ANLP

17 - dependency parsing (structure, II)

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before

- what is grammatical knowledge?
- how can we *write down* / *induce* grammatical knowledge?
- how can we process inputs efficiently, given the grammatical knowledge

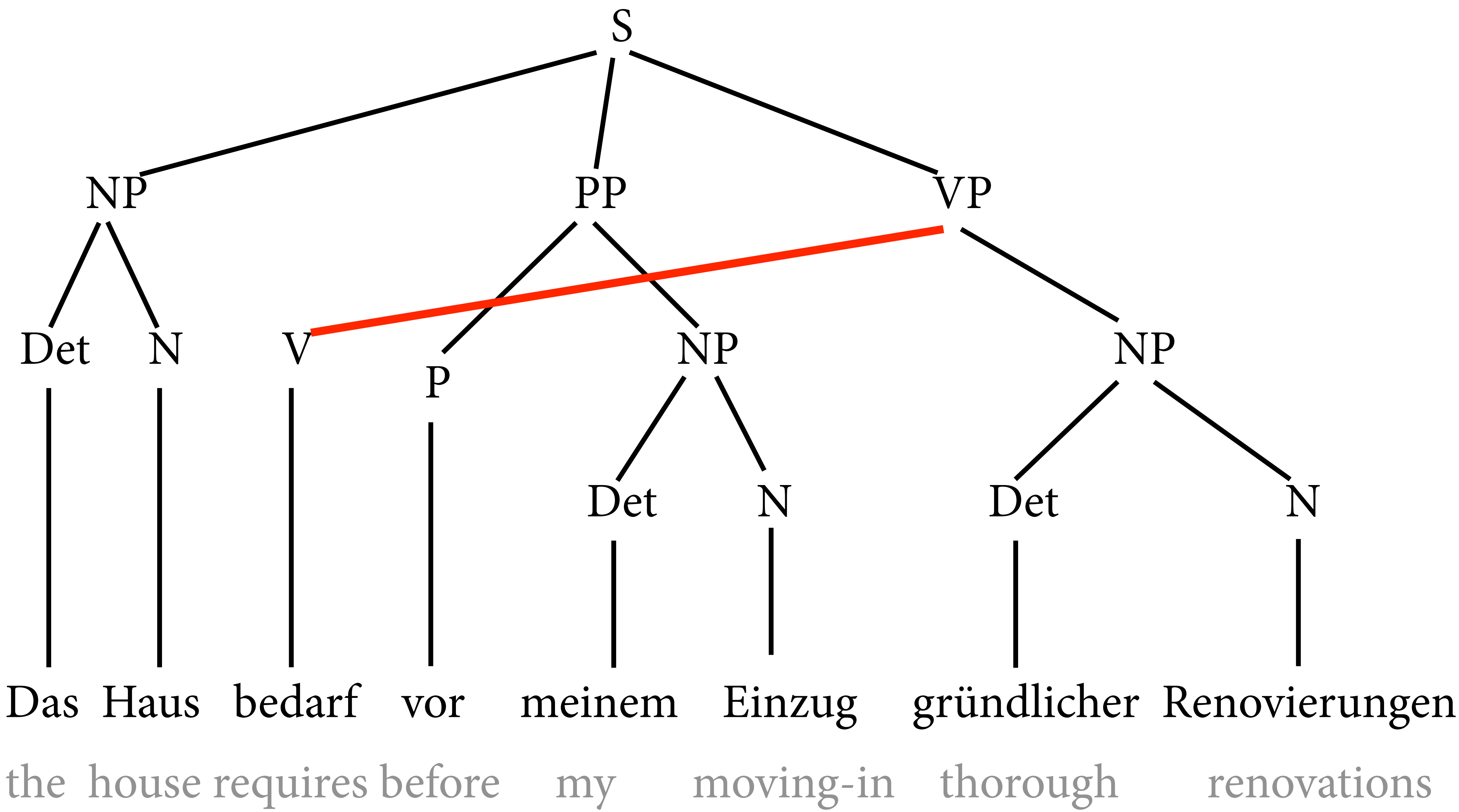
today

- what is grammatical knowledge?
- how can we *induce* grammatical knowledge so that we can process input efficiently?

Discontinuous constituents

- So far, we have talked about *phrase-structure* parsing.
  - substrings form constituents of various syntactic categories
  - every constituent must be a contiguous substring
- This assumption mostly correct for English.
  For other languages, it doesn't work so well.

Example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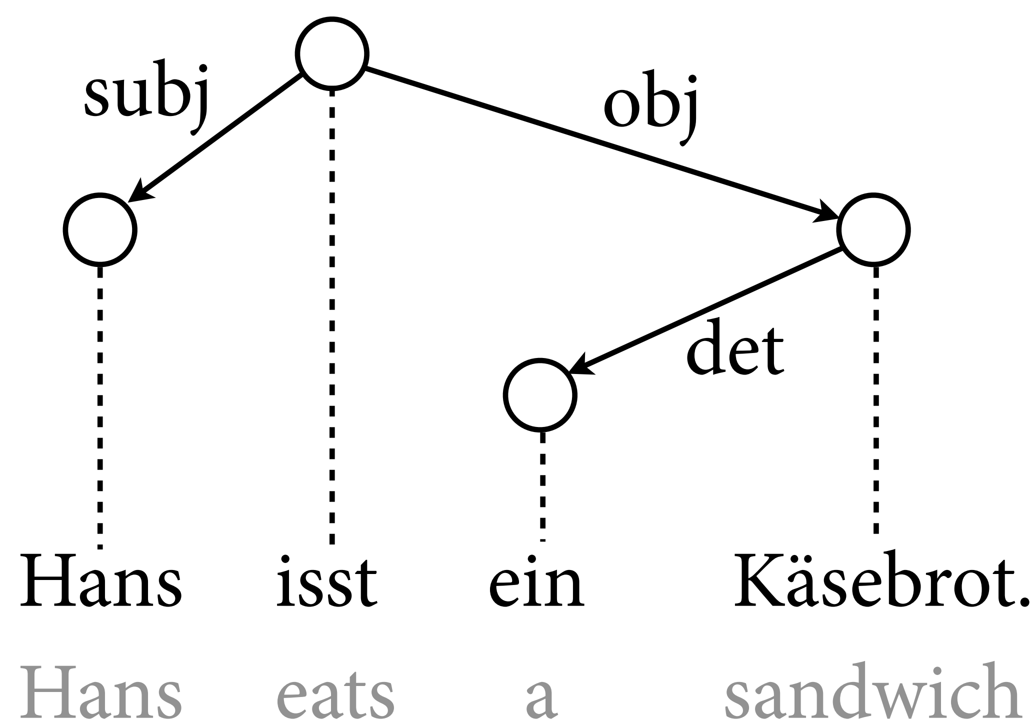
Renovierungen.
the
house
requires
before
my
moving-in
thorough
renovations

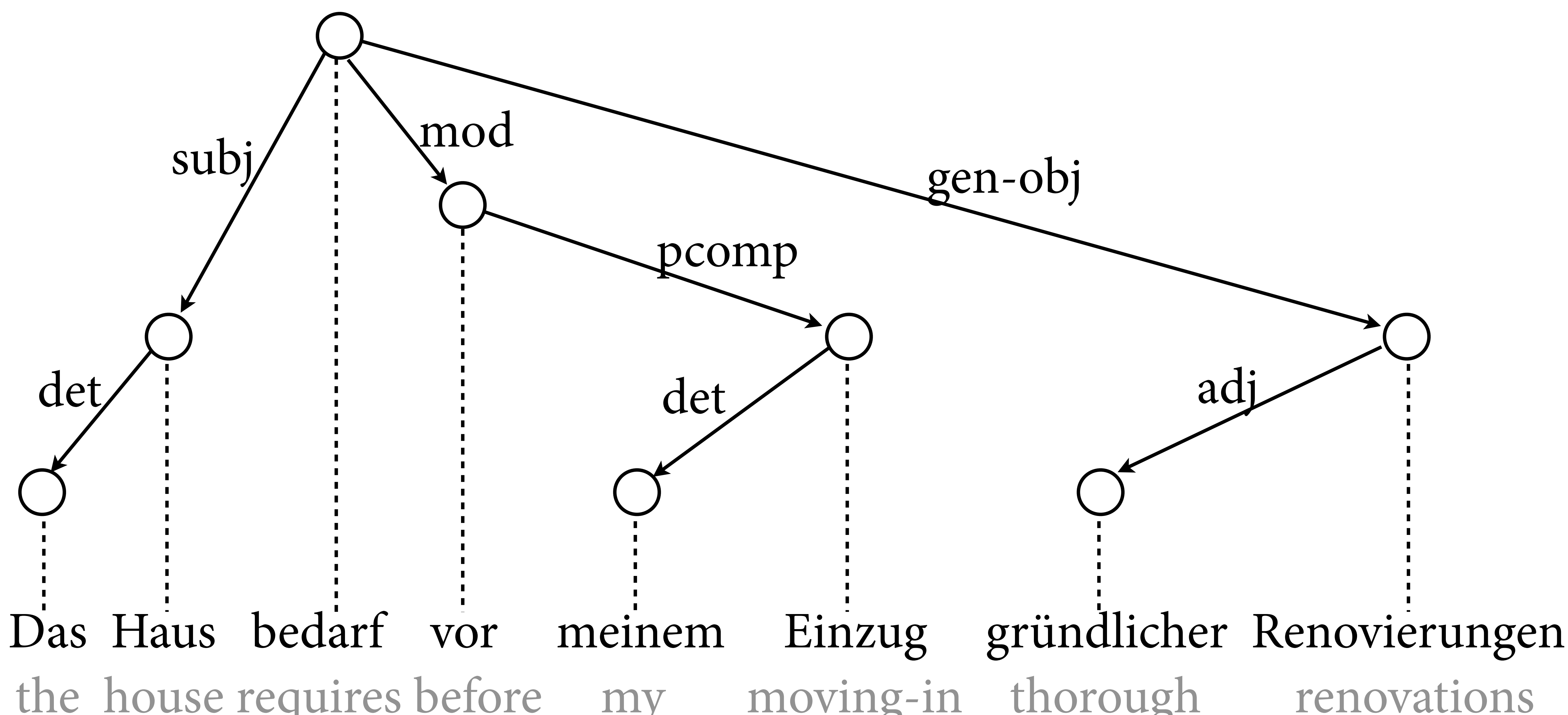
Dependency trees

- Basic idea:
  - no constituents, just relations between words
  - nodes of tree = words; edges = relations
  - grammar specifies valency of each word
- Brief history:
  - Tesniere 1953, posthumously
  - Prague School during Cold War
  - very important in CL since 2005 or so (Nivre, McDonald)

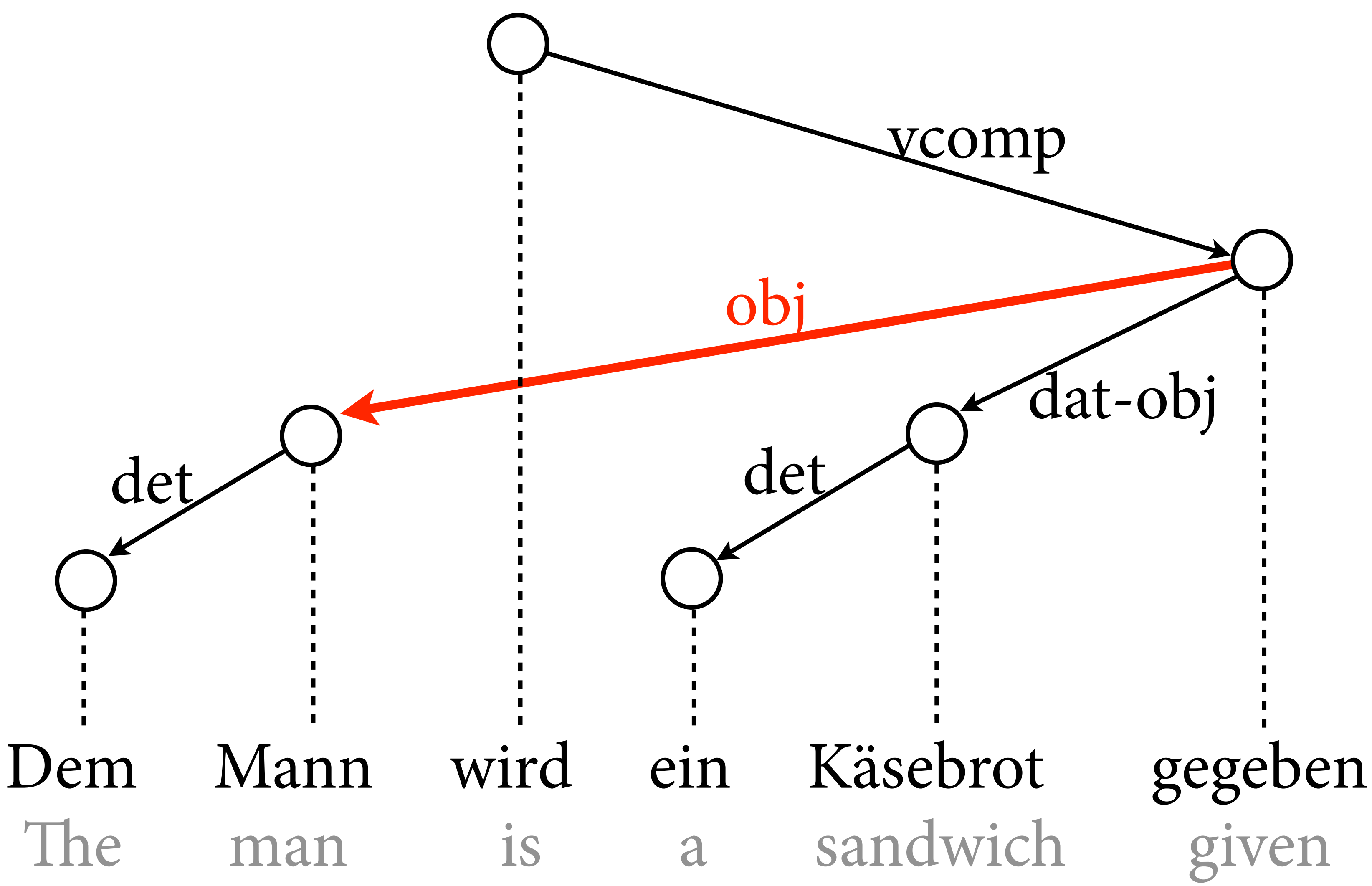
A dependency tree



A dependency tree

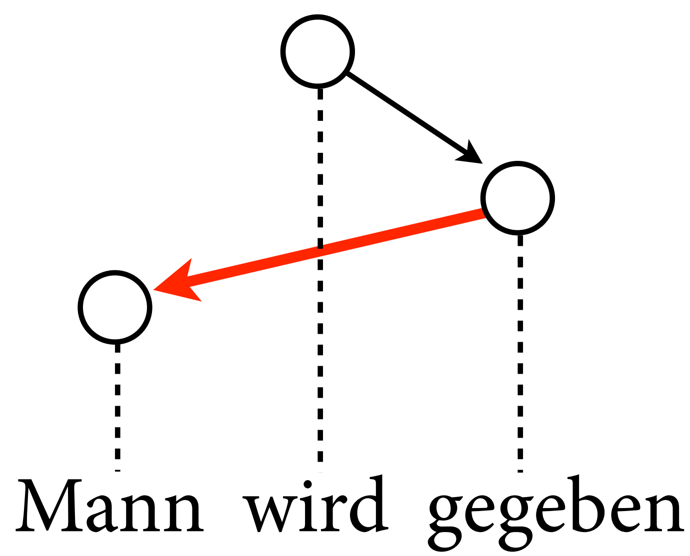


A dependency tree



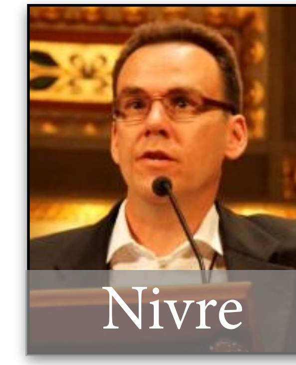
Projectivity

- Dependency tree may have *crossing edges*, which cross the *projection line* of another word.

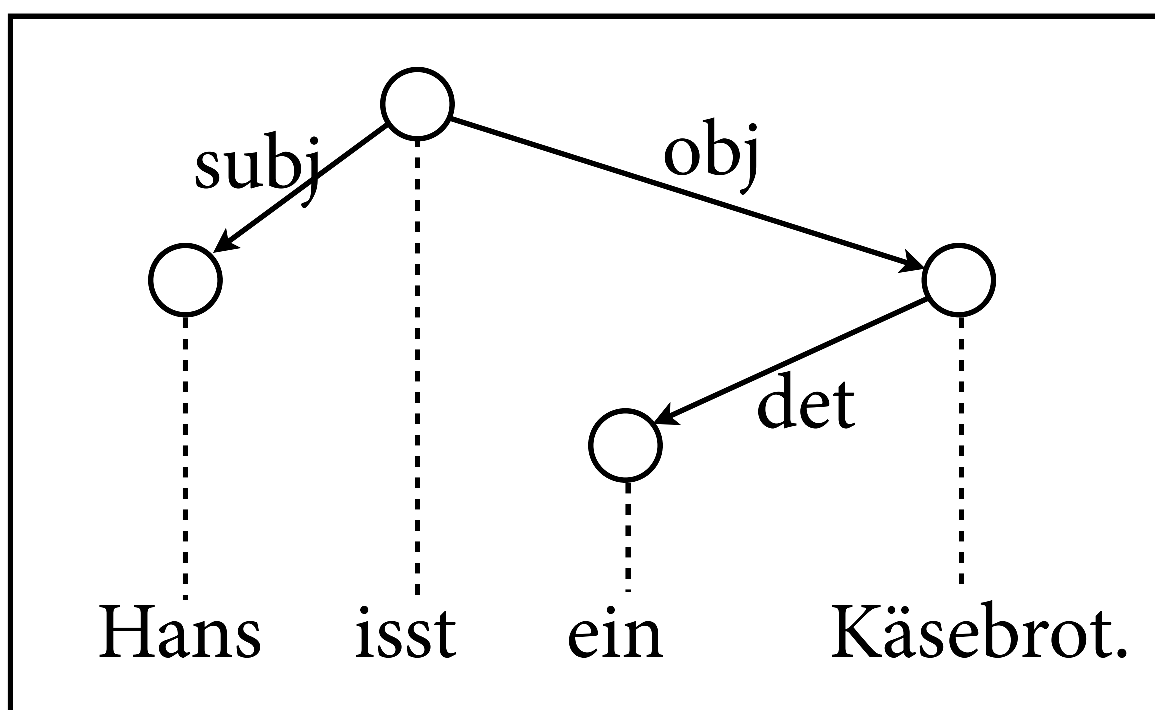


- A dependency tree is called *projective* iff it has no crossing edges.

Nivre-style dependency parsing



- Idea by Joakim Nivre (2003):
  - read sentence word by word, left to right
  - after each word, select a *parser operation* from large set by consulting a machine-learned classifier
  - original algorithm constructs only projective trees; can be extended to non-projective parsing too



Parser Items

- given sentence $w_1 \ldots w_n$, parser manipulates items of form(σ, τ, h, d):
  - τ sorted list of integers j, ..., n for a given j
    = part of input that was not yet read
  - σ is stack of integers < j
    = roots of subtrees that we have already read
  - h(i) is parent of i-th word; by default h(i) = 0 ("child of root")
  - d(i) is label of edge (h(i), i); if h(i) = 0, d(i) = r0

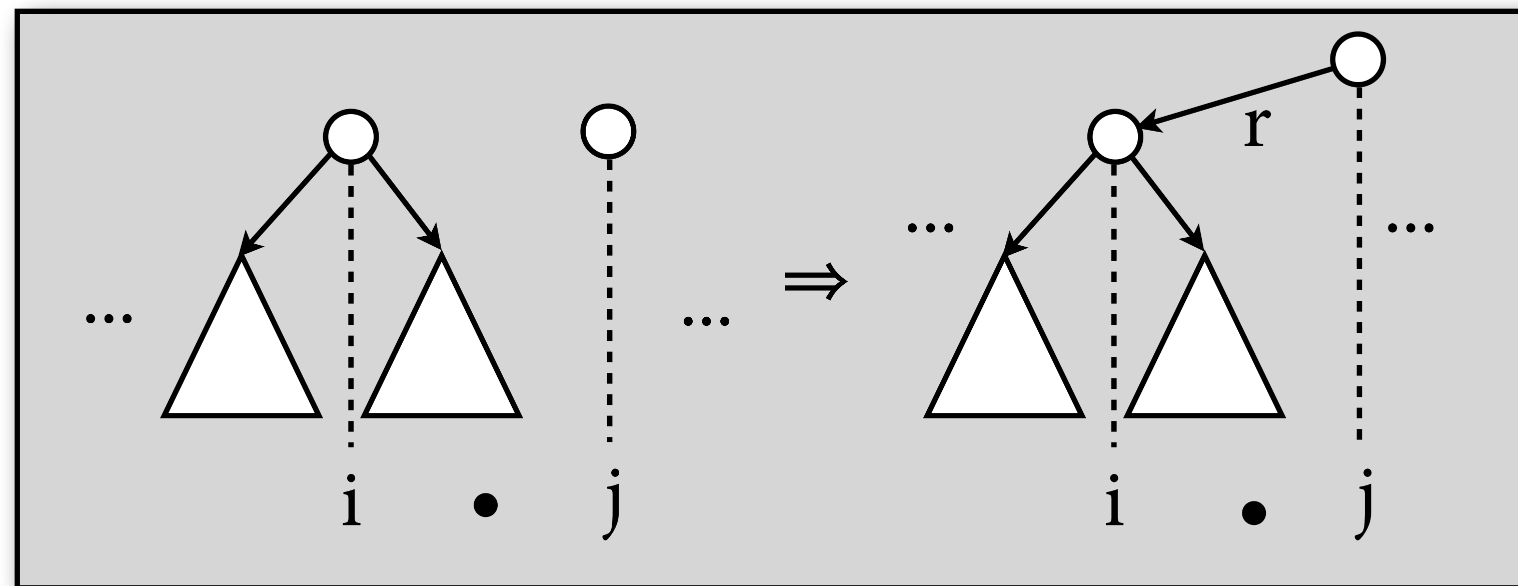
Parser Items

- start item: $(\varepsilon, (1, \ldots, n), h_0, d_0)$ where
  - $h_0(i) = 0$ for all i: no parents known yet
  - $d_0(i) = r_0$ for all i: no edge labels known yet
- goal items: $(\sigma, \varepsilon, h, d)$ für some σ, h, d
  - h, d describe dependency tree for given input
  - σ need not be empty, holds root(s)

Left-Arc operation

- Left-Arc(r): Topmost token *i* on stack becomes left r-child of next input token *j*.

$$\frac{(\sigma\cdot i,\ \ j\cdot\tau,\quad h, d)\quad h(i) = 0}{(\sigma,\quad j\cdot\tau,\quad h[i\mapsto j], d[i\mapsto r])}$$

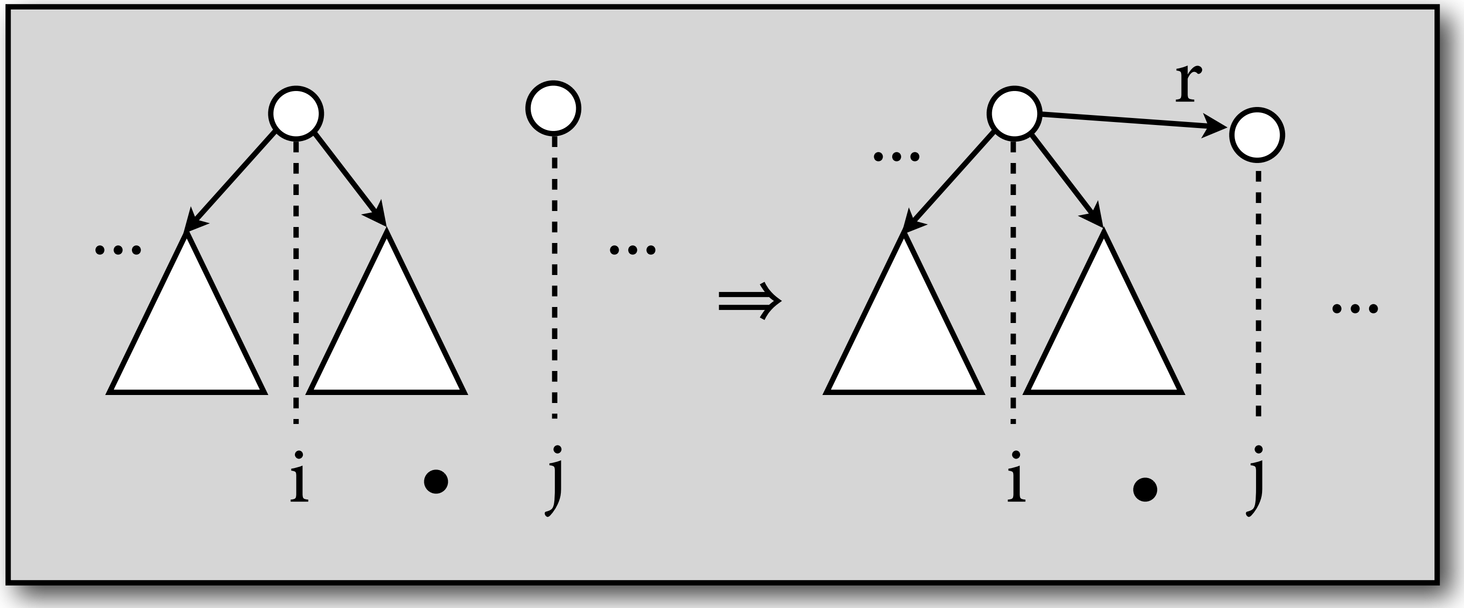


- *i* disappears from stack, because *i* can't get further children in a projective tree

Right-Arc operation

- Right-Arc(r): Input token *j* becomes (right) r-child of topmost stack token *i*.

$$\frac{(\sigma\cdot i,\quad j\cdot\tau,\quad h, d)\qquad h(j)=0}{(\sigma\cdot i\cdot j,\ \tau,\quad h[j\mapsto i], d[j\mapsto r])}$$

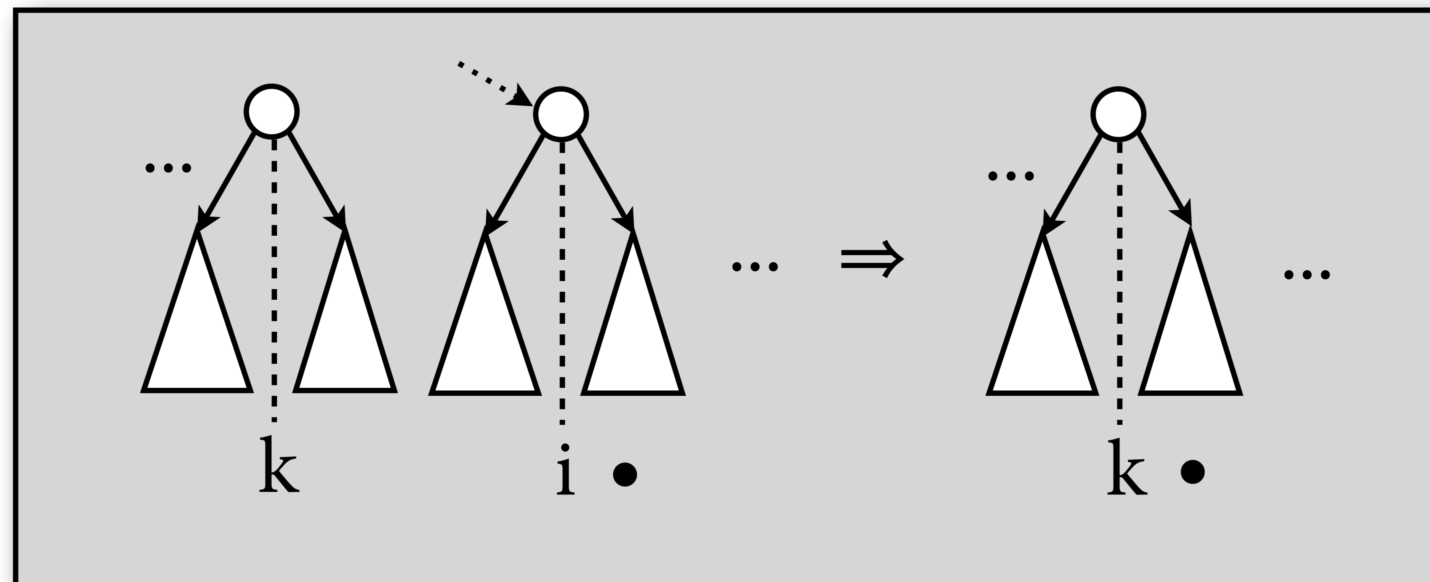


- *i*, *j* both remain on stack because they can receive further children (on the right).

Reduce operation

- Reduce: Remove topmost token from stack.

$$\frac{(\sigma \cdot i,\ \ \tau,\ \ h, d) \quad h(i) \neq 0}{(\sigma,\ \ \tau,\ \ h, d)}$$



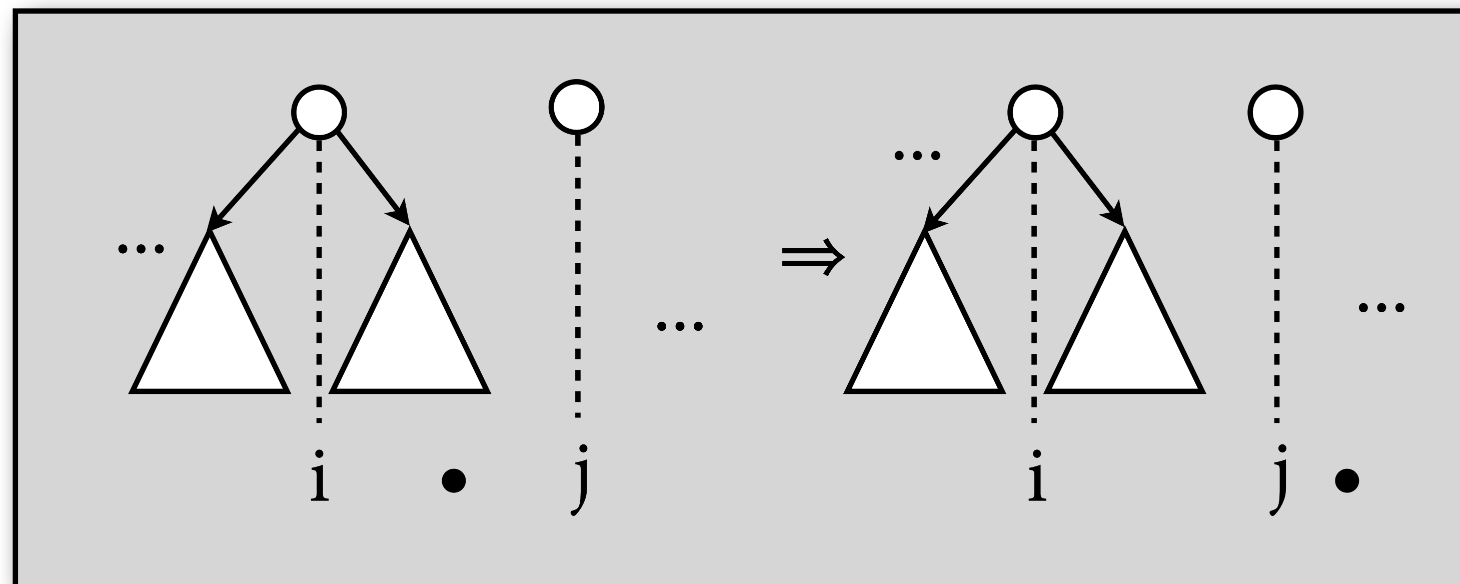
- This decides that we have seen all children of *i*, and makes words further to the left available for receiving further right children.

- Rule requires that *i* already has a parent.

Shift operation

- Shift: Moves next input token *j* to stack.

$$\frac{(\sigma, \quad j \cdot \tau, \quad h, d)}{(\sigma \cdot j, \quad \tau, \quad h, d)}$$



- Decides that *j* and any word *i* on stack are in disjoint tree positions.

Example run

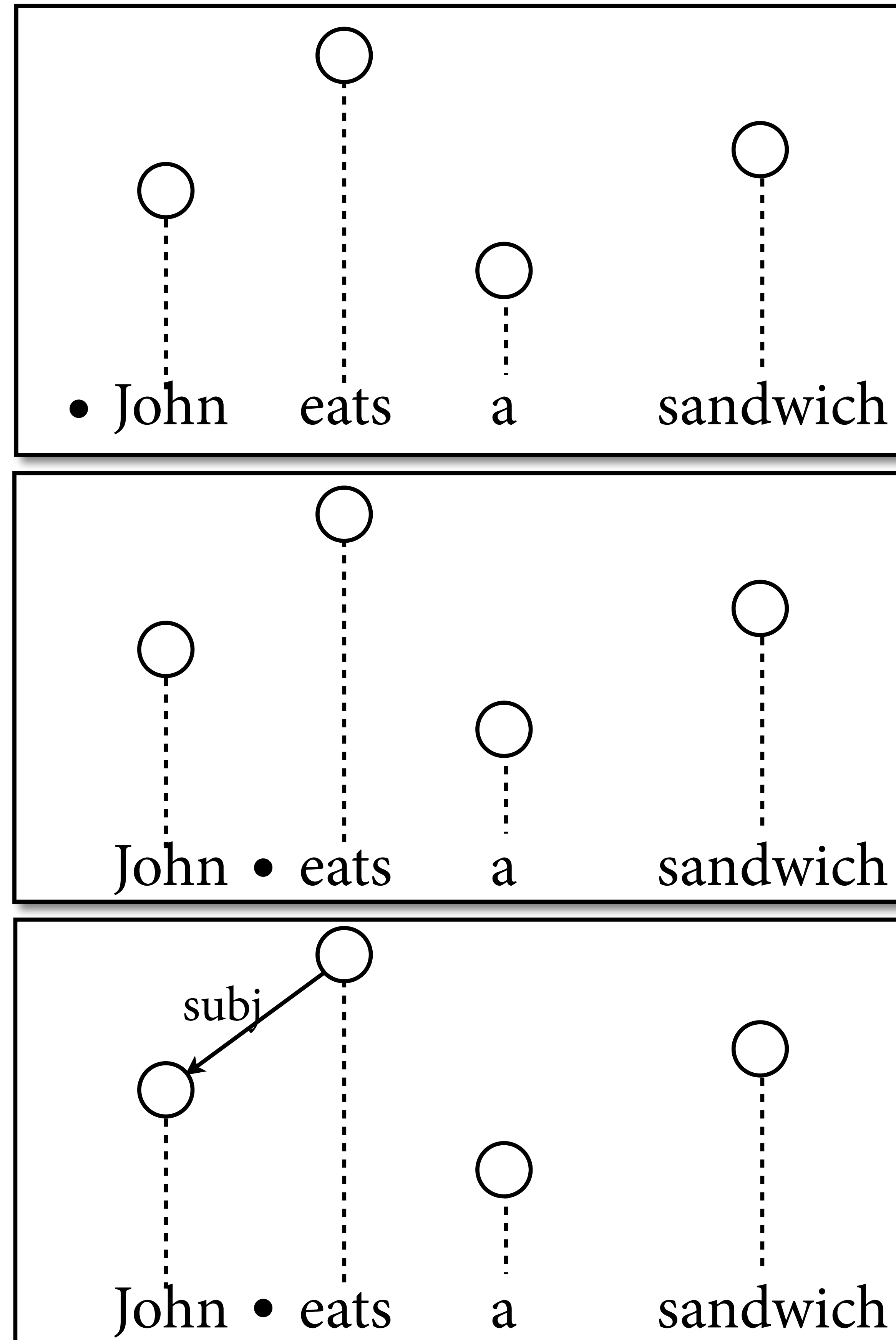
(ε, J eats a sw)

⇓ Shift

(J, eats a sw)

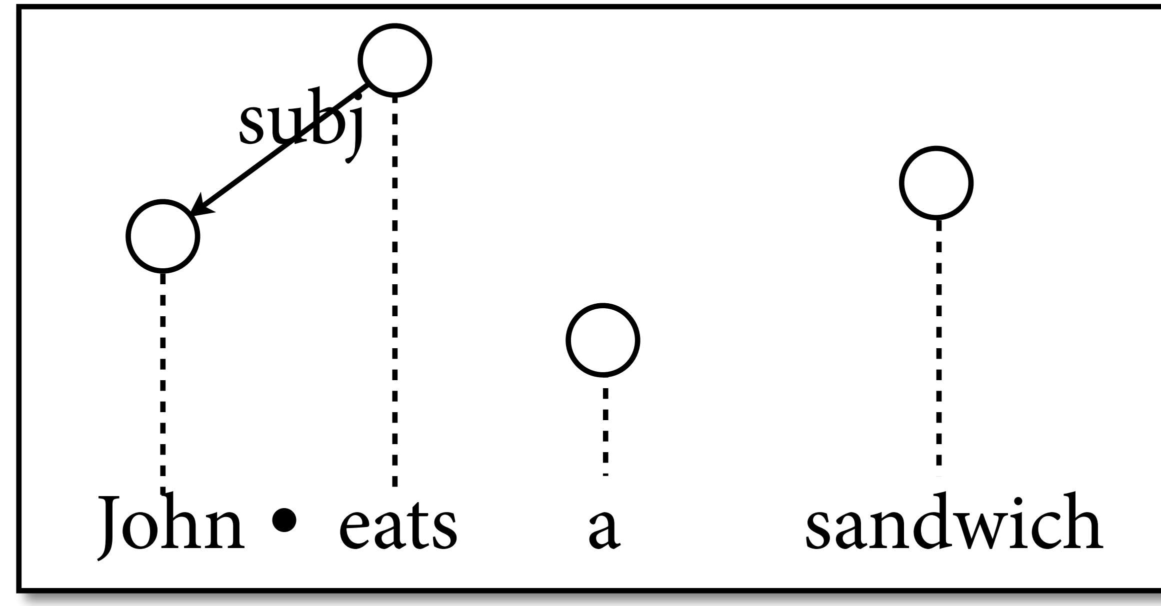
⇓ Left-Arc(subj)

(ε, eats a sw)



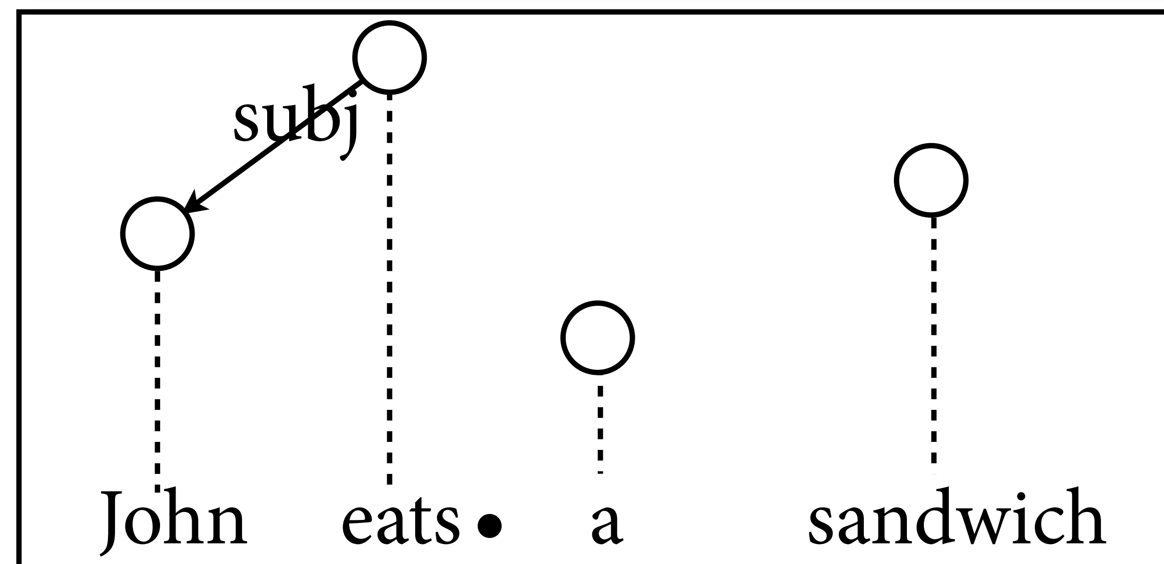
Example run

(ε, eats a sw)



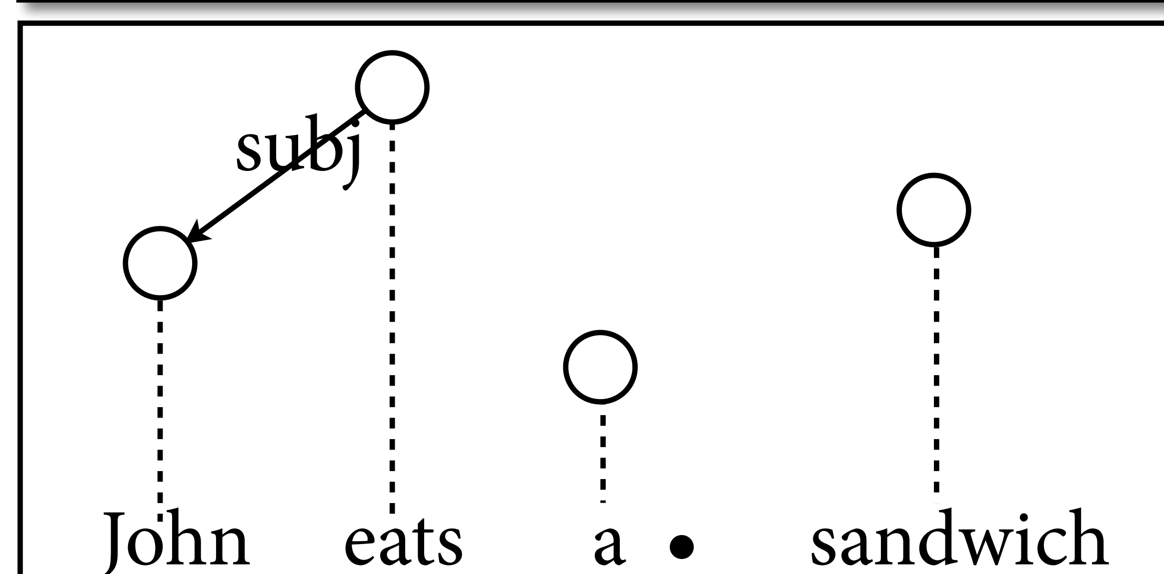
⇓ Shift

(eats, a sw)



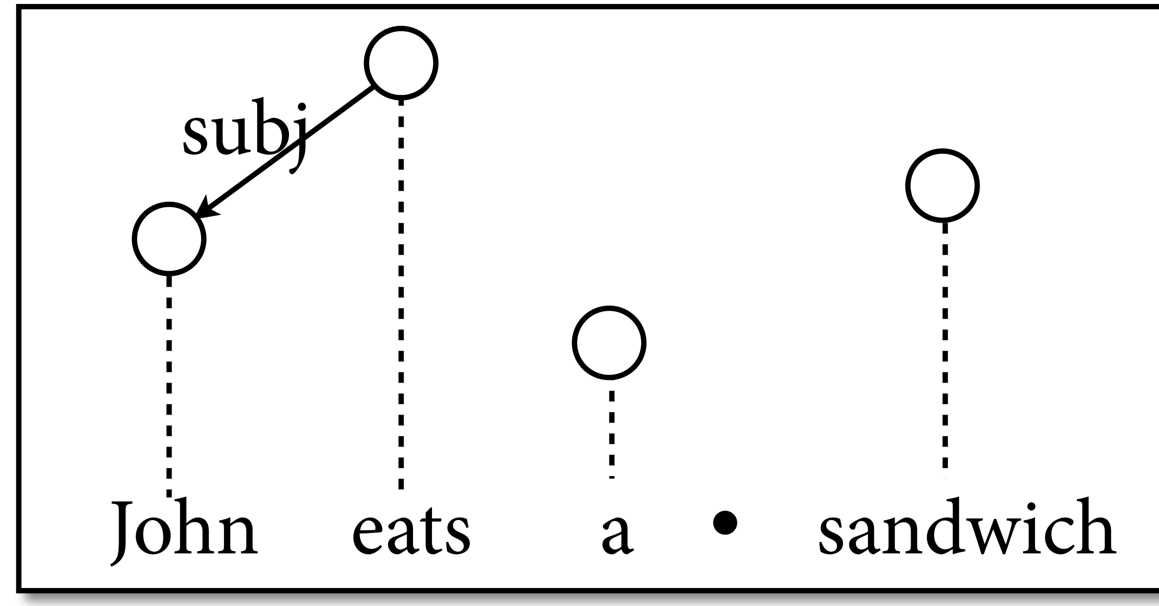
⇓ Shift

(eats a, sw)



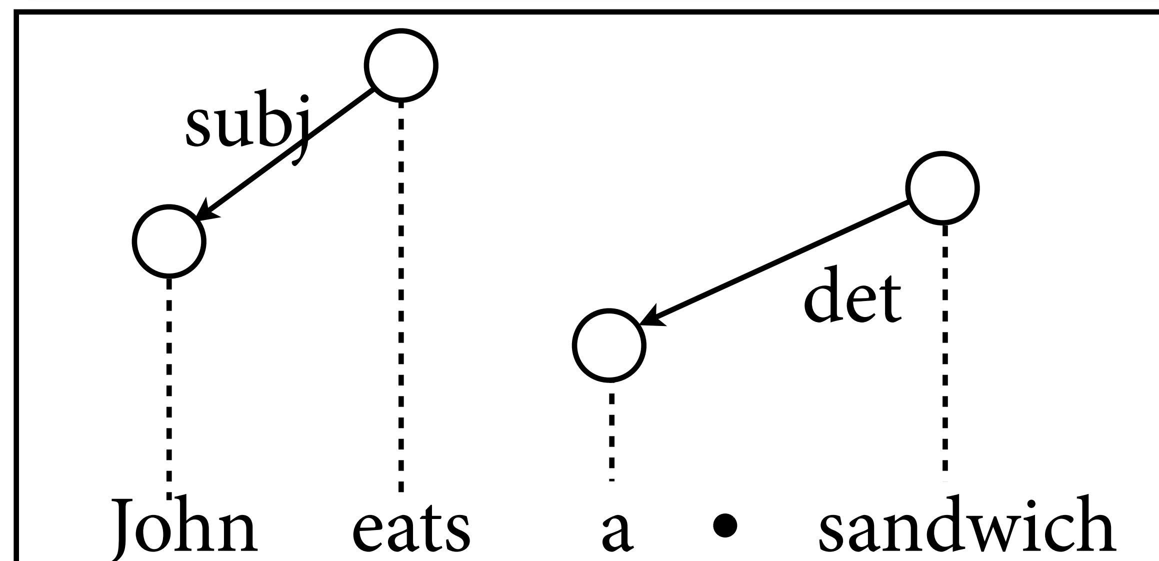
Example run

(eats a, sw)



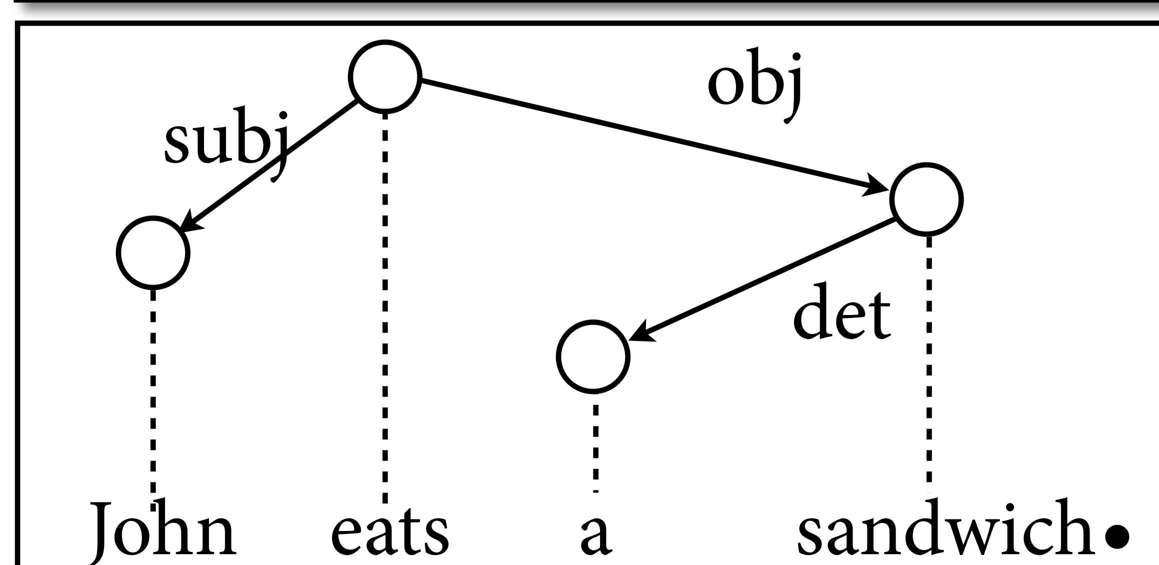
⇓ Left-Arc(det)

(eats, sw)



⇓ Right-Arc(obj)

(eats sw, ε)



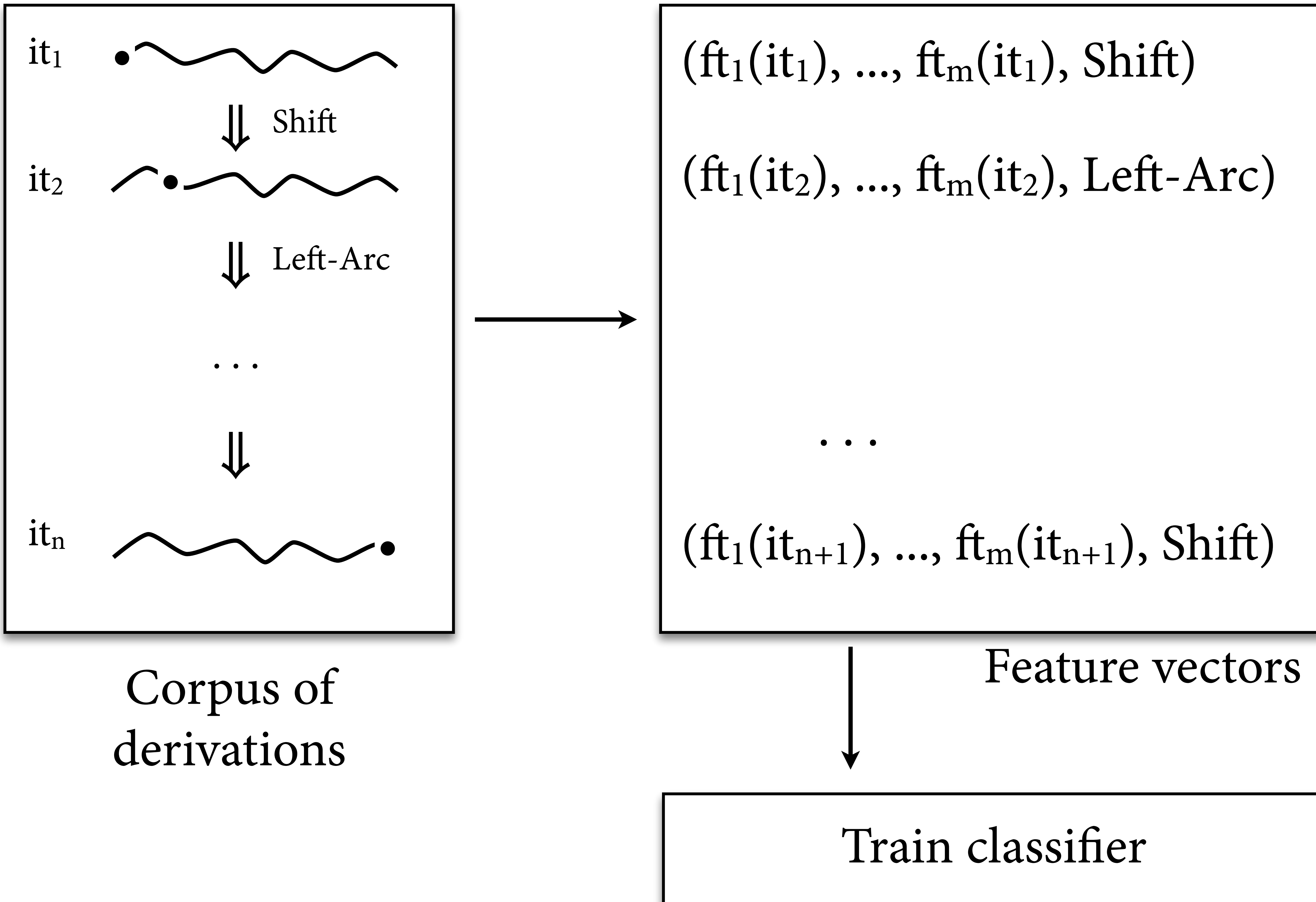
Parsing as Classification

- Can now do deterministic parsing as follows:

```
c = start-item
while (c not goal-item and can apply
       at least one parsing operation to c):
    op = next-operation(c)
    c = perform-operation(c, op)
```

- “next-operation” chooses parsing operation to be applied to c. How do we get it?

Learning classifier

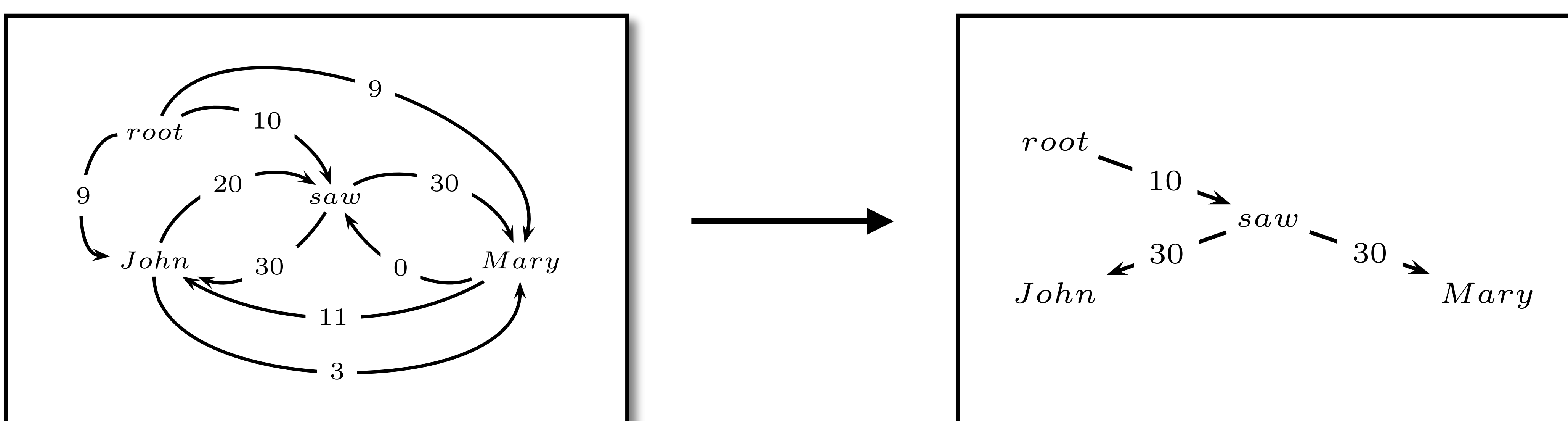


Features in MaltParser

- MaltParser (= standard implementation of Nivre algorithm) offers “toolbox” for features:
  - σ_i: i-th stack token (from the top)
  - τ_i: i-th token in remaining input
  - h(x): parent of x in the tree
  - l(x), r(x): leftmost (rightmost) child of x in the tree
  - p(x): POS tag of x
  - d(x): edge label from h(x) into x
  - build arbitrary terms from these, e.g. $p(l(\sigma_0))$
- Instead of engineering the features, can also use neural network classifier → Google SyntaxNet.

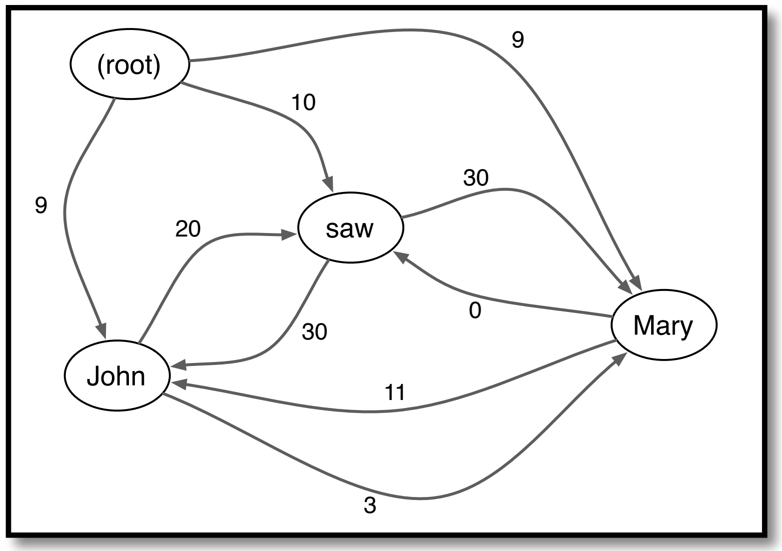
The MST Parser

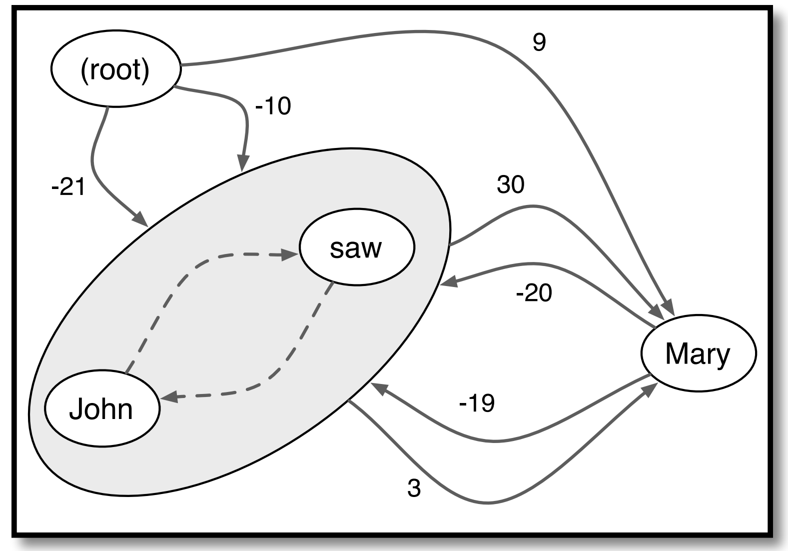
- Alternative idea (McDonald & Pereira, ca 2005):
  - take graph where nodes are words of sentence, and a directed edge between each two nodes
  - weight of edge represents how plausible a statistical model finds this edge
  - then calculate *maximum spanning tree*, i.e. tree that contains all nodes and has maximum sum of edge weights.



Computing MSTs

Using the Chu-Liu-Edmonds algorithm, runtime $O(n^2)$



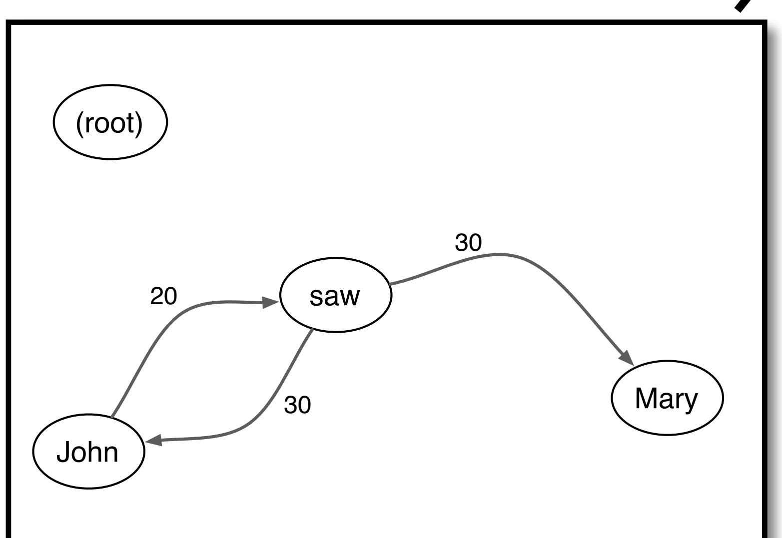


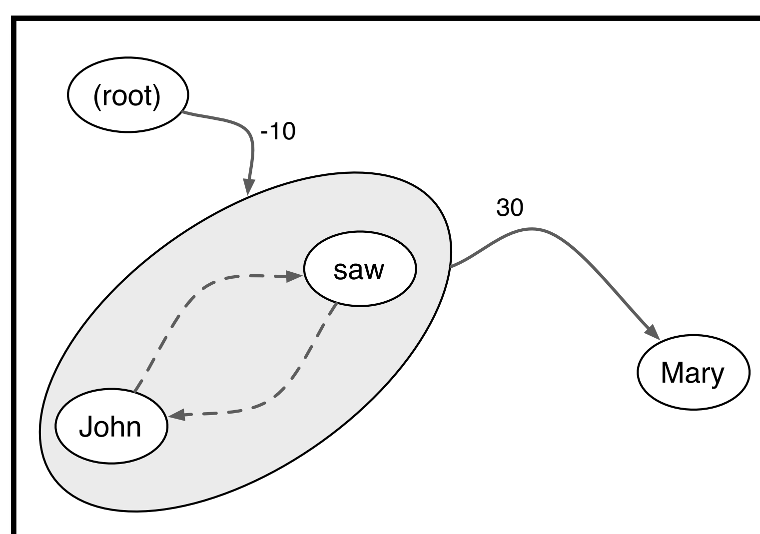
weight of new edge =
weight of old edge (u,v)
- weight of best edge into v

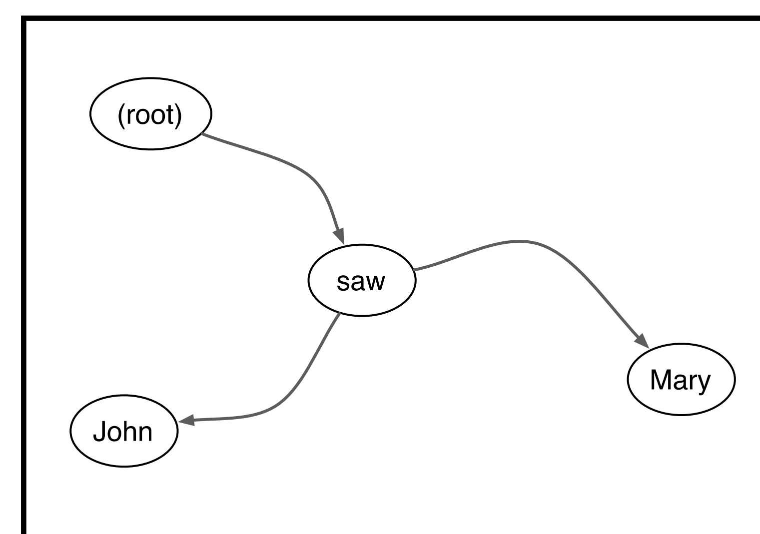
pick best
incoming edges

contract
cycles

pick best
incoming edges







Features

Basic Uni-gram Features
p-word, p-pos
p-word
p-pos
c-word, c-pos
c-word
c-pos

Basic Big-ram Features
p-word, p-pos, c-word, c-pos
p-pos, c-word, c-pos
p-word, c-word, c-pos
p-word, p-pos, c-pos
p-word, p-pos, c-word
p-word, c-word
p-pos, c-pos

In Between POS Features
p-pos, b-pos, c-pos
Surrounding Word POS Features
p-pos, p-pos+1, c-pos-1, c-pos
p-pos-1, p-pos, c-pos-1, c-pos
p-pos, p-pos+1, c-pos, c-pos+1
p-pos-1, p-pos, c-pos, c-pos+1

p = parent; c = child; b = word between parent and child in string

- Learn weight for each feature from training data.
  - using MIRA algorithm, which tries to maximize difference between score of correct parse and score of best wrong parse
- Instead of features, can also use neural model, e.g. Kiperwasser & Goldberg 2016.

Evaluation

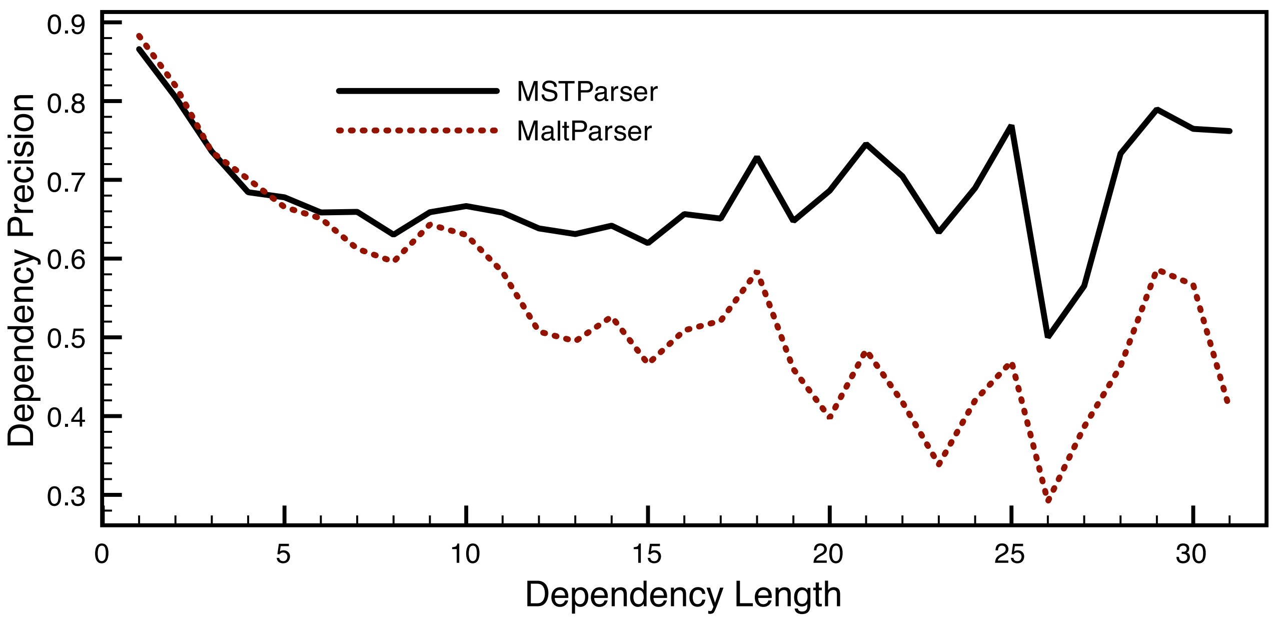
- Which proportion of edges predicted correctly?
  - *label accuracy:*
    #(nodes with correct label of incoming edge) / #nodes
  - *unlabeled attachment score:*
    #(nodes with correct parent) / #nodes
  - *labeled attachment score (LAS):*
    #(nodes with correct parent and edge label) / #nodes

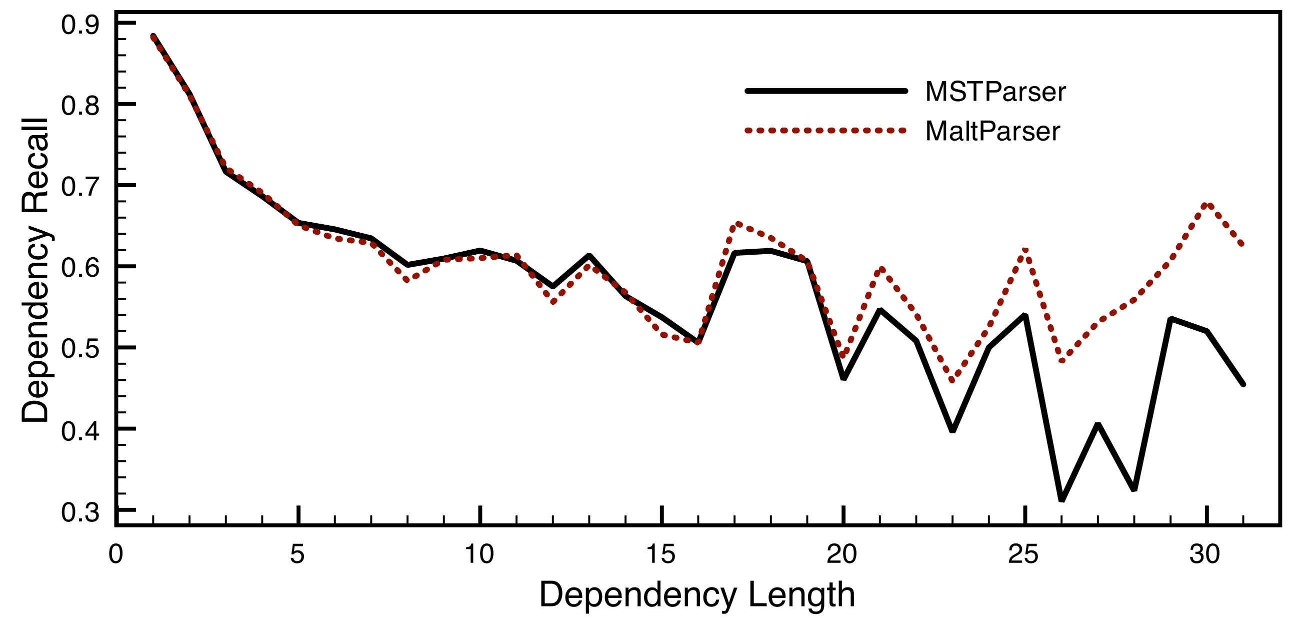
Nivre vs McDonald

	McDonald	Nivre
Arabic	66.91	66.71
Bulgarian	87.57	87.41
Chinese	85.90	86.92
Czech	80.18	78.42
Danish	84.79	84.77
Dutch	79.19	78.59
German	87.34	85.82
Japanese	90.71	91.65
Portuguese	86.82	87.60
Slovene	73.44	70.30
Spanish	82.25	81.29
Swedish	82.55	84.58
Turkish	63.19	65.68
Overall	80.83	80.75

LAS in CoNLL-X Shared Task on Multilingual Dependency Parsing (2006)

Comparison





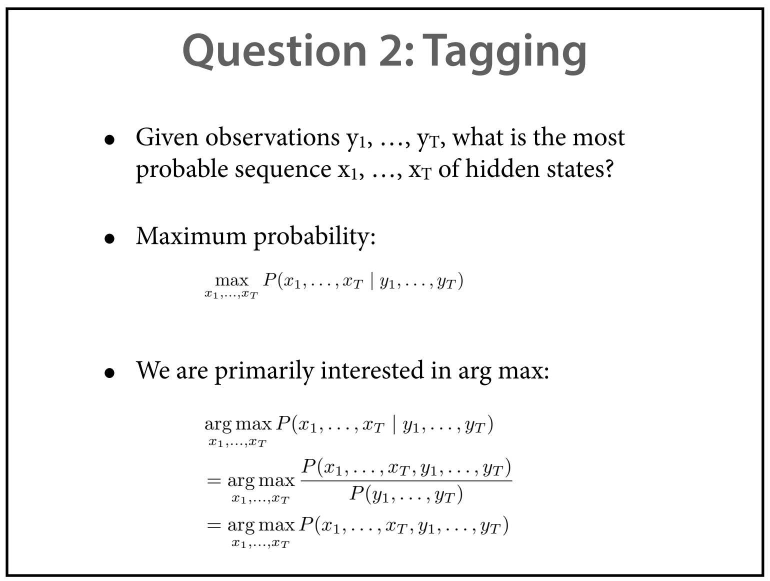
- Observation (McDonald & Nivre 07): MaltParser and MSTParser make complementary mistakes.
  - MSTParser computes globally optimal tree, whereas MaltParser predicts local parsing choices.
  - MSTParser features can only look at individual edges, whereas MaltParser features can look at global tree structure.

Summary

- Dependency parsing: fundamentally different style of parsing algorithm than with PCFGs.
- Much newer parsing style, but now just as popular as PCFG parsing in current research.
- Very fast in practice (e.g. MaltParser is O(n)); Google SyntaxNet does ~600 words/sec.
- State of the art:
  - LAS around 92 on English, around 90 on German
  - cool recent work trains on one language, directly used to parse a different one (with Universal Dependencies)

slide credits

slides that look like this



come from

earlier editions of this class (ANLP), given by Alexander Koller

and their use is gratefully acknowledged. I try to make any modifications obvious, but if there are errors on a slide, assume that I added them.