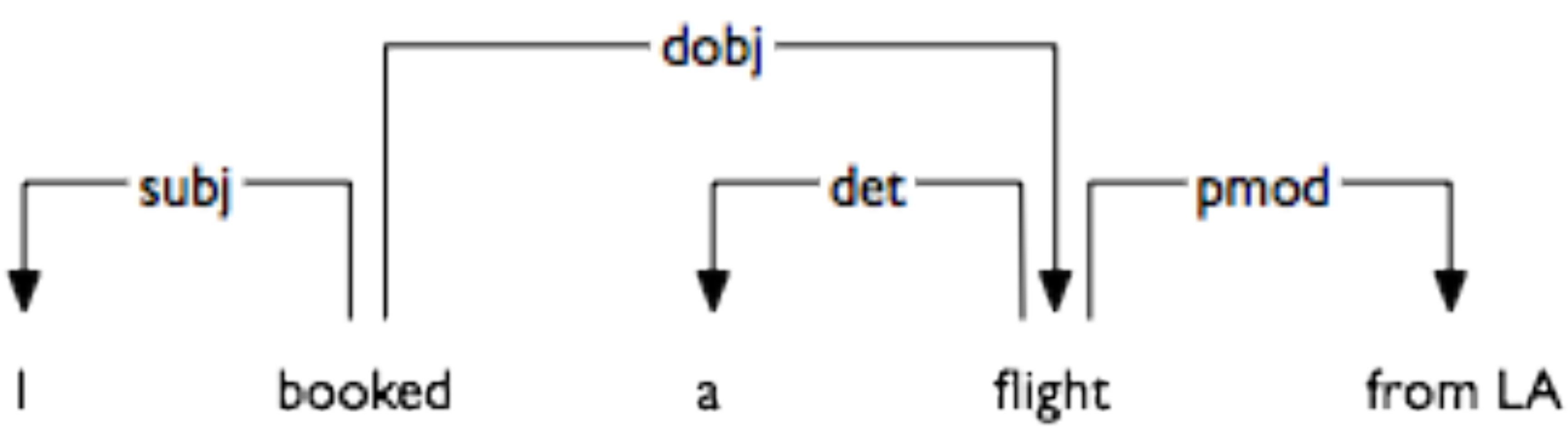
Arc-factored dependency parsing

Ambiguity

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



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Ambiguity

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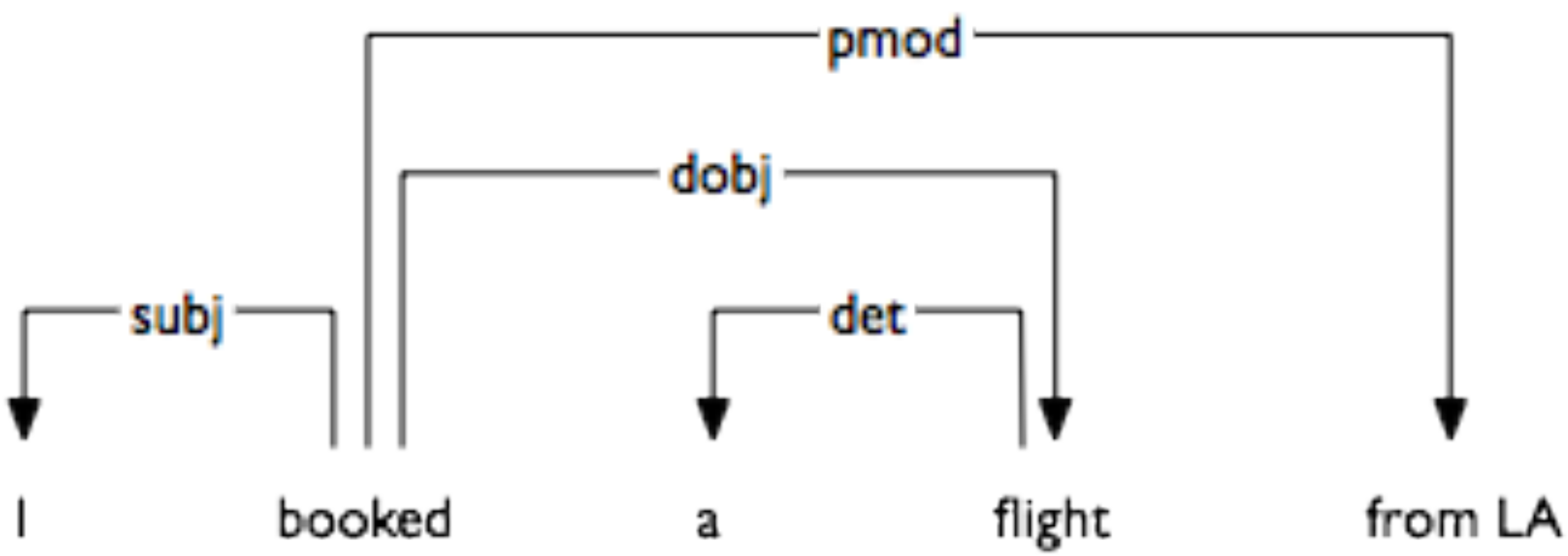

Disambiguation

- 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.

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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?

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The arc-factored model

- Split the dependency tree t into parts $p_1, \ldots, p_n$, 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.

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The arc-factored model

$$Score(x, y) = \sum_{(i,l,j) \in A_y} Score(i, l, j, x)$$

- A_y is the arc set of the dependency tree y
- $Score(i, l, j, x)$ is the score of the arc (i,l,j) for the sentence x

The arc-factored model

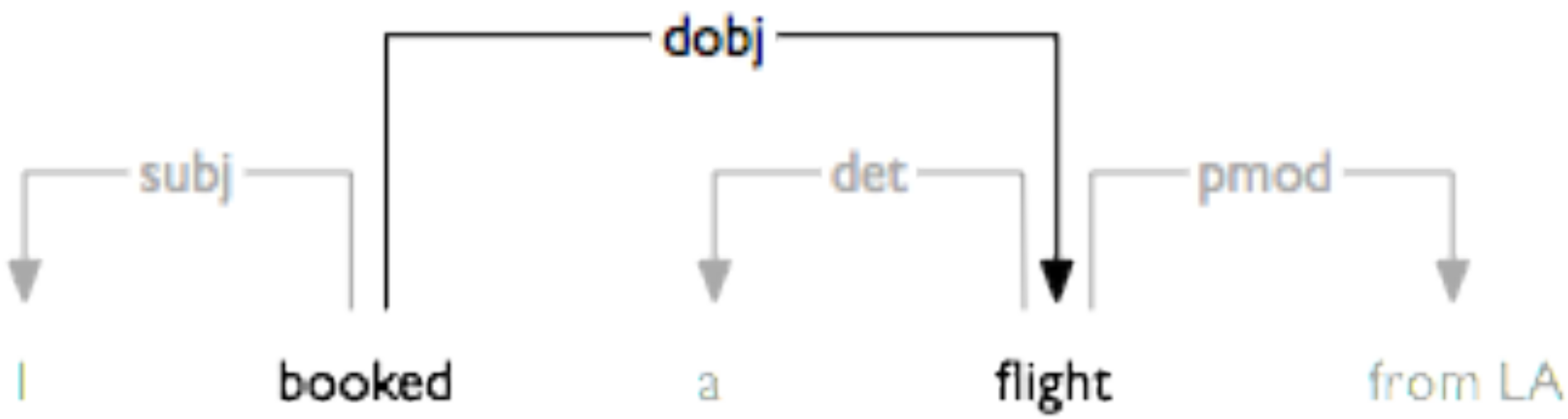
- The best parse tree is one with the highest score

$$y^* = \underset{y \in GEN(x)}{argmax} \sum_{(i,l,j) \in A_y} Score(i,l,j,x)$$

- GEN(x) is the set of all spanning trees

$$GEN(x) = \{y | y \text{ is a spanning tree in } G_x = (V_x, V_x * l * V_x)\}$$

Features

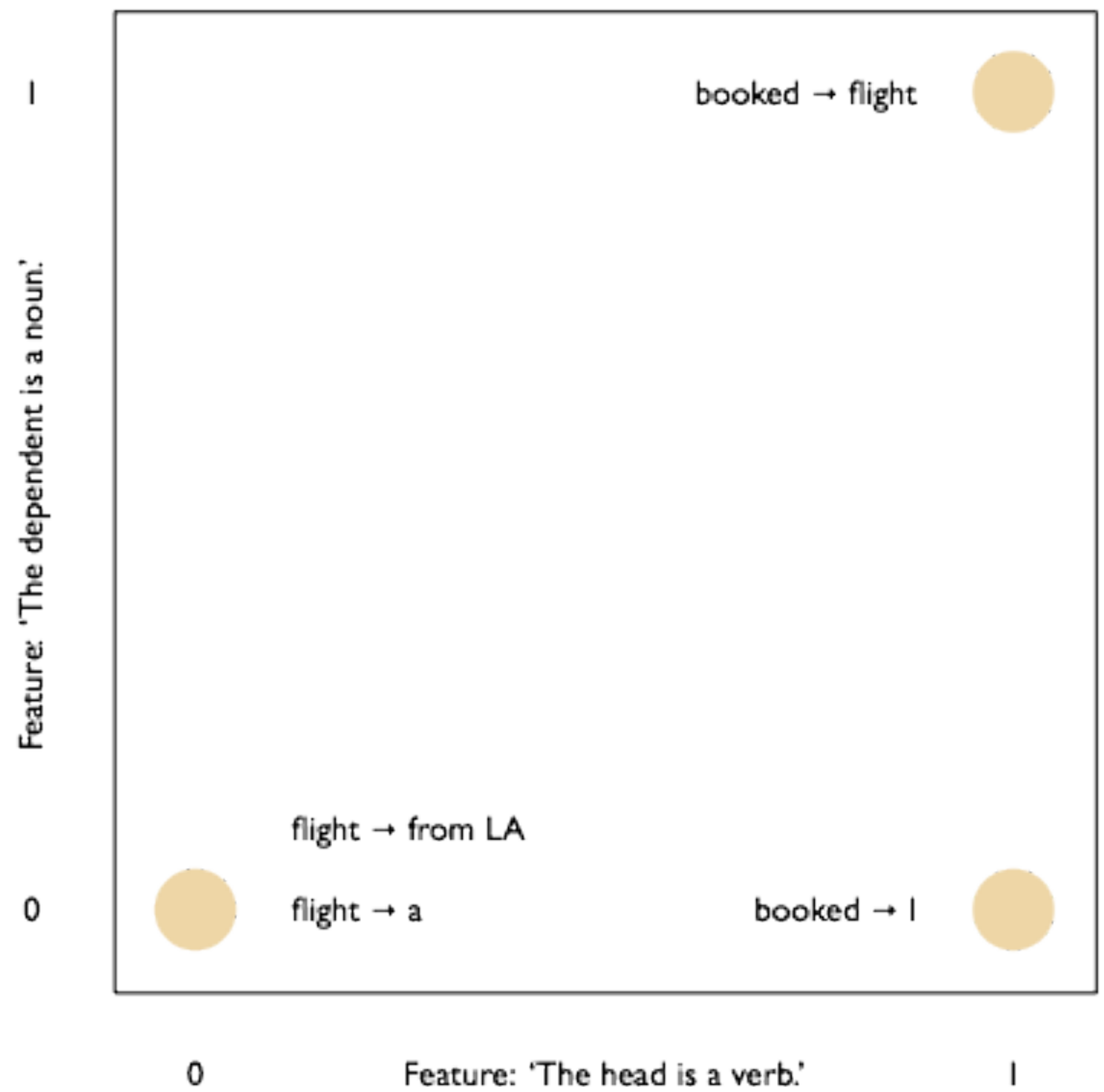


- To score an arc, we define features that are likely to be relevant in the context of parsing.
- We represent an arc by its feature vector.

Examples of features

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



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:
- $\text{score}(h \rightarrow d) = f_1 w_1 + \ldots + f_n w_n$

Feature weights

$$score(i,l,j,x) = \sum_{k=1}^{n} f_k(i,l,j,x).\boldsymbol{w}_k$$

- $f_k(i,l,j,x)$ is a feature function representing some salient property of the arc (i,l,j) in the context of x
- $\boldsymbol{w}_k$ is a real-valued feature weight, reflecting the tendency of $f_k(i,l,j,x)$ to co-occur with a good or bad parse tree

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 data: $\mathcal{T} = \{(x^i, y^i)\}_{i=1}^{|\mathcal{T}|}$

$\mathbf{w} \leftarrow 0$
for $n : 1..N$
  for $i : 1..|\mathcal{T}|$
    $y^* \leftarrow \textsc{Parse}(x^i, \mathbf{w})$
    if $y^* \neq y^i$
      $\mathbf{w} \leftarrow \textsc{Update}(\mathbf{w}, y^*, y^i)$
return w

$\textsc{Parse}(x, \mathbf{w})$

return $\operatorname{argmax}_{y \in \mathrm{GEN}(x^i)} \sum_{(i,l,j) \in A_y} \sum_{k=1}^{K} \mathbf{f}_k(i, l, j, x^i) \cdot \mathbf{w}_k$

$\textsc{Update}(\mathbf{w}, y^*, y^i)$

for $k : 1..K$
  for $(i, l, j) \in A_{y^*}$
    $\mathbf{w}_k \leftarrow \mathbf{w}_k - \mathbf{f}_k(i, l, j, x)$
  for $(i, l, j) \in A_{y^i}$
    $\mathbf{w}_k \leftarrow \mathbf{w}_k + \mathbf{f}_k(i, l, j, x)$

Training using structured prediction

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

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
- 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.

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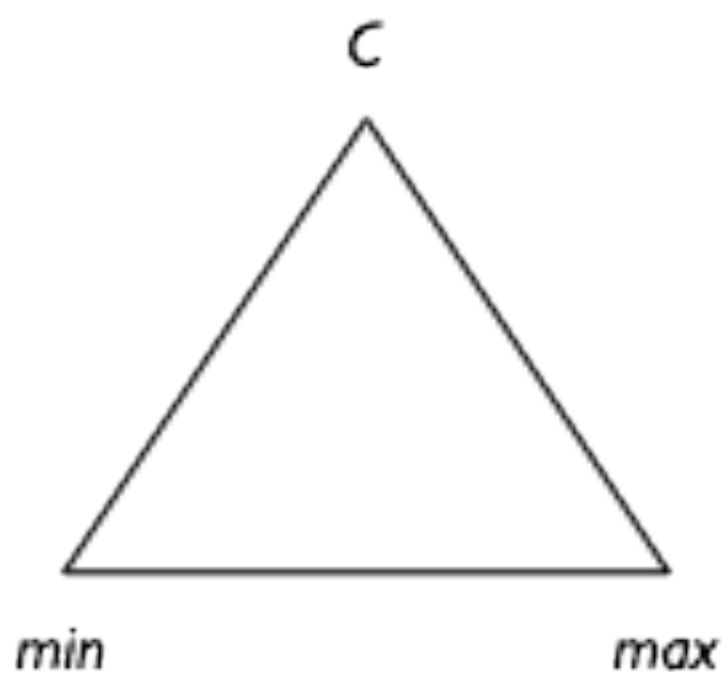
Collins' algorithm

Collins' algorithm

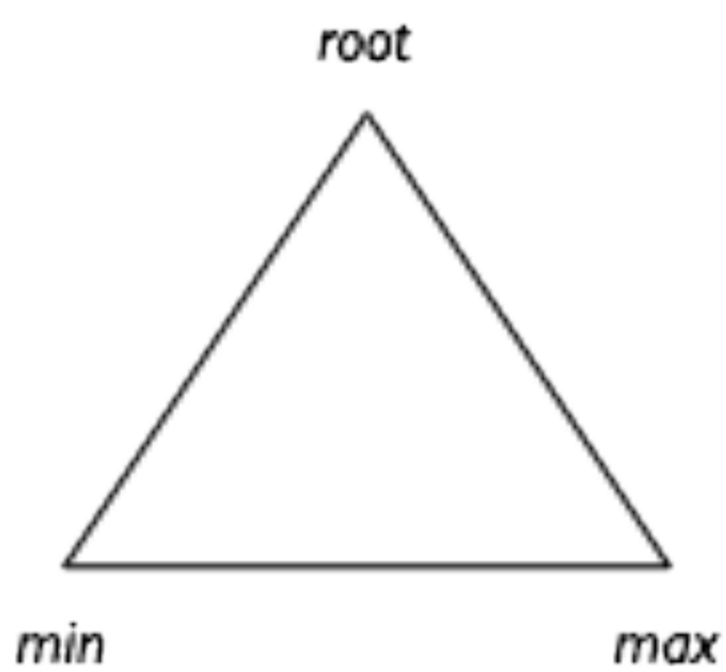
- Collin's algorithm is a simple algorithm for computing the highest-scoring dependency tree under an arc-factored scoring model.
- It can be understood as an extension of the CKY algorithm to dependency parsing.
- Like the CKY algorithm, it can be characterized as a bottom-up algorithm based on dynamic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

Signatures, CKY



[*min*, *max*, *C*]

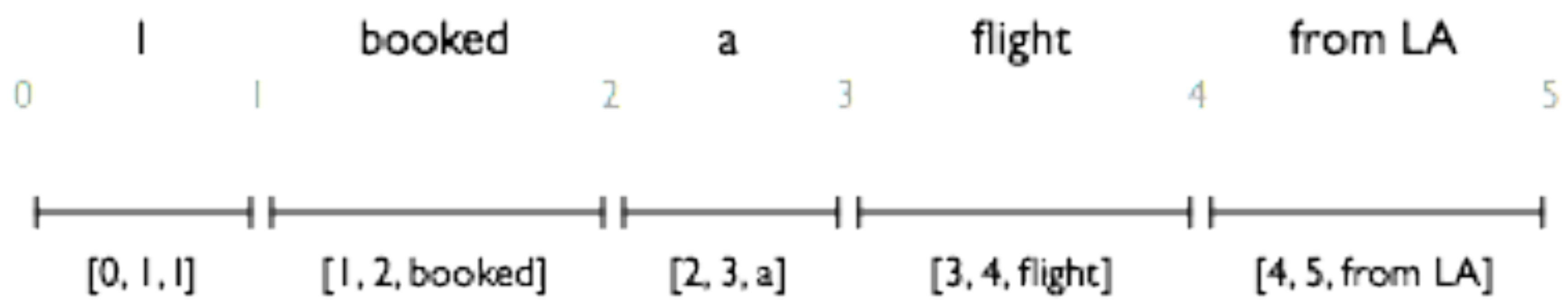
Signatures, Collins'



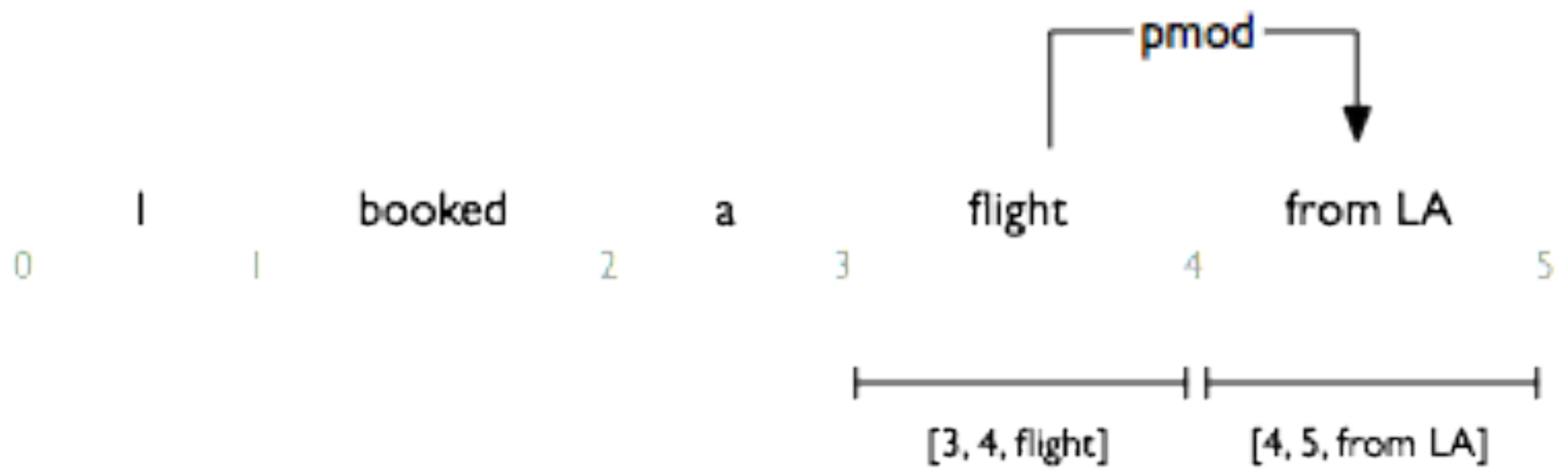
[*min*, *max*, *root*]

Collins' algorithm

Initialization



Adding a left-to-right arc



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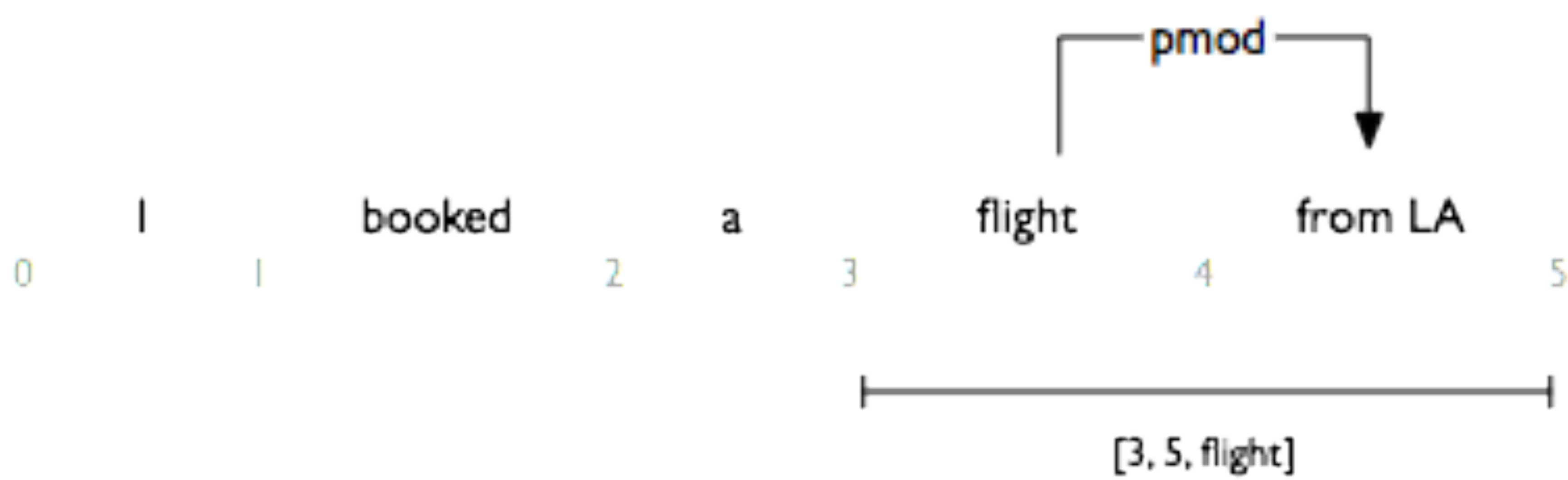

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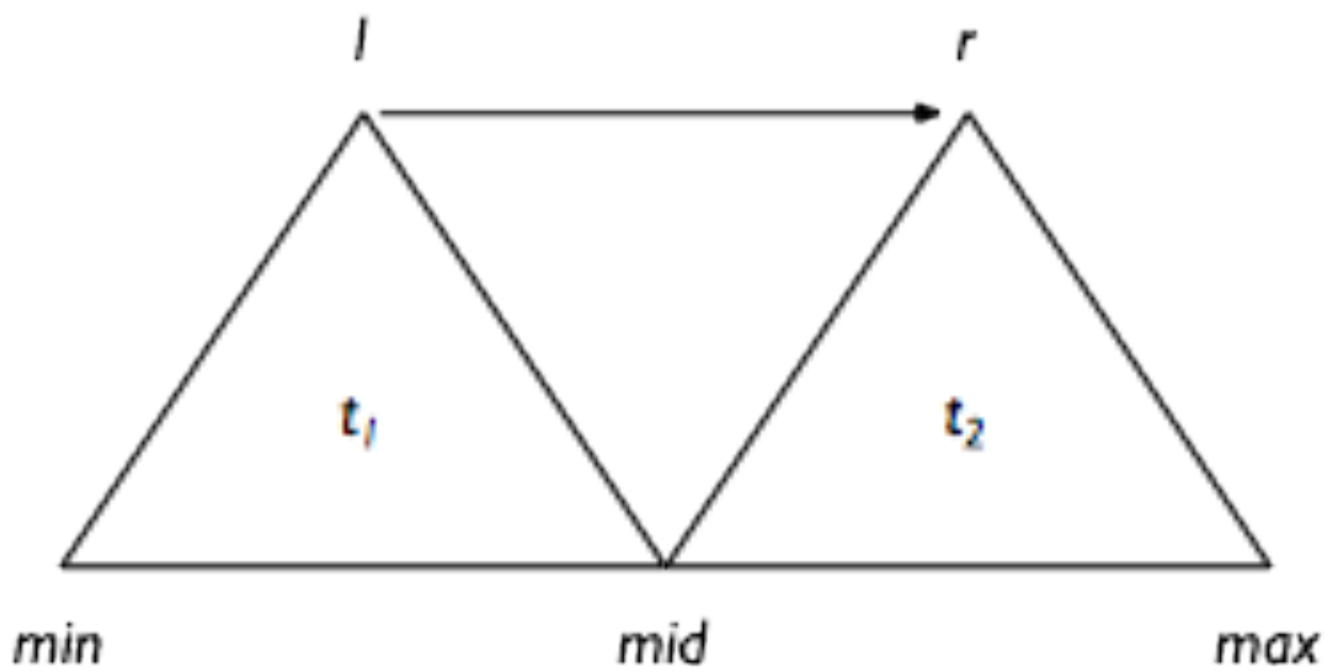

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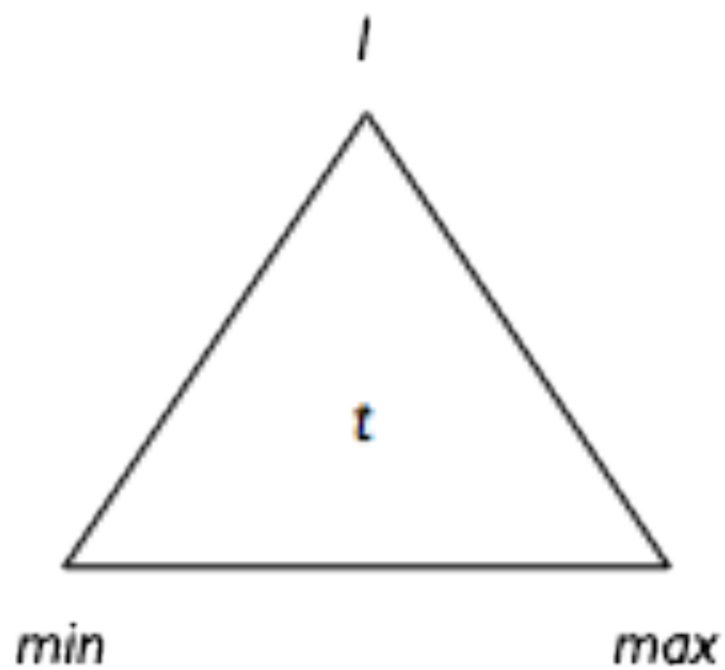


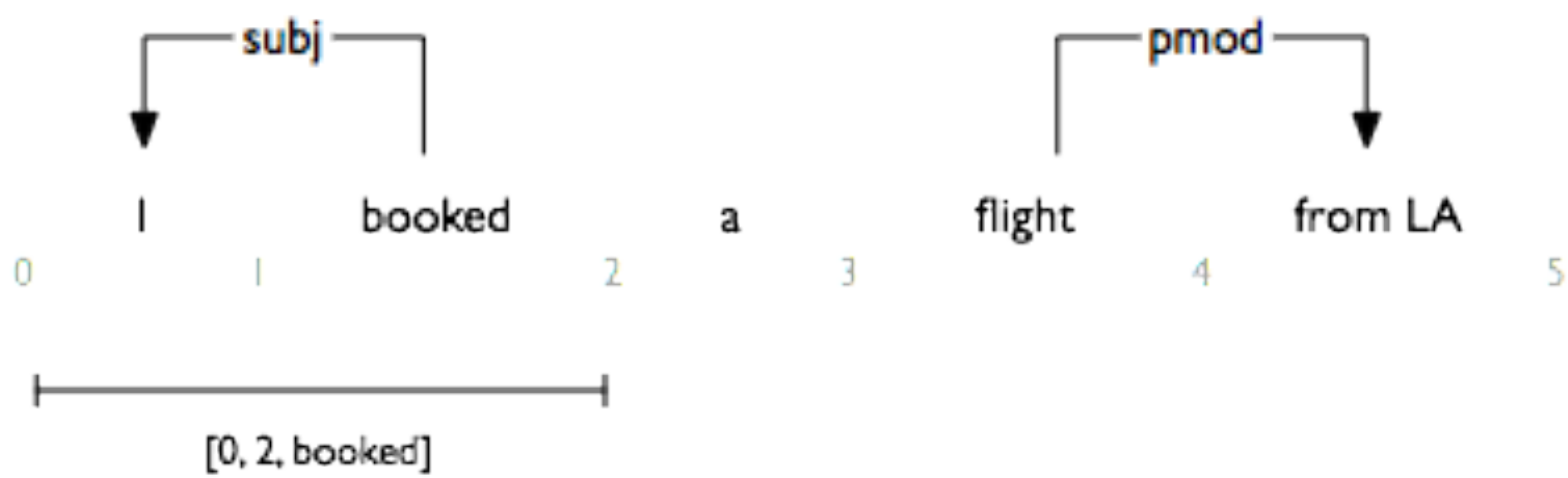
score(t) = score(t_1) + score(t_2) + score($l \longrightarrow r$)

Adding a left-to-right arc

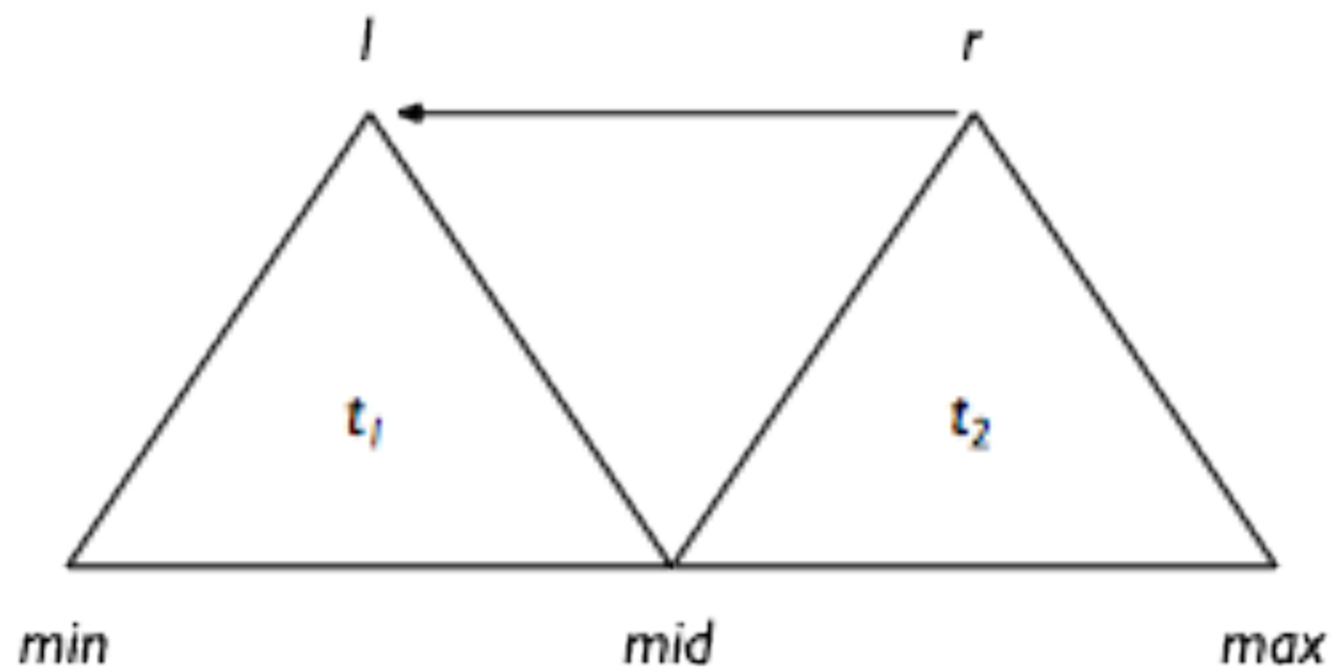
```
for each [min, max] with max - min > 1 do
  for each l from min to max - 2 do
    double best = score[min][max][l]
    for each r from l + 1 to max - 1 do
      for each mid from l + 1 to r do
        t1 = score[min][mid][l]
        t2 = score[mid][max][r]
        double current = t1 + t2 + score(l → r)
        if current > best then
          best = current
    score[min][max][l] = best
```

Adding a right-to-left arc

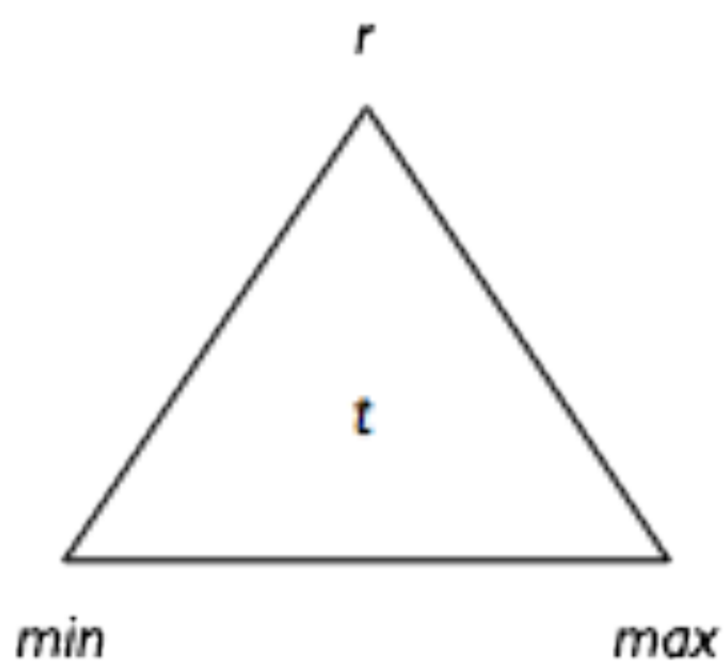
Adding a right-to-left arc



Adding a right-to-left arc



Adding a right-to-left arc



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

Adding a right-to-left arc

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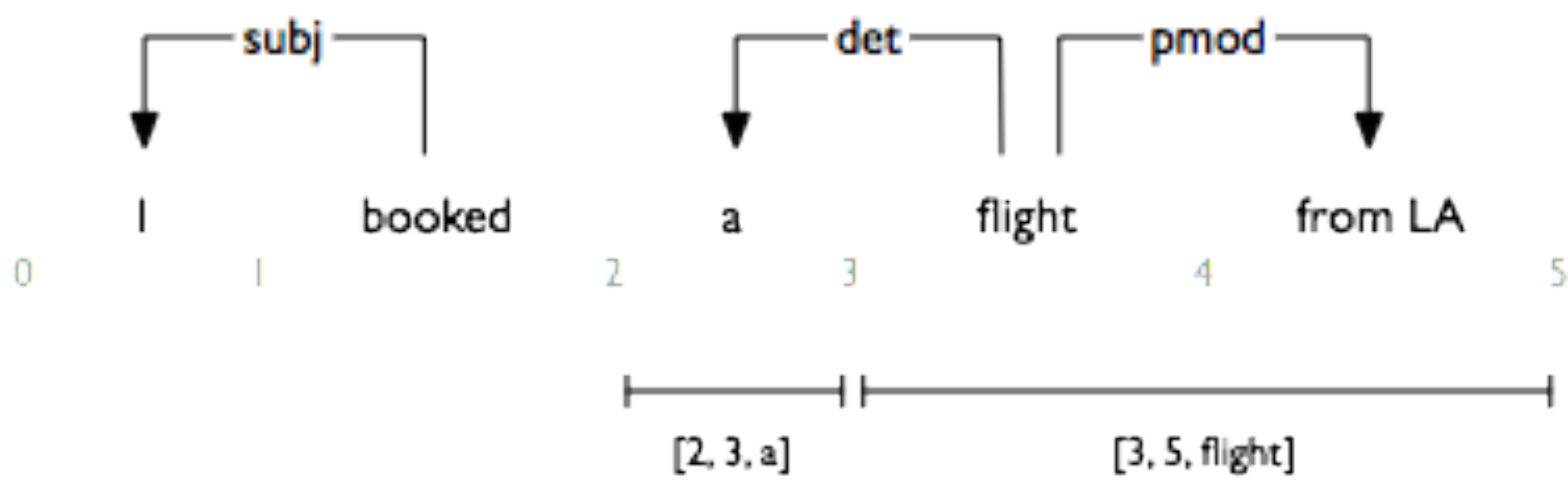
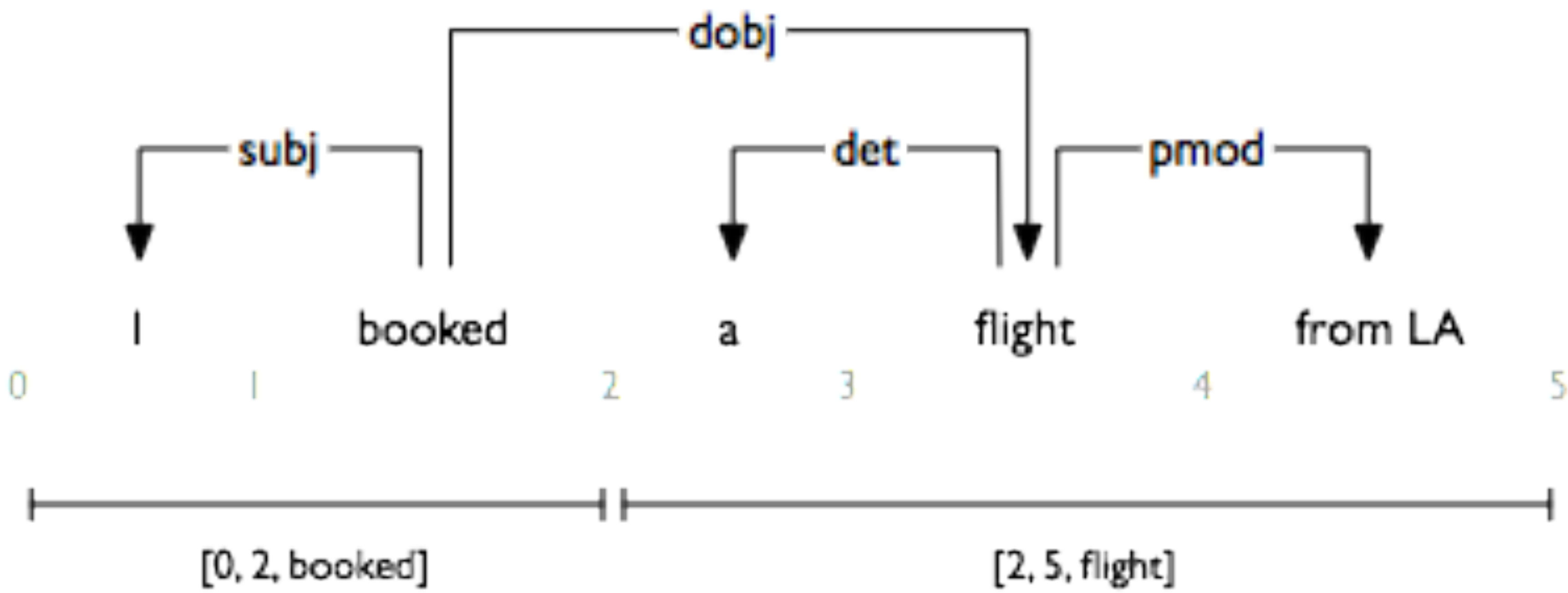
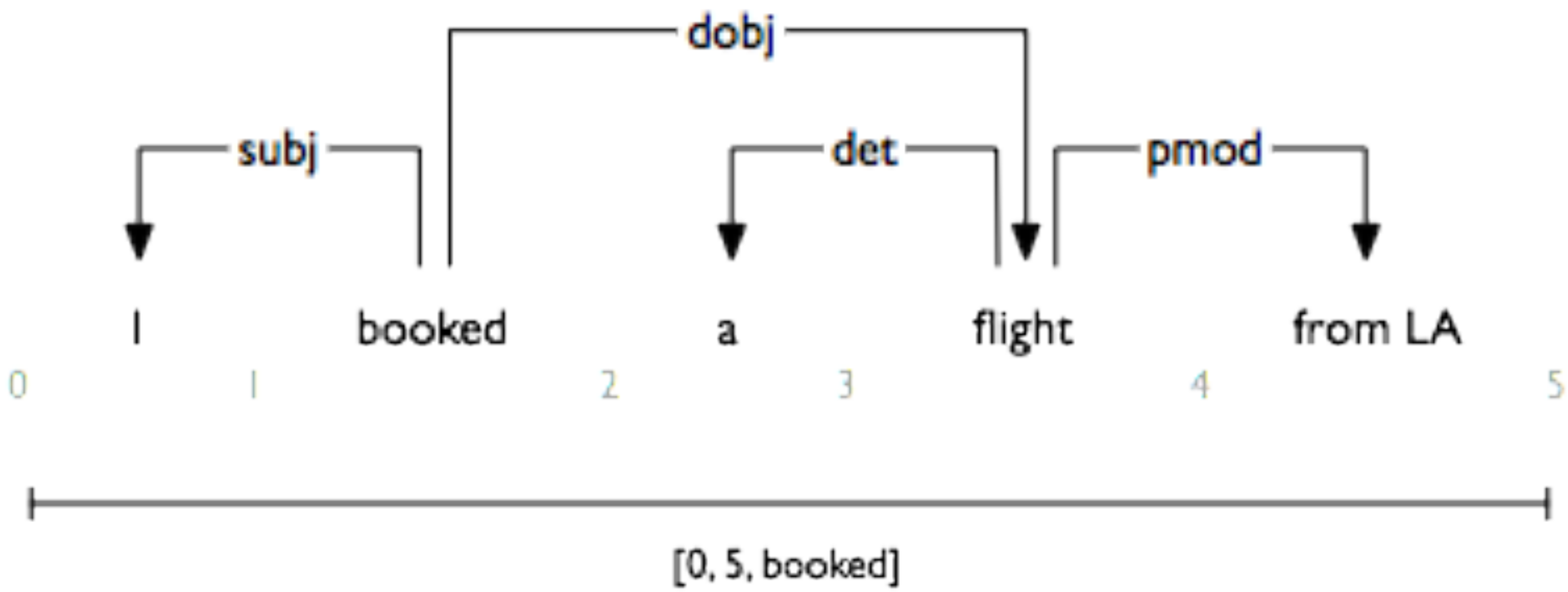
Finishing up



Finishing up



Finishing up



Complexity analysis

- Runtime?
- Space?

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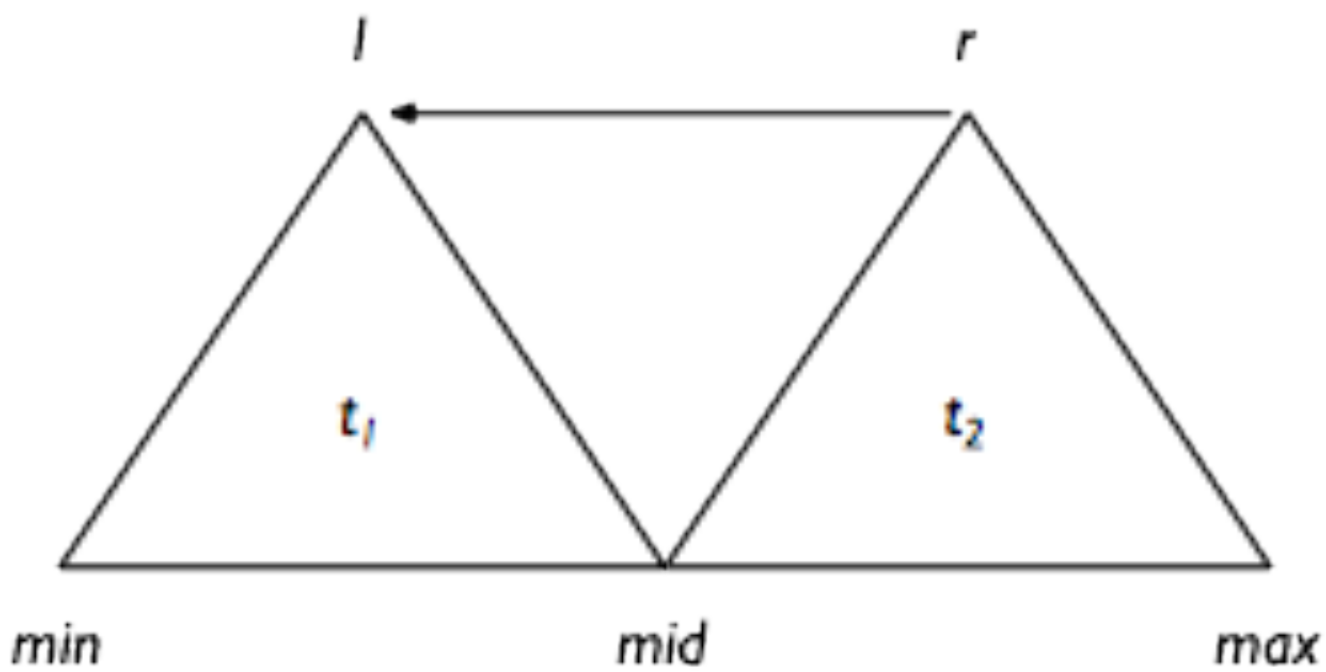

Complexity analysis

- 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 in the next lecture