Graph-based Dependency Parsing

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Reader's Digest

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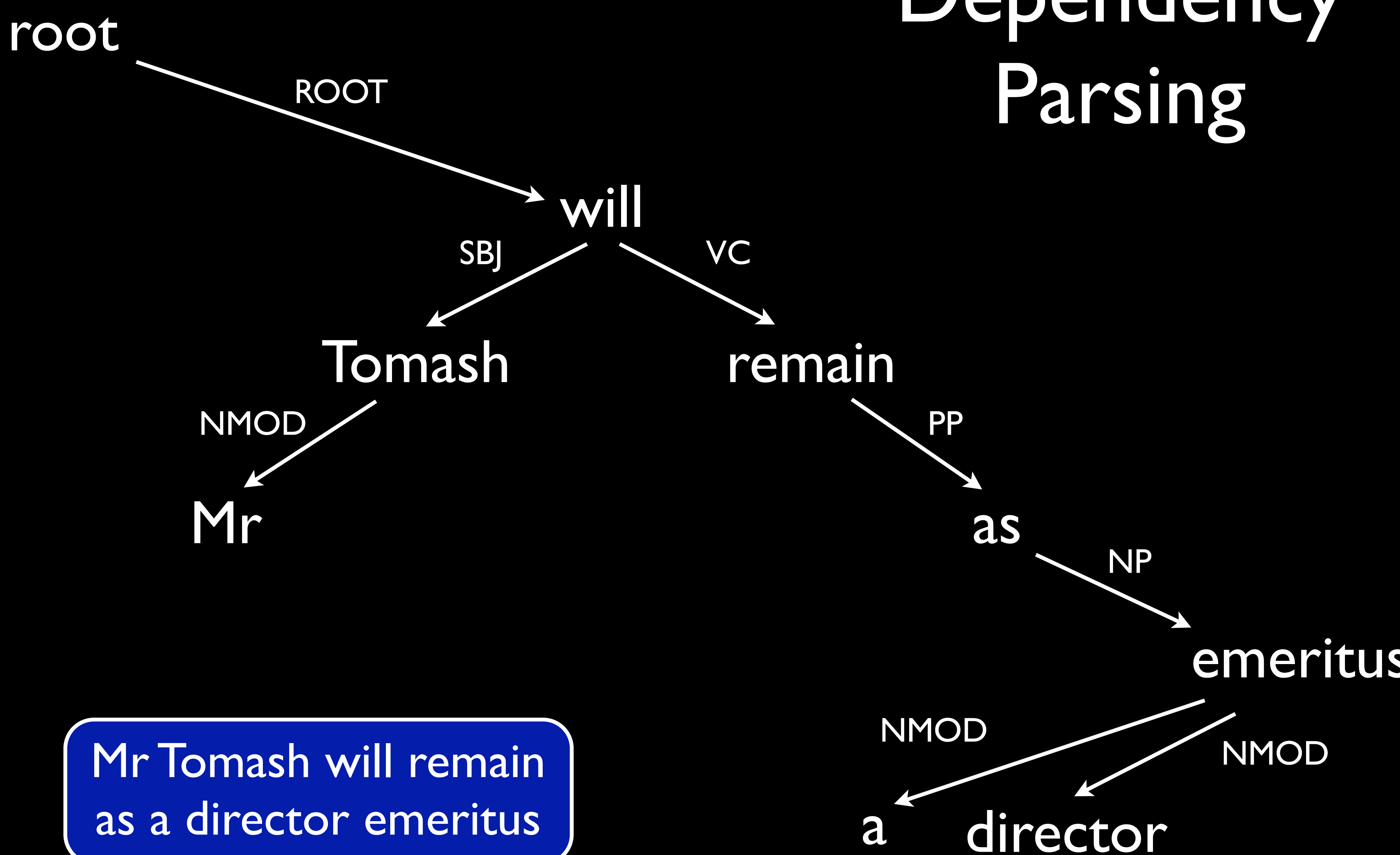
Dependency Parsing



Mr Tomash will remain as a director emeritus

Definitions

$L = \{l_1, l_2, \ldots, l_m\}$ Arc label set

$X = x_0 x_1 \ldots x_n$ Input sentence

Y Dependency Graph/Tree

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root

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Y Dependency Graph/Tree

$\boxed{(i, j, k) \in Y \text{ indicates } x_i \xrightarrow{l_k} x_j}$

Graph-based Parsing

Factor the weight/score graphs by subgraphs

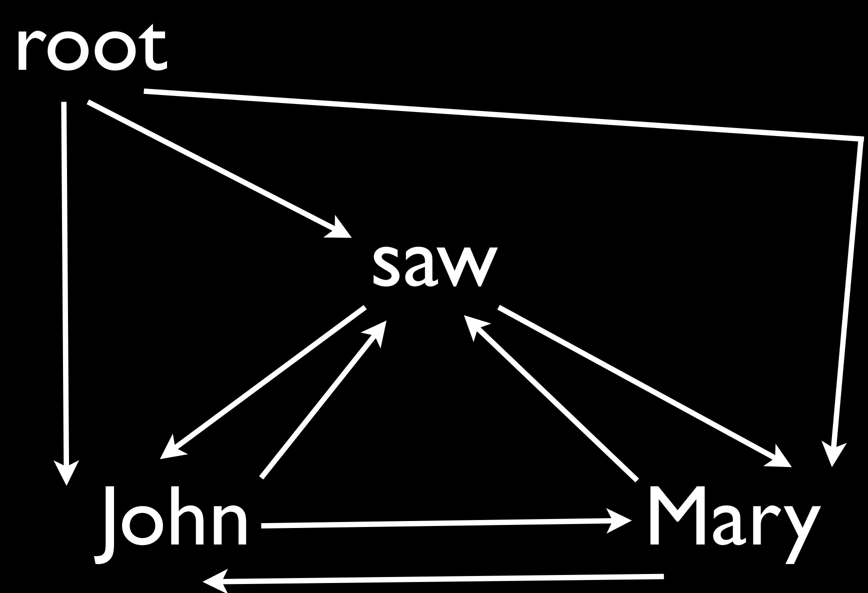
$$\boxed{w(Y) = \prod_{\tau \in Y} w_\tau}$$

τ is from a set of subgraphs
of interest, e.g., arcs, adjacent arcs

Product vs. Sum:

$$Y = \arg\max_Y \prod_{\tau \in Y} w_\tau = \arg\max_Y \sum_{\tau \in Y} \log w_\tau$$

Arc-factored Graph-based Parsing



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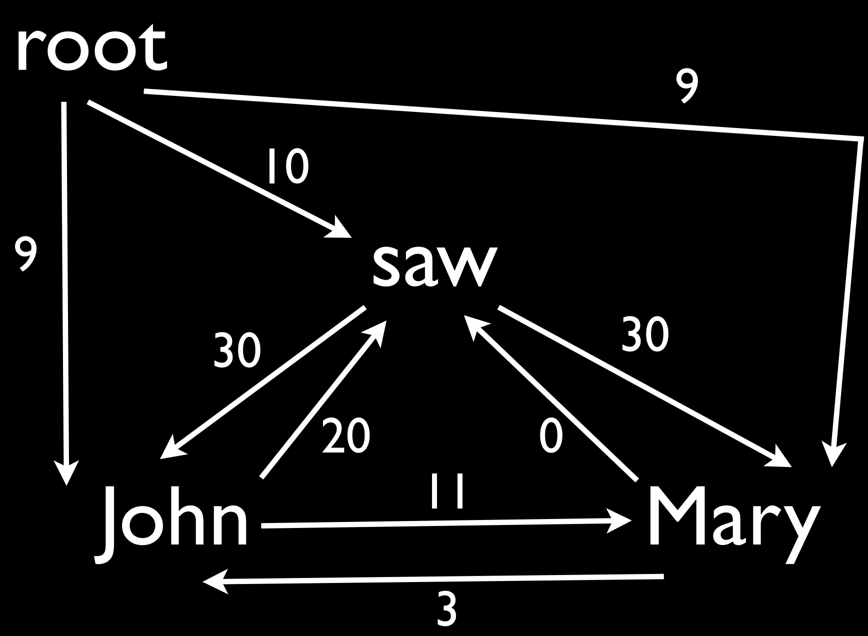
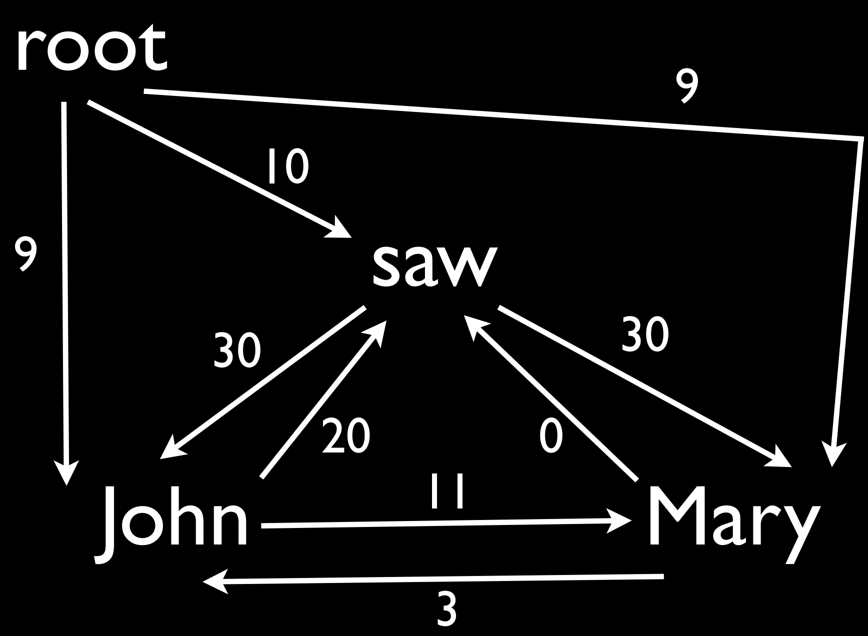


Learn to weight arcs

$$w(Y) = \prod_{a \in Y} w_a$$

Arc-factored Graph-based Parsing



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Inference/Parsing/Argmax

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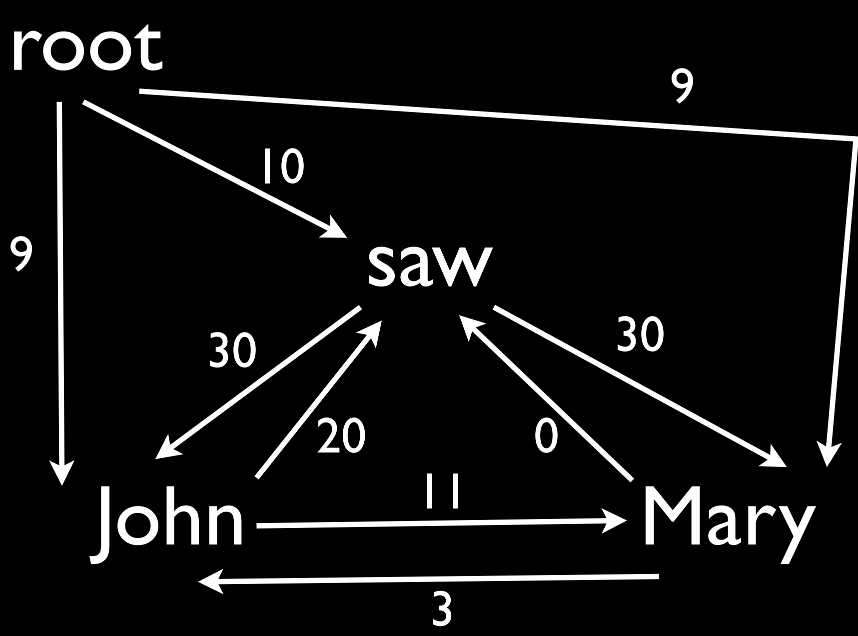

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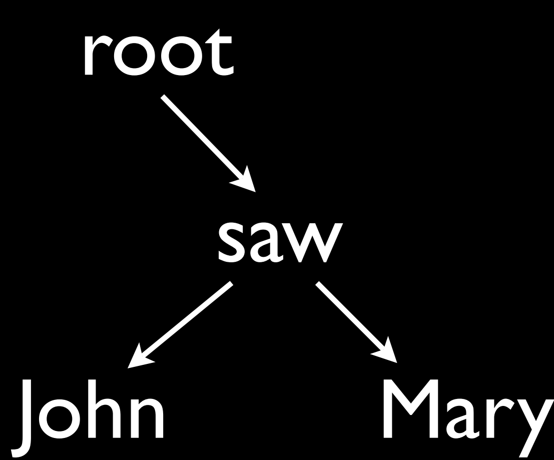
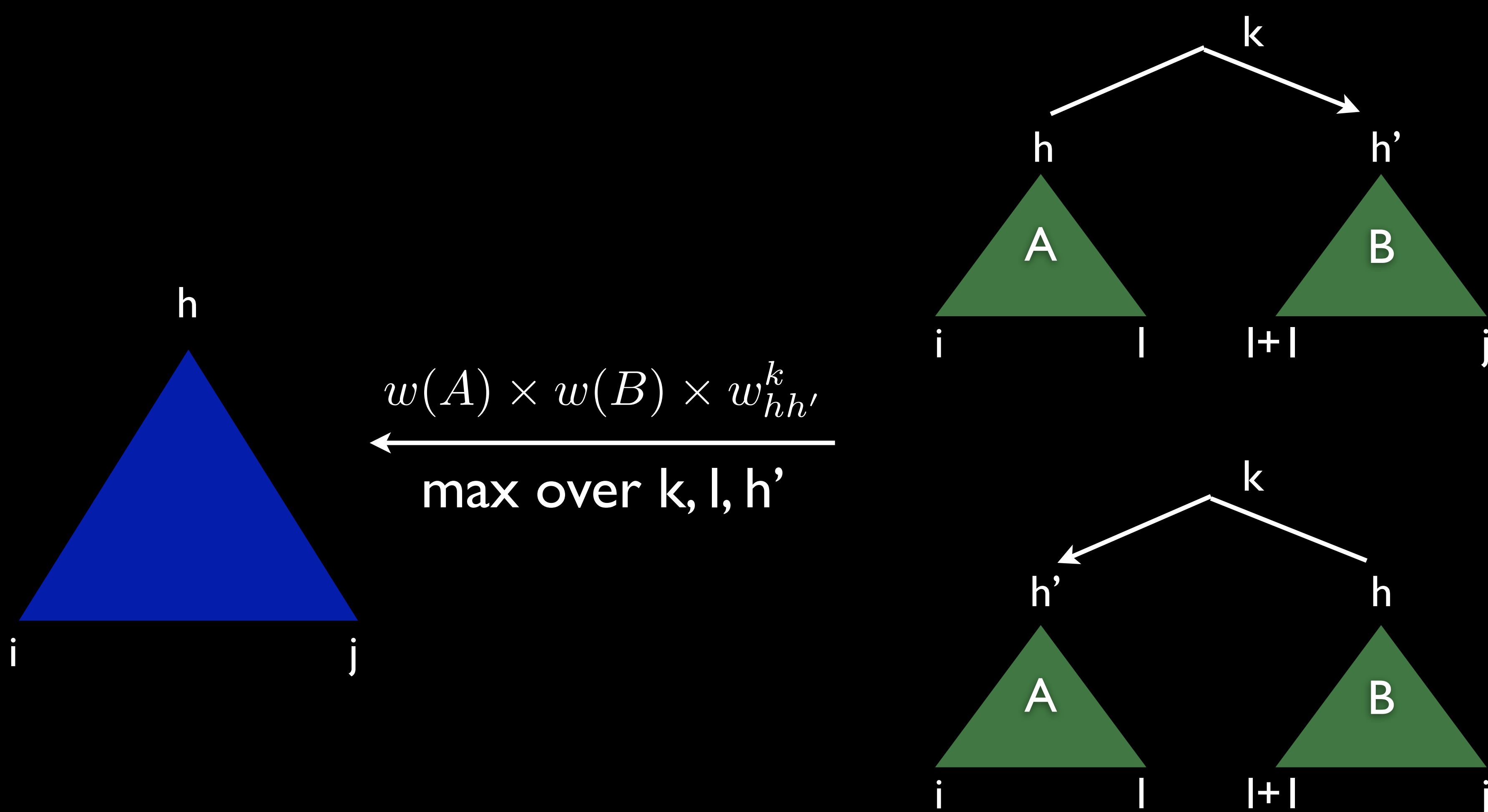


Arc-factored Projective Parsing

W[i][j][h] = weight of best tree spanning words i to j rooted at word h

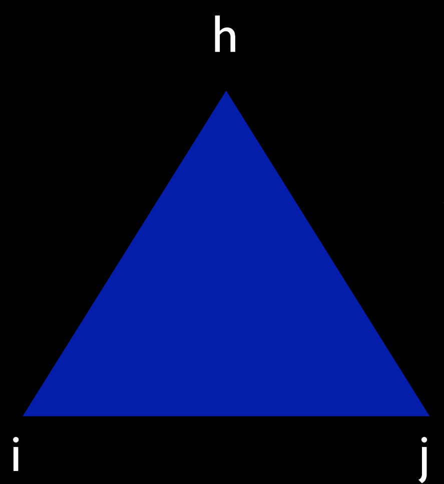


Arc-factored Projective Parsing

W[i][j][h] = weight of best tree spanning
words i to j rooted at word h

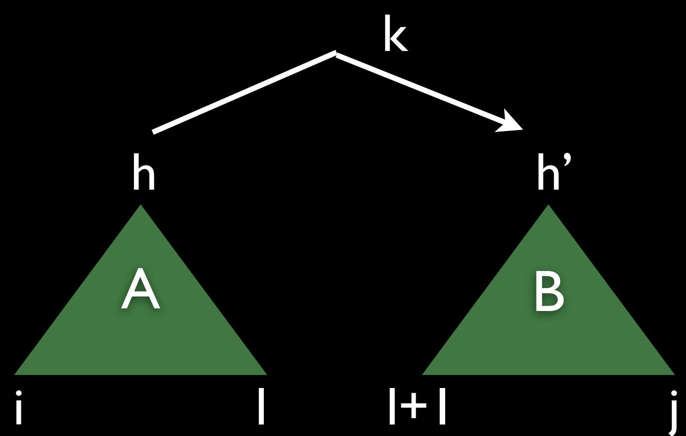
Eisner '96

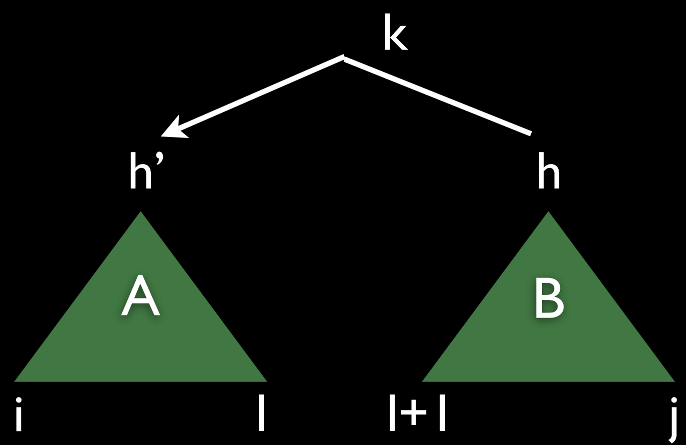
$$O(|L|n^5) \longrightarrow O(n^3 + |L|n^2)$$



$$w(A) \times w(B) \times w^k_{hh'}$$

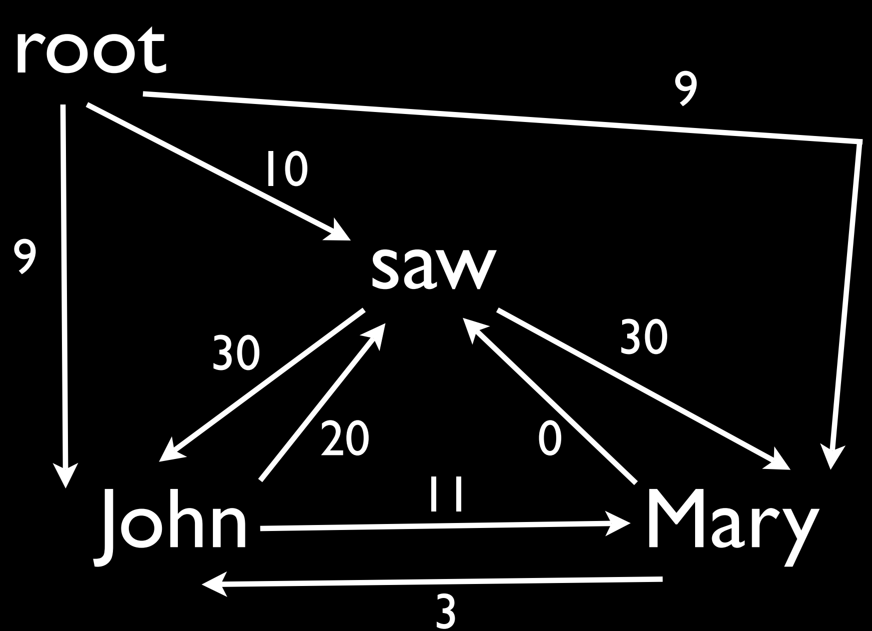
max over k, l, h'





Arc-factored Non-projective Parsing

- Non-projective Parsing (McDonald et al ’05)
  - Inference: $O(|L|n^2)$ with Chu-Liu-Edmonds MST alg
  - Greedy-Recursive algorithm



Spanning trees

|||

Valid dependency graphs

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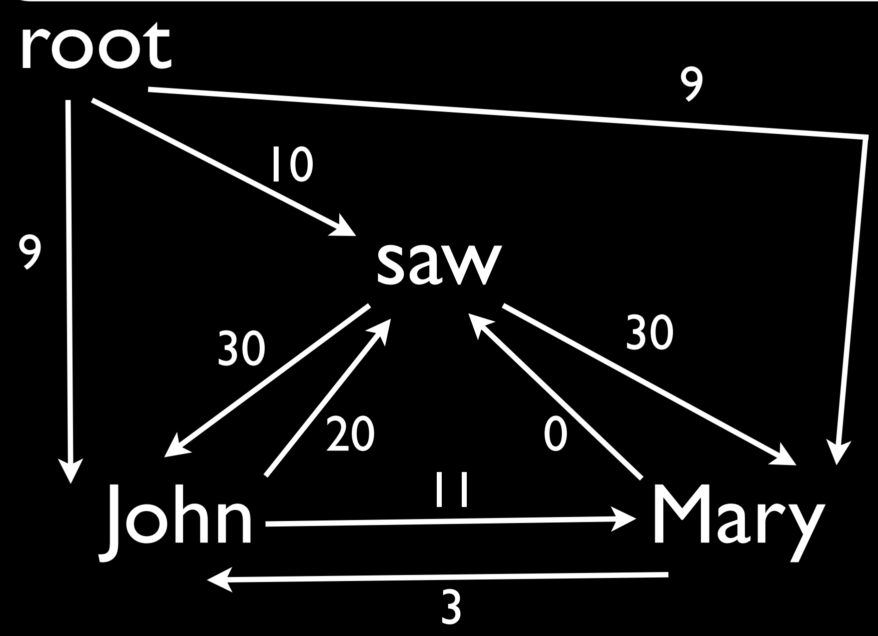
We win with non-projective algorithms! ... err ...



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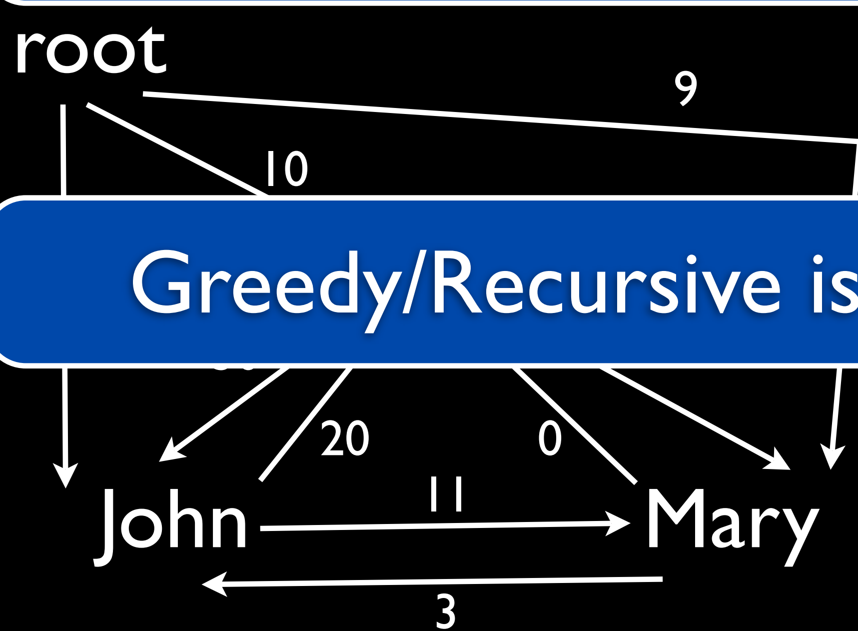

Spanning trees

Greedy/Recursive is not what we are used to

Valid dependency graphs

Beyond Arc-factored Models

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- But does not model linguistic reality
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Arity

- Arity of a word = # of modifiers in graph
- Model arity through preference parameters

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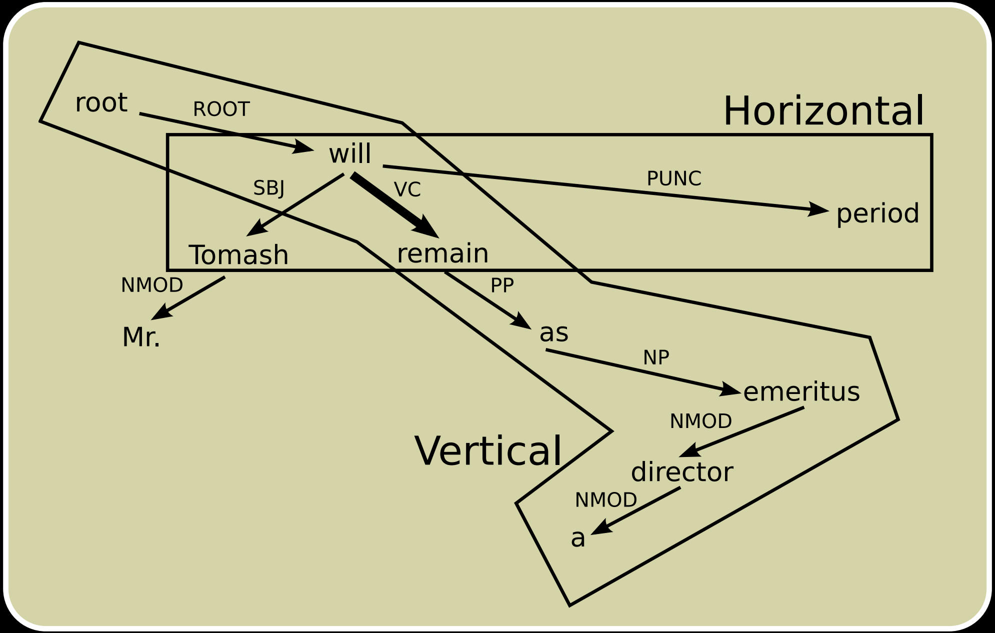


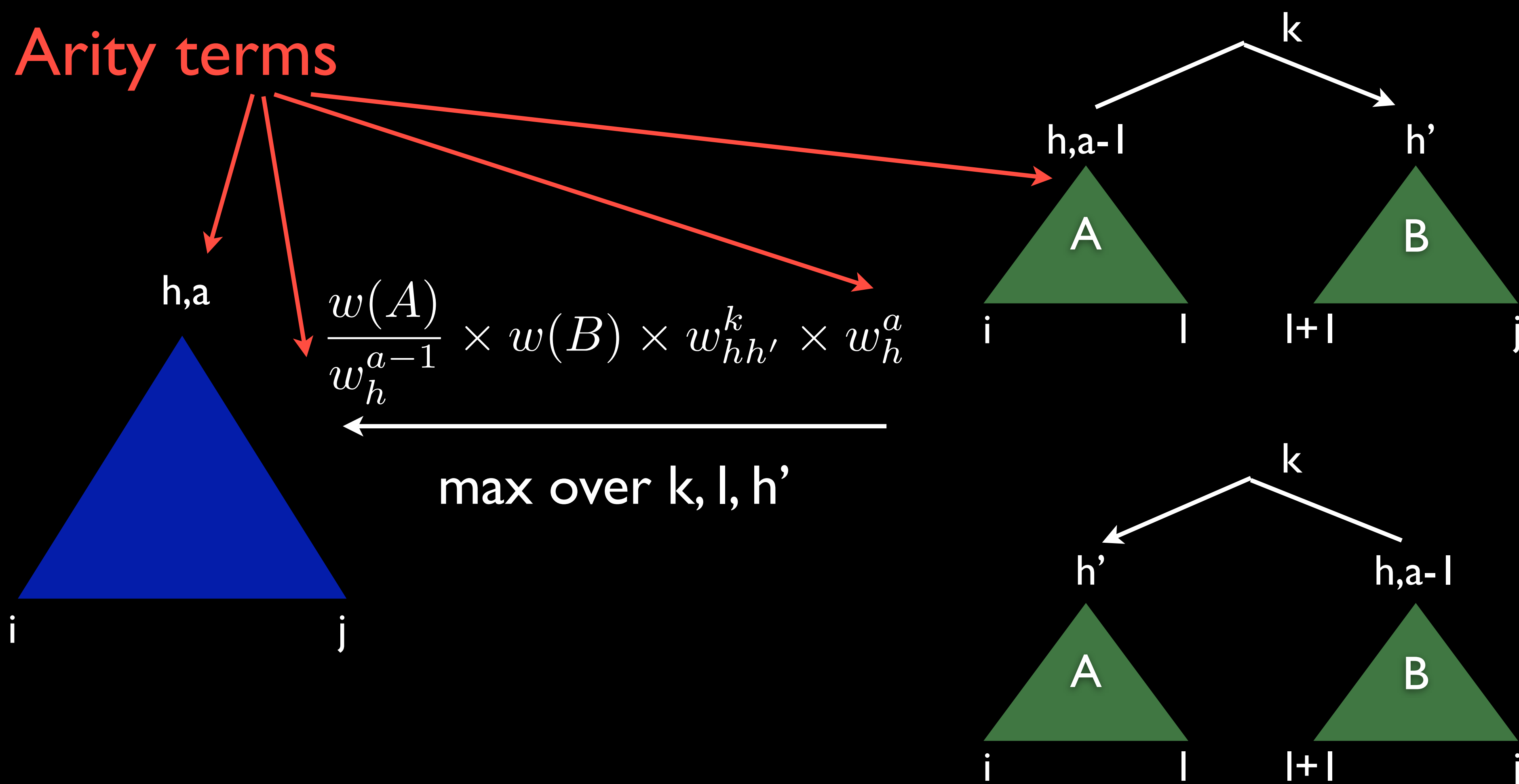
Markovization

Vertical/Horizontal

Adjacent arcs

Projective -- Easy

W[i][j][h][a] = weight of best tree spanning words i to j rooted at word h with arity a



Non-projective -- Hard

- McDonald and Satta '07
  - Arity (even just modified/not-modified) is NP-hard
  - Markovization is NP-hard
  - Can basically generalize to any non-local info
  - Generalizes Nehaus and Boker '97

Arc-factored: non-projective "easier"
Beyond arc-factored: non-projective "harder"

Non-projective Solutions

- In all cases we augment w(Y)

$$w(Y) = \prod_{(i,j,k)} w_{ij}^k \times \beta$$

Arity/Markovization/etc

- Calculate w(Y) using:
  - Approximations (Jason's talk!)
  - Exact ILP methods
  - Chart-parsing Algorithms
  - Re-ranking
  - MCMC

Annealing Approximations

(McDonald & Pereira 06)

$$w(Y) = \prod_{(i,j,k)} w_{ij}^k \times \beta$$

- Start with initial guess
- Make small changes to increase w(Y)

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Initial guess: $\arg\max_Y \prod_{(i,j,k)} w_{ij}^k$

Arc Factored

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- Start with initial guess
- Make small changes to increase w(Y)

Initial guess: $\arg\max_{Y} \prod_{(i,j,k)} w_{ij}^{k}$ ← Arc Factored

Until convergence

Find arc change to maximize $w(Y) = \prod_{(i,j,k)} w_{ij}^{k} \times \beta$

Make the change to guess

Annealing Approximations

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$$w(Y) = \prod_{(i,j,k)} w_{ij}^k \times \beta$$

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Initial guess: $\arg\max_{Y} \prod_{(i,j,k)} w_{ij}^k$

Arc Factored

Until convergence

Find arc change to maximize

Make the change to guess

Good in practice, but suffers from local maxima

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Integer Linear Programming (ILP)

(Riedel and Clarke 06, Kubler et al 09, Martins, Smith and Xing 09)

- An ILP is an optimization problem with:
  - A linear objective function
  - A set of linear constraints
- ILPs are NP-hard in worst-case, but well understood w/ fast algorithms in practice
- Dependency parsing can be cast as an ILP

Note: we will work in the log space

$$Y = \arg\max_{Y \in Y(G_X)} \sum_{(i,j,k)} \log w_{ij}^{k}$$

Arc-factored Dependency Parsing as an ILP

(from Kubler, MDonald and Nivre 2009)

Define integer variables:

$$a_{ij}^k \in \{0, 1\}$$

$$a_{ij}^k = 1 \text{ iff } (i, j, k) \in Y$$

$$b_{ij} \in \{0, 1\}$$

$$b_{ij} = 1 \text{ iff } x_i \rightarrow \ldots \rightarrow x_j \in Y$$

Arc-Factored Dependency Parsing as an ILP

(from Kubler, McDonald and Nivre 2009)

$$\max_{\mathbf{a}} \sum_{i,j,k} a_{ij}^k \times \log w_{ij}^k$$

such that:

$$\sum_{i,k} a_{i0}^k = 0 \qquad \forall j : \sum_{i,k} a_{ij}^k = 1$$

$$\forall i,j,k : b_{ij} - a_{ij}^k \geq 0$$

$$\forall i,j,k : 2b_{ik} - b_{ij} - b_{jk} \geq -1$$

$$\forall i : b_{ii} = 0$$

Constrain arc assignments to produce a tree

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Arc-Factored Dependency Parsing as an ILP

(from Kubler, McDonald and Nivre 2009)

$$\max_{\mathbf{a}} \sum_{i,j,k} a_{ij}^k \times \log w_{ij}^k$$

Can add non-local constraints & preference parameters
Riedel & Clarke '06, Martins et al. 09

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Dynamic Prog/Chart-based methods

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- Gomez-Rodriguez et al. 09, Kuhlmann 09
  - For well-nested dependency trees of gap-degree 1
    - Kuhlmann & Nivre: Accounts for >> 99% of trees
    - $O(n^7)$ deductive/chart-parsing algorithms

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Chart-parsing == easy to extend beyond arc-factored assumptions

What is next?

- Getting back to grammars?
- Non-projective unsupervised parsing?
- Efficiency?

Getting Back to Grammars

- Almost all research has been grammar-less
  - All possible structures permissible
  - Just learn to discriminate good from bad
- Unlike SOTA phrase-based methods
  - All explicitly use (derived) grammar

Getting Back to Grammars

Getting Back to Grammars

- Projective == CF Dependency Grammars
  - Gaifman (65), Eisner & Blatz (07), Johnson (07)

Getting Back to Grammars

- Projective == CF Dependency Grammars
  - Gaifman (65), Eisner & Blatz (07), Johnson (07)
- Mildly context sensitive dependency grammars
  - Restricted chart parsing for well-nested/gap-degree 1
  - Bodirsky et al. (05): capture LTAG derivations

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- Mildly context sensitive dependency grammars
  - Restricted chart parsing for well-nested/gap-degree 1
  - Bodirsky et al. (05): capture LTAG derivations
- ILP == Constraint Dependency Grammars (Maruyama 1990)
  - Both just put constraints on output
  - CDG constraints can be added to ILP (hard/soft)
  - Annealing algs == repair algs in CDGs

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  -
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Questions

1. Can we flush out the connections further?
2. Can we use grammars to improve accuracy and parsing speeds?

Non-projective Unsupervised Parsing

- McDonald and Satta 07
  - Dependency model w/o valence (arity) is tractable
  - Not true w/ valence
- Klein & Manning 04, Smith 06, Headden et al. 09
  - All projective
  - Valence++ required for good performance

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Non-projective Unsupervised Systems?

Efficiency / Resources

Swedish

	Malt Joint	MST pipeline	MST joint	MST Joint Feat Hash	MST Joint Feat Hash Coarse to Fine
	$O(nL)$	$O(n^3 + nL)$	$O(n^3L^2)$	$O(n^3L^2)$	$O(n^2kl^2)$
LAS	84.6	82.0	83.9	84.3	84.1
Parse time	-	1.00	~125.00	~30.00	4.50
Model size	-	88 Mb	200 Mb	11 Mb	15 Mb
# features	-	16 M	30 M	30 M	30 M

Pretty good, but still not there! -- A*?, More pruning?

Summary

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- Where we've been
  - Arc-factored: Eisner / MST
  - Beyond arc-factored: NP-hard
    - Approximations
    - ILP
    - Chart-parsing on defined subset

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- Where we've been
  - Arc-factored: Eisner / MST
  - Beyond arc-factored: NP-hard
    - Approximations
    - ILP
    - Chart-parsing on defined subset
- What's next
  - The return of grammars?
  - Non-projective unsupervised parsing
  - Making models practical on web-scale

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