Recent Advances in Dependency Parsing

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NAACL Tutorial, Los Angeles
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Topic-Author Clouds of NAACL-HLT 2010

Quite popular

Courtesy: http://www.wordle.net

Dependency Parsing Events in Recent Years

- CoNLL-X Shared Task: Multi-lingual Dependency Parsing in 2006
  - http://nextens.uvt.nl/~conll/

- Tutorial by Joachim Nivre and Sandra Kuebler at COLING-ACL in 2006
  - http://aclweb.org/mirror/acl2006/program/tutorials/dependency.html

- CoNLL Shared Task: Joint Parsing of Syntactic and Semantic Dependencies in 2008
  - http://www.yr-bcn.es/conll2008/

A Few Notes

- This tutorial is focused on **recent development** in dependency parsing
  - After 2006
- Although this tutorial is on dependency parsing, most approaches are applicable to other formalisms
  - E.g., phrase-structure parsing or synchronous parsing for MT
- The field is really parsing instead of dependency parsing
  - Read all the parsing papers if you can!

Tutorial Goals

- Introduce data-driven dependency parsing (graph-based, transition-based and integrated models)
- Improve dependency parsing via statistical machine learning approaches
  - Explore more features with better learning algorithms
  - Better parsing strategies (efficiency and accuracy)
  - Using extra information sources

Outline

- Part A: introduction to dependency parsing
- Part B: graph-based dependency parsing models
- Part C: transition-based dependency parsing models
- Part D: the integrated models
- Part E: other recent trends in dependency parsing

Part A: Introduction to Dependency Parsing

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- Part A: introduction to dependency parsing
  - **Dependency syntax**
  - Dependency parsing approaches
- Part B: graph-based dependency parsing models
- Part C: transition-based dependency parsing models
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Ambiguities In NLP

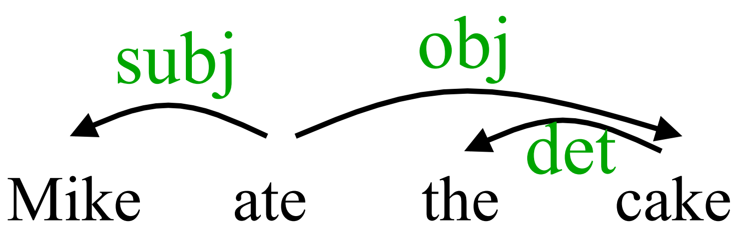
"I saw her duck."

How about

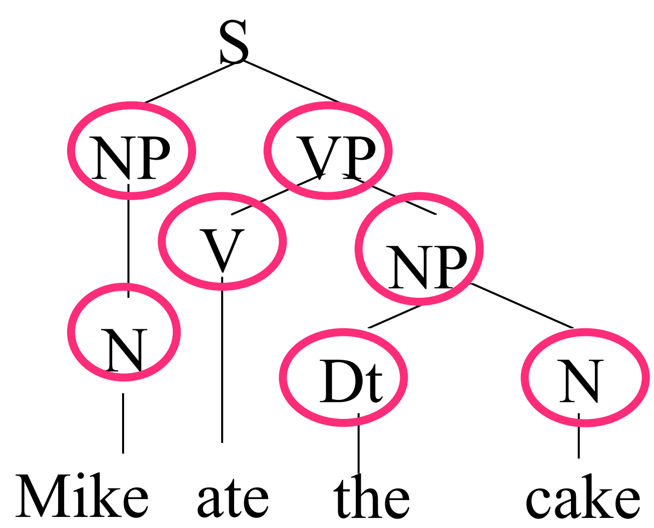
"I saw her duck with a telescope."

Dependency Structure vs. Constituency Structure

Parsing is one way to deal with the ambiguity problem in natural language.



Dependency structure



Constituency structure

Dependency Syntax

- A dependency structure represents syntactic relations (**dependencies**) between word pairs in a sentence
  - By drawing a link between the two words

- For the link: **a** **telescope**

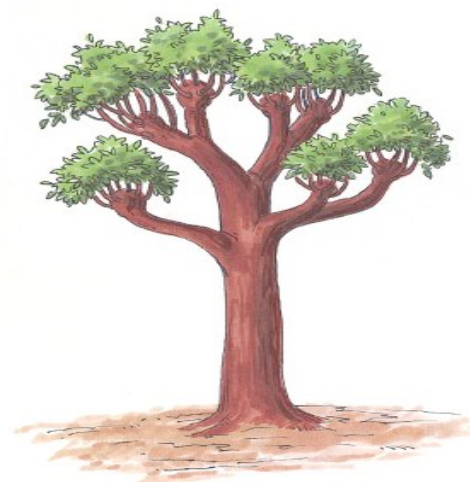
The **head** of ***a*** is ***telescope***

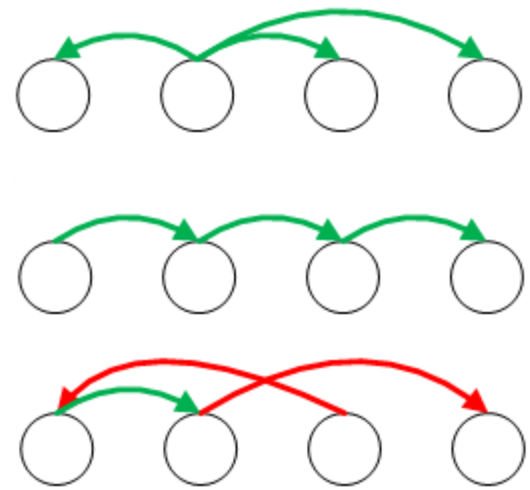
- Modifier
- Dependent
- Child

- Head
- Governor
- Parent

Dependency Graphs

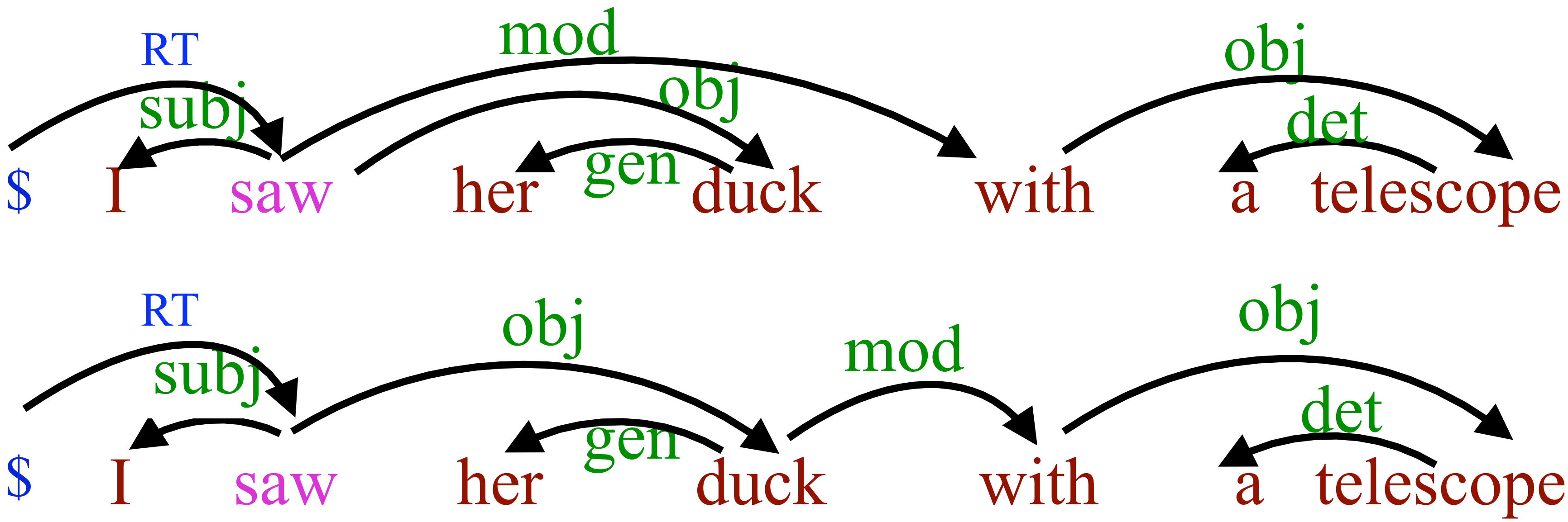
- A dependency structure is a directed graph G with the following constraints:
  - Connected
  - Acyclic
  - Single-head
  - Projective



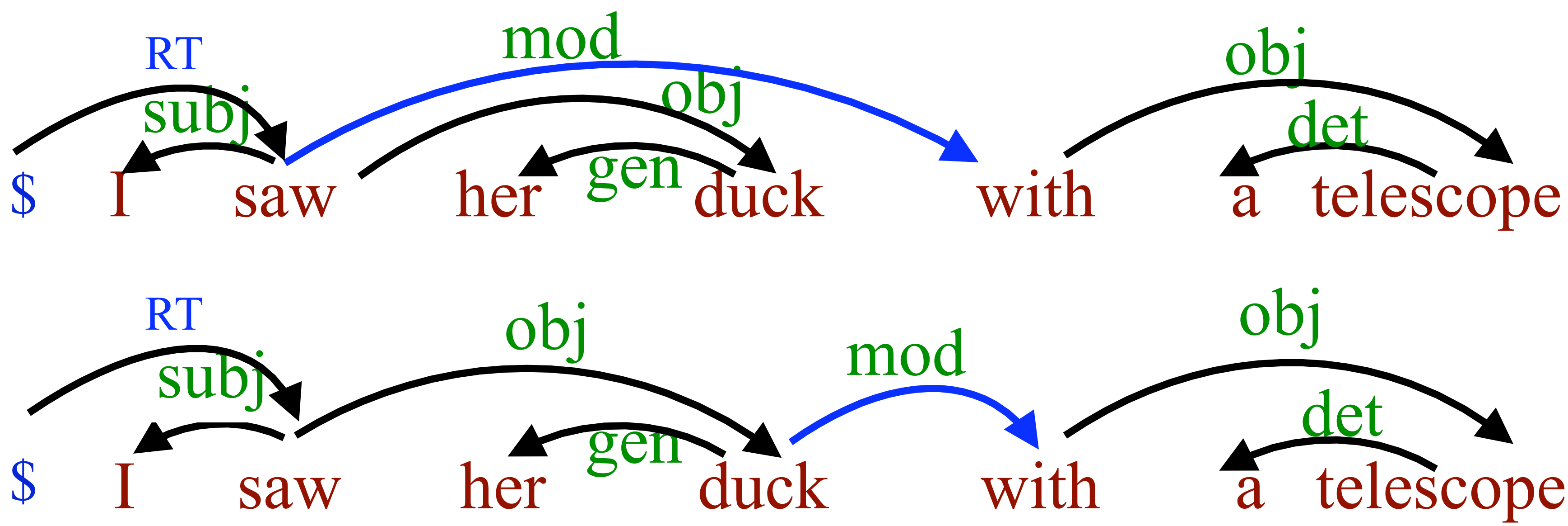


No crossing links (a word and its dependents form a contiguous substring of the sentence)

Dependency Trees

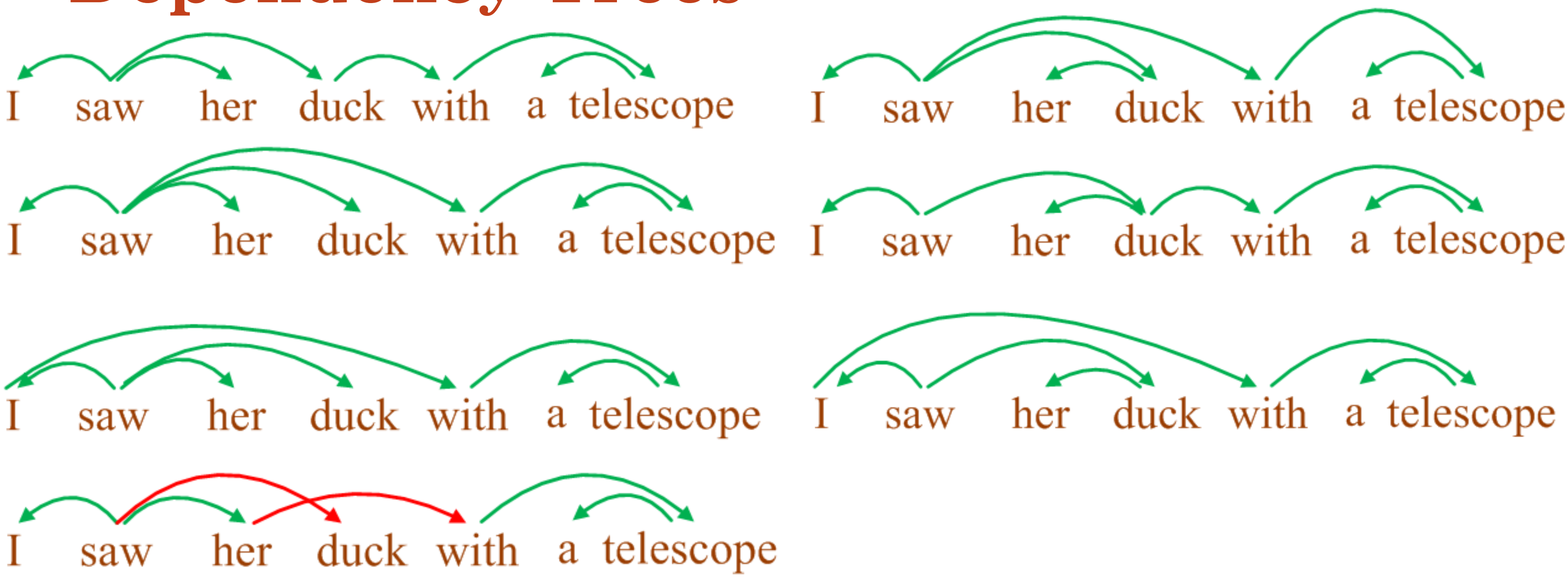


Dependency Trees



Dependency Trees

How many trees for a 20-word sentence?
Over one million!!



Over 100 possible trees for this seven-word sentence!

Non-projective Dependency Trees

- With crossing links
- Not so frequent in English
  - All the dependency trees from Penn Treebank are projective
- Common in other languages (Kuhlmann & Satta 09)
  - 23% sentences are non-projective in the Prague Dependency Treebank of Czech
  - Percentage in German and Dutch are even higher

• Long-distance dependencies
• Languages with free word order, such as German and Dutch

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- Part B: graph-based dependency parsing models
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Dependency Parsing

- The problem:
  - Input: a sentence
  - Output: a dependency tree (**connected**, **acyclic**, **single-head**)

- Grammar-based parsing
  - Context-free dependency grammar
  - Constraint dependency grammar

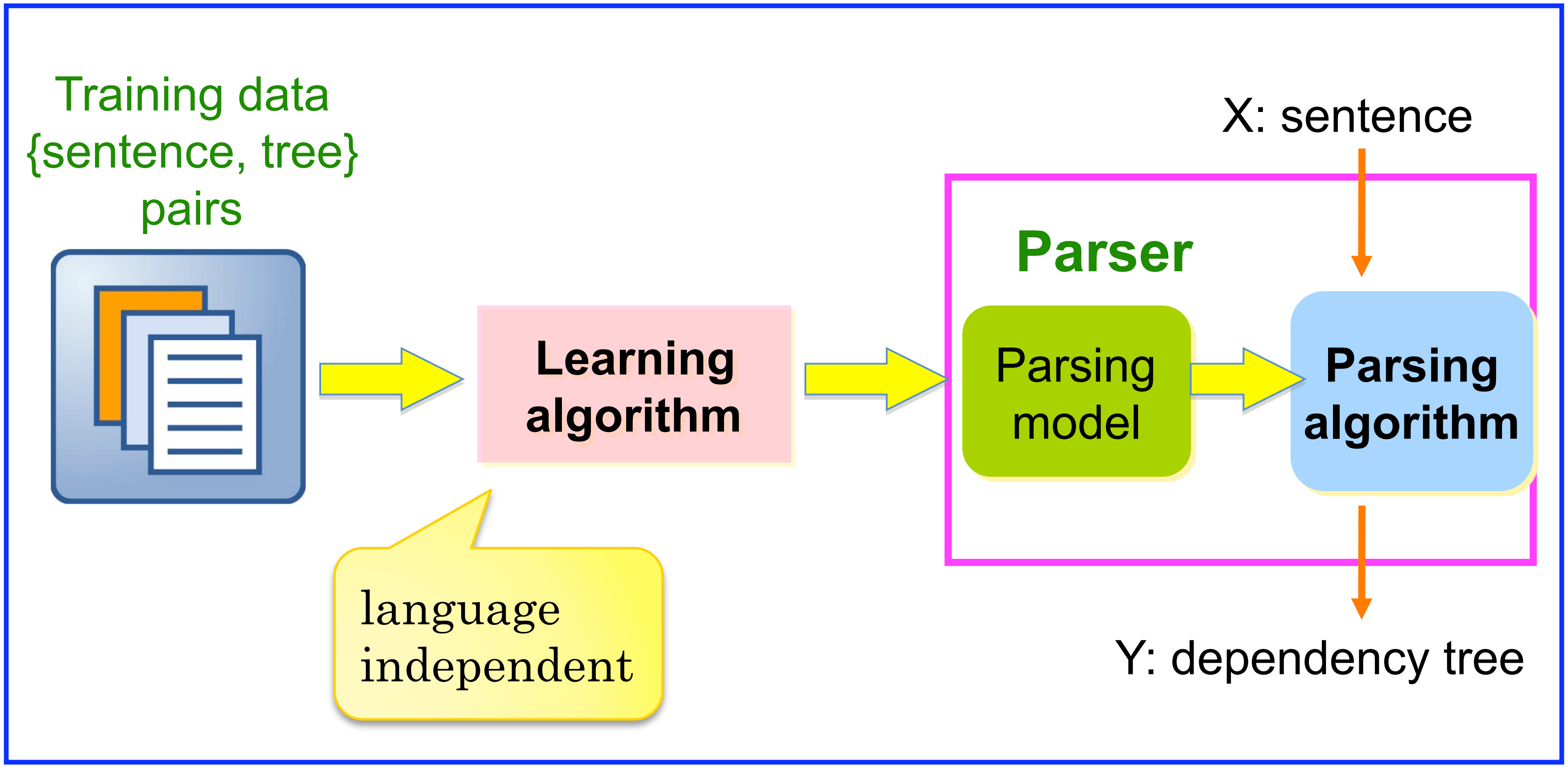
• **Ambiguities handling**
• **Incomplete search**

Data Driven Dependency Parsing

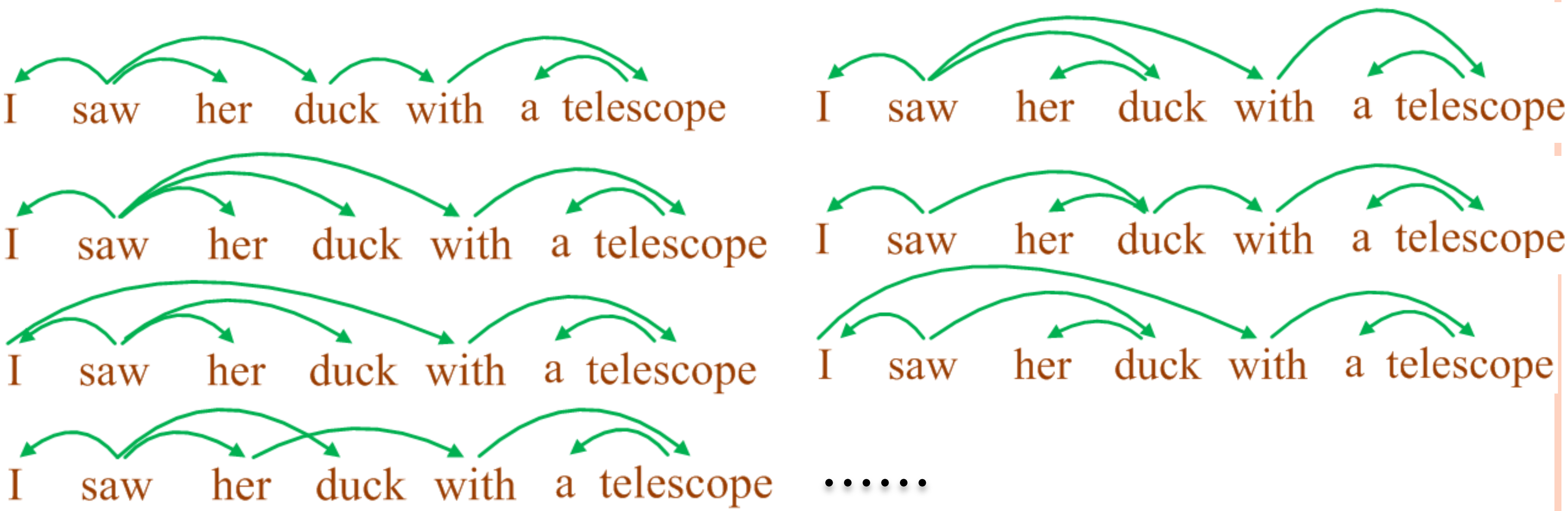
- **Data-driven parsing**
  - No grammar / rules needed; any tree is possible
  - Parsing decisions are made based on learned models
  - Can deal with ambiguities well

- **Three approaches**
  - Graph-based models
  - Transition-based models
  - Hybrid models

Data-driven Parsing Framework



Graph-based Models



- Score each possible output
- Search for a tree with the highest score
- Often use Dynamic Programming to explore search space

Graph-based Models

- Define a space of candidate dependency trees for a sentence
  - **Learning**: induce a model for scoring an entire tree
  - **Parsing**: find a tree with the highest score, given the induced model
  - Exhaustive search
  - Features are defined over a limited parsing history
  - Represented by Eisner 96, McDonald et al. 05a, McDonald et al. 05b and Wang et al. 07

Transition-based Models

- Define a transition system for mapping a sentence to its dependency tree
  - Predefine some **transition actions**
  - **Learning**: induce a model for predicting the next state transition, given the transition history
  - **Parsing**: construct the optimal transition sequence, given the induced model
  - Greedy search / beam search
  - Features are defined over a richer parsing history
  - Represented by Yamada & Matsumoto 03, Nivre & Scholz 04, Zhang & Clark 08, Huang et al. 09

Comparison

- Graph-based models
  - Find the optimal tree from all the possible ones
  - Global, exhaustive
- Transition-based models
  - Predefine some actions (shift and reduce)
  - Find the optimal action sequence
  - Local, Greedy or beam search
- The two models produce different types of errors
  - Error distribution (McDonald & Nivre 07)
  - Have complementary strengths

Hybrid Models

- Three integration methods
  - Ensemble approach: parsing time integration (Sagae & Lavie 2006)
  - Feature-based integration (Nivre & Mcdonald 2008)
  - Single model combination (Zhang & Clark 2008)
- Advantages
  - Gain benefits from both models

Summary – Introduction to Dependency Parsing

- Dependency Syntax

- Dependency parsing approaches
  - Graph-based models
  - Transition-based models
  - Hybrid models

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Part B: Graph-based Dependency Parsing Models

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  - Features
  - Learning approaches
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Dependency Parsing Model

- $\boldsymbol{X}$: an input sentence
- $\boldsymbol{Y}$: a candidate dependency tree
- $\boldsymbol{x_i \rightarrow x_j}$: a dependency link from word $\boldsymbol{i}$ to word $\boldsymbol{j}$
- $\Phi(X)$: the set of possible dependency trees over $\boldsymbol{X}$

Edge/link based factorization (Eisner 96)

$$Y^* = \arg\max_{Y \in \Phi(X)} score(Y \mid X)$$
$$= \arg\max_{Y \in \Phi(X)} \sum_{(x_i \rightarrow x_j) \in Y} score(x_i \rightarrow x_j)$$

- Applicable to both **probabilistic** and **non-probabilistic** models

Edge Based Factorization

$$Y^* = \arg\max_{Y \in \Phi(X)} \sum_{(x_i \rightarrow x_j) \in Y} score(x_i \rightarrow x_j)$$

$$score(x_i \rightarrow x_j) = \vec{f}(x_i \rightarrow x_j) \cdot \vec{\theta}$$

Standard linear classifier

A vector of features

A vector of feature weights

- The score of a link is dot product between feature vector and feature weights
  - What features we can use? (later)
  - What learning approaches can lead us to find the best tree with the highest score (later)

Score of a Link

- The score of each link is based on the features
- The features for the word pair: (***saw***, ***duck***)
  - (***saw***, ***duck***) = 1
  - POS (***saw***, ***duck***): (VBD, NN) = 1
  - PMI (***saw***, ***duck***) = 0.27 (PMI: pointwise mutual information)
  - dist (***saw***, ***duck***) = 2 dist2(***saw***, ***duck***) = 4

$$score\ (saw, duck)$$
$$= 1 * \theta_{(saw,\ duck)} + 1 * \theta_{(VB,\ NN)} + 0.27 * \theta_{PMI} + 2 * \theta_{dist} + 4 * \theta_{dist2}$$

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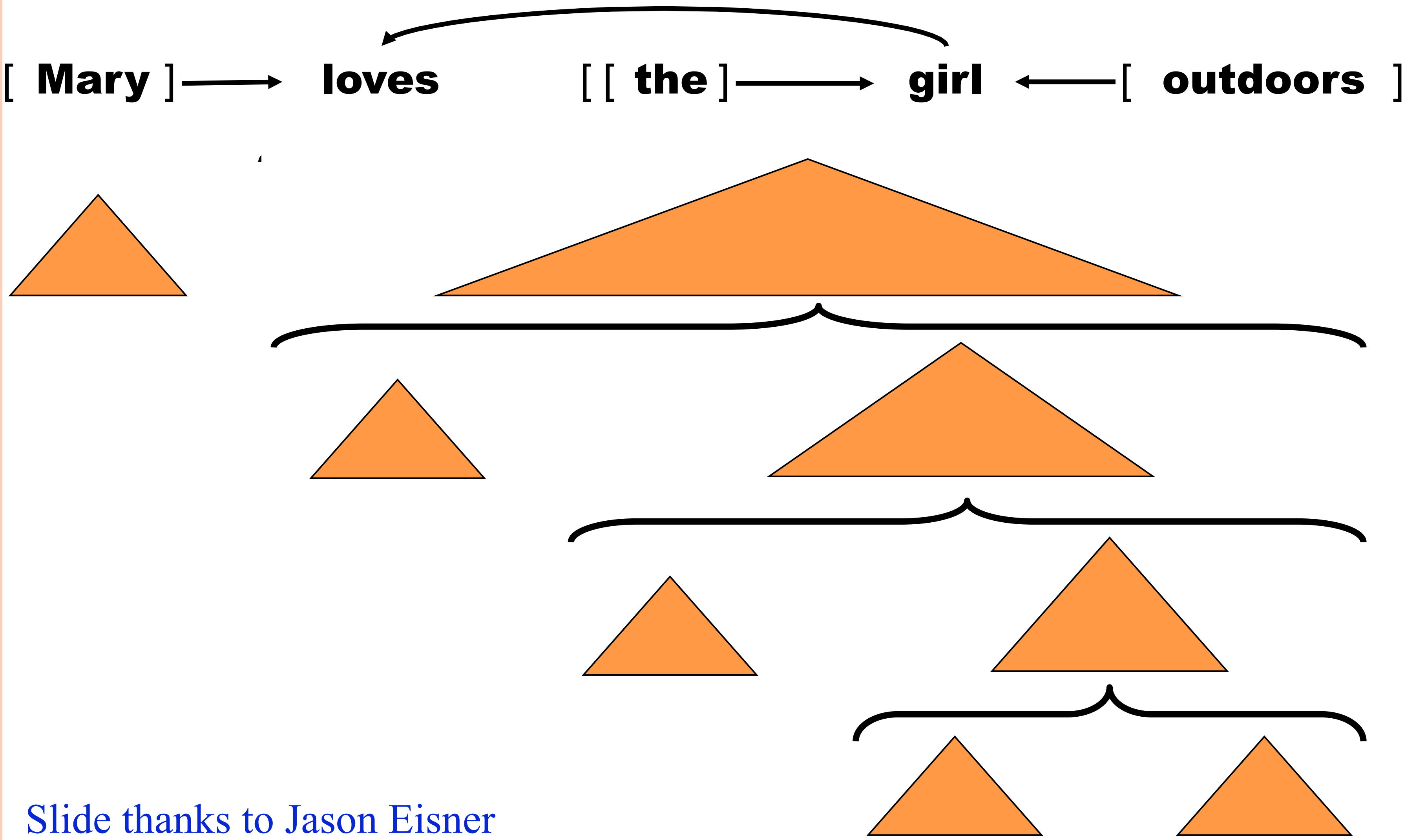
Comparison of Some Popular Dependency Parsing Algorithms

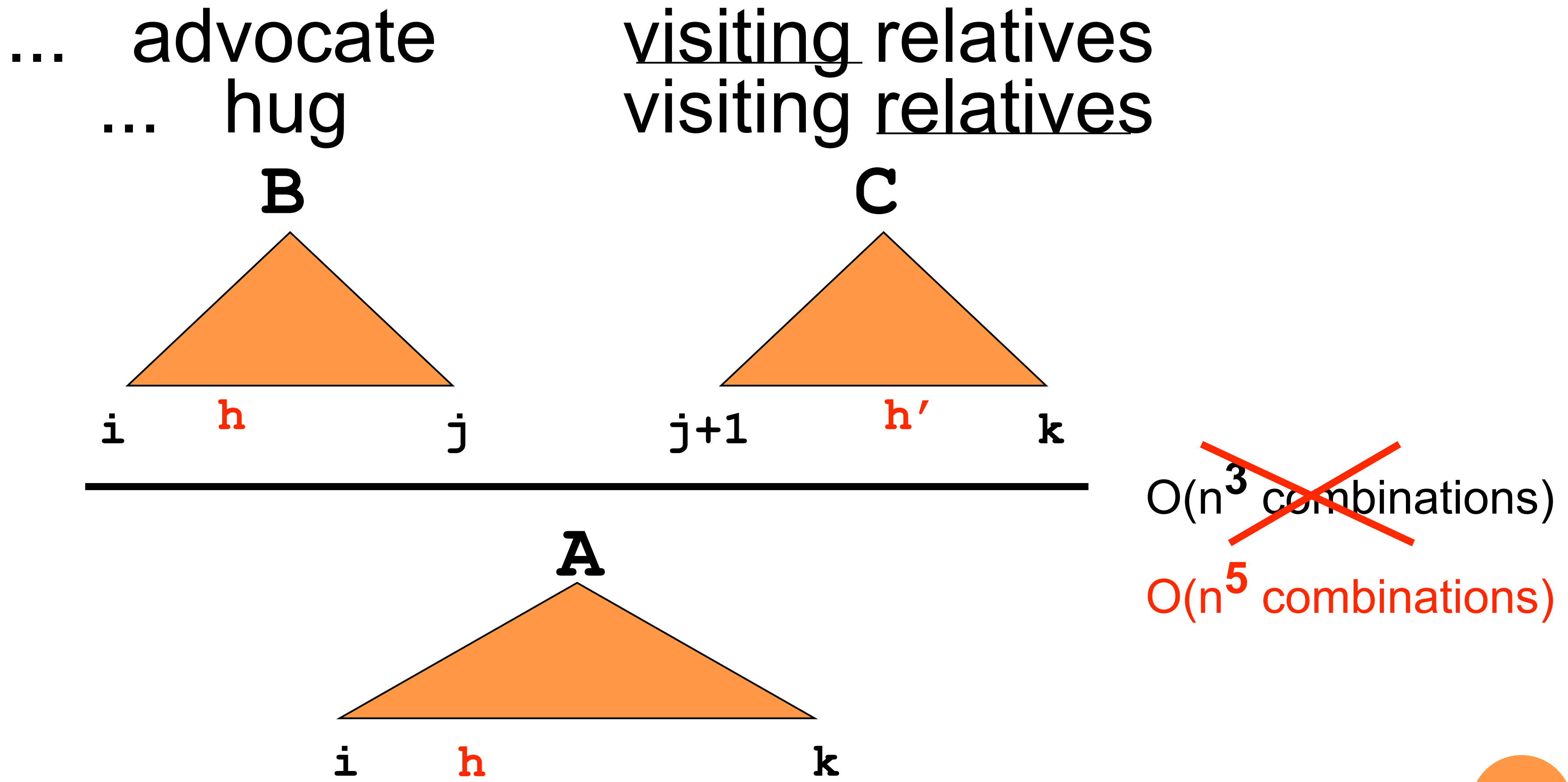
Name	Inventor	Projectivity	Complexity
CKY-style chart parsing	Cocke–Younger–Kasami	Projective	$O(n^5)$
Eisner $O(n^3)$ parsing alg.	Eisner (96)	Projective	$O(n^3)$
Maximum Spanning Tree	Chu-Liu-Edmonds (65, 67)	Non-projective	$O(n^2)$
Shift-Reduce style parsing	Yamada, Nivre	Projective	$O(n)$

The CKY-style algorithm O(n^5)



Slide thanks to Jason Eisner

Why CKY is $O(n^5)$ not $O(n^3)$



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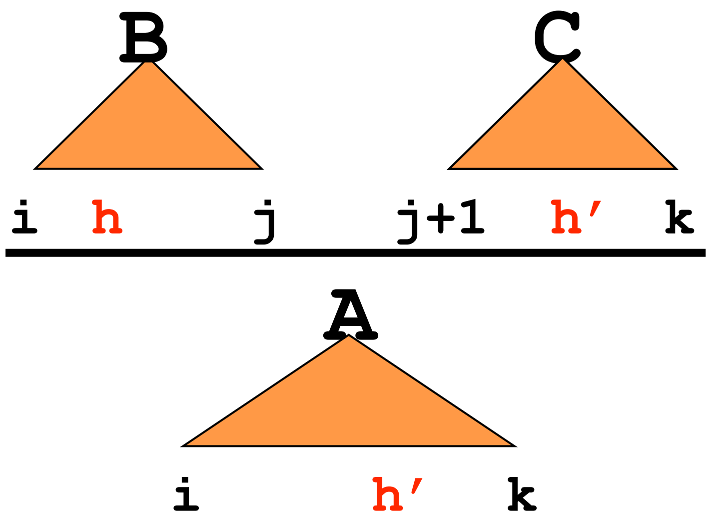
$O(n^4)$ Parsing Algorithm
(Eisner&Satta 99)



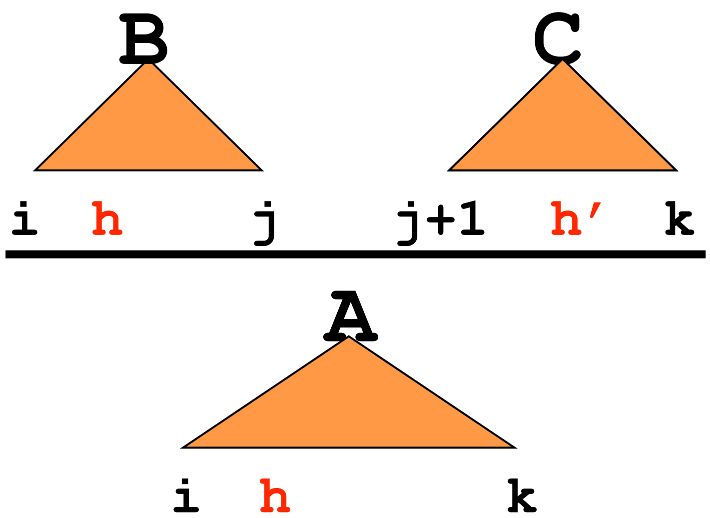
- Combine what B and C?
  - must try different-width C's (vary **k**)
  - must try different midpoints **j**
  - Separate these!

Slide thanks to Jason Eisner

$O(n^4)$ Parsing Algorithm

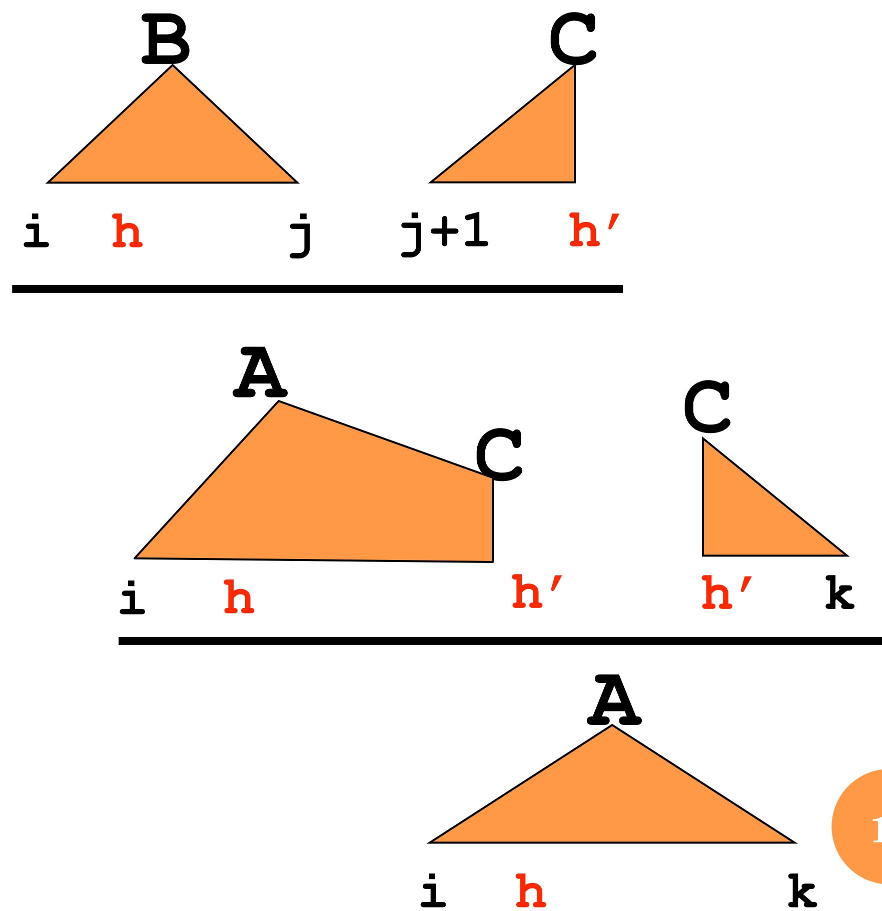
(Eisner&Satta 99)

(the old CKY way)



Step 1: (i, j, h, h')
$O(n^4)$

Step 2: (i, h, h', k)
$O(n^4)$



Slide thanks to Jason Eisner

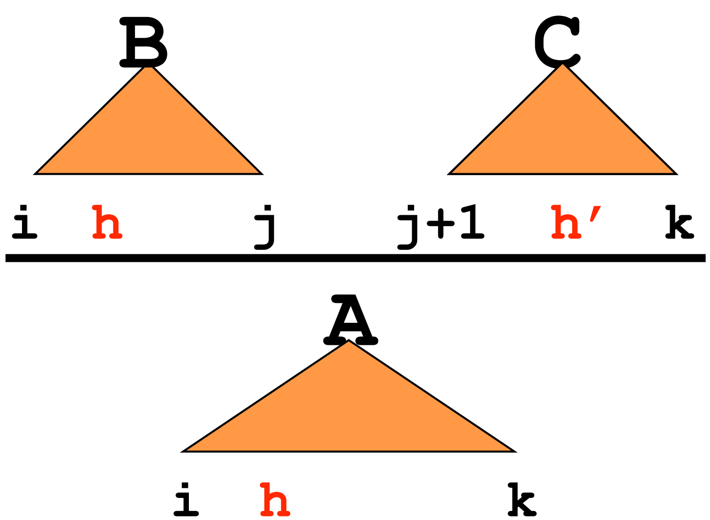
We Can Do Better

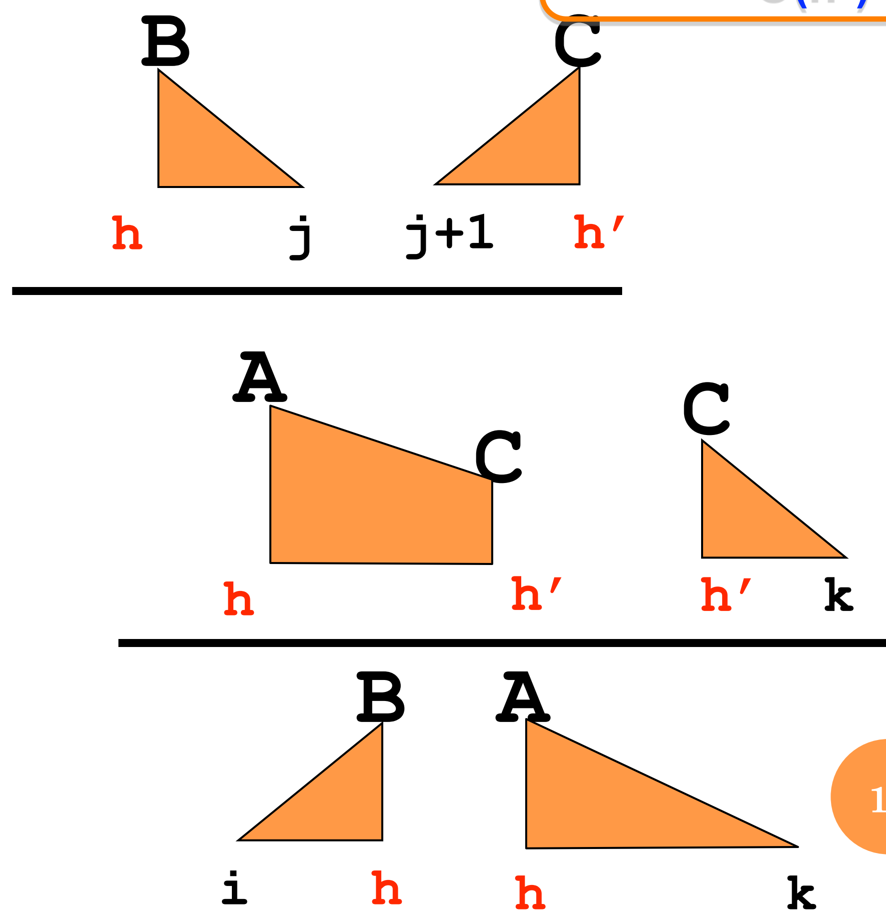
Step 1: (j, h, h’) $O(n^3)$

Step 2: (h, h’, k) $O(n^3)$

Step 3: (i, h, k) $O(n^3)$

(the old CKY way)





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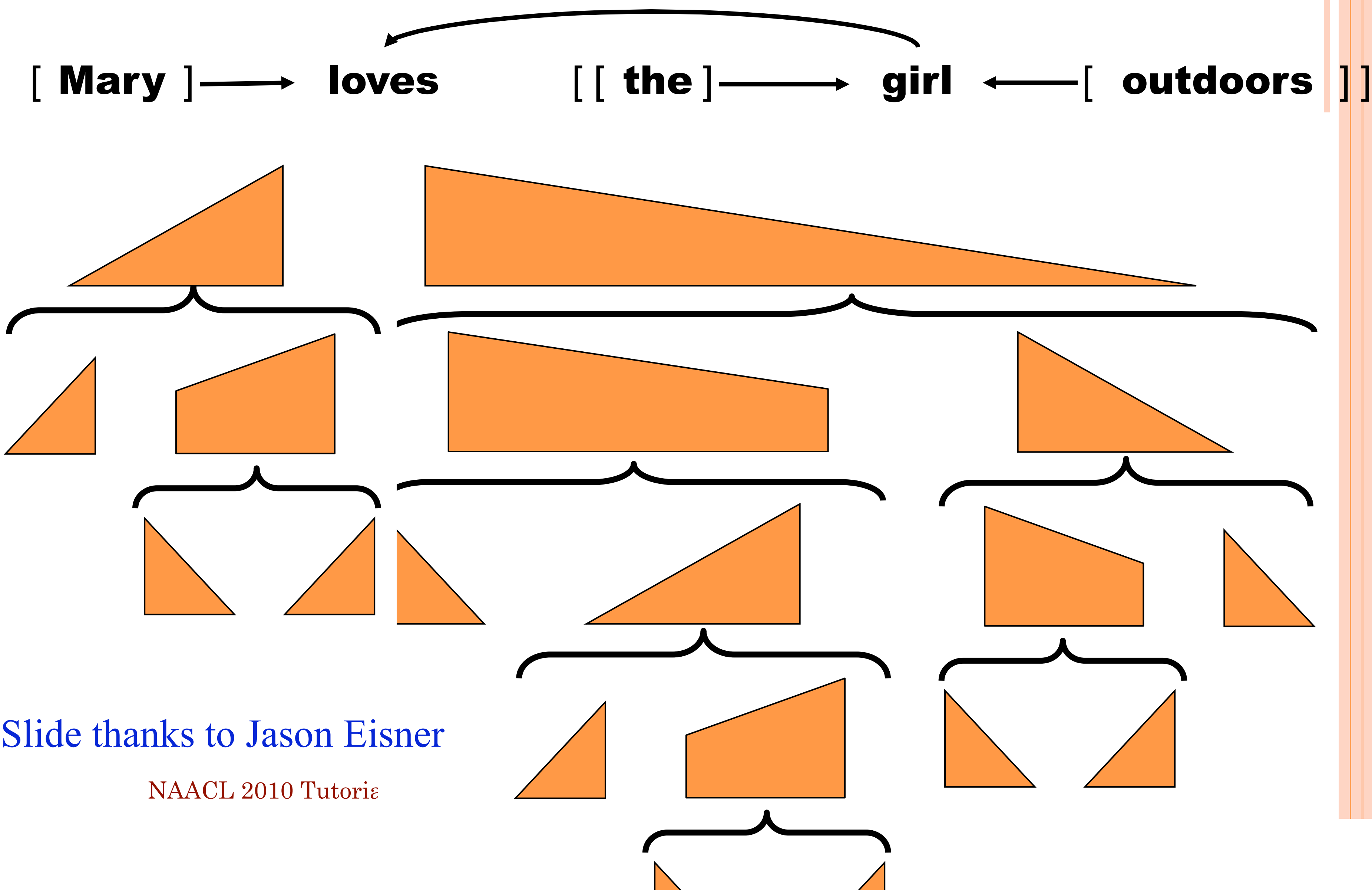
The O(n^3) Half-Tree Parsing Algorithm (Eisner 96)



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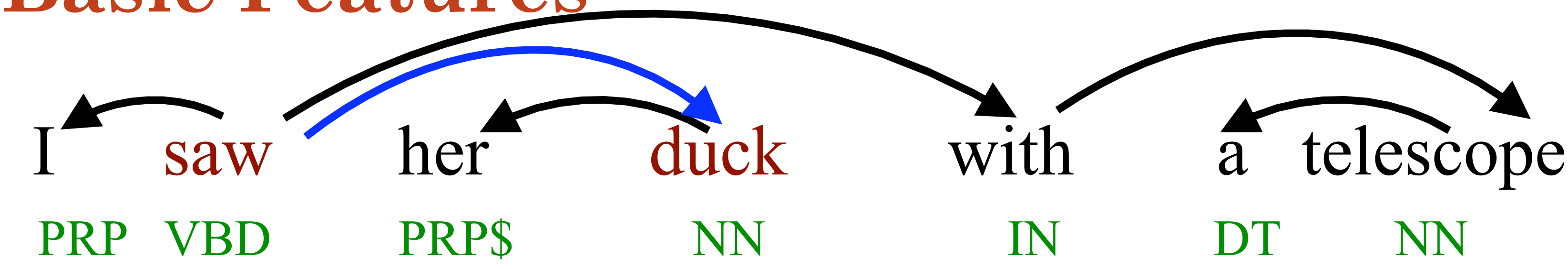
Basic Features



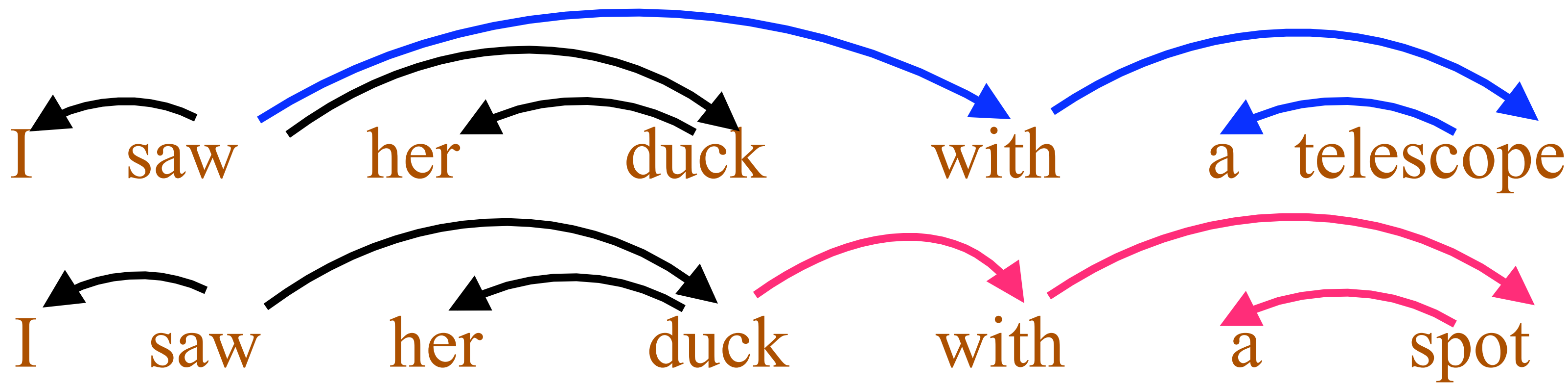
- Uni-gram features
- Bi-gram features
- In between POS features
- Surrounding word POS features

Saw_VBD, saw, VBD duck_NN, duck, NN
saw_VBD_duck_NN, VBD_duck_NN, saw_duck_NN, saw_VBD_NN, saw_VBD_duck, Saw_duck, VBD_NN
VBD_PRP$_NN
VBD_PRP$_PRP$_NN, PRP_VBD_PRP$_NN, VBD_PRP$_NN_IN, PRP_VBD_NN_IN

Non-local Features

- Also known as **dynamic features**
- Take into account the link labels of the surrounding word-pairs when predicting the label of current pair
  - Commonly used in sequential labeling (McCallum et al. 00, Toutanova et al. 03)
- A simple but useful idea for improving parsing accuracy
  - Wang et al. 05
  - McDonald and Pereira 06

Non-local Features



- A word's children are generated first, before it modifies another word
  - Define a canonical order

- "with telescope/with spot" are the dynamic features for deciding whether generating a link between "saw & with" or "duck & with"

Features from Other Resources

- Cluster-based features (Wang et al. 05, Koo et al. 08)
- Subtrees from auto-parsed data (W. Chen et al. 09)
- Alignment features from bilingual data (Huang et al. 09)

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Learning Approaches for Dependency Parsing

- Local learning approaches
  - Learn a local link classifier given a set of features defined on the **local training examples**

> Word pairs along with corresponding features extracted from the training data

- Global learning approaches
- Unsupervised/Semi-supervised learning approaches
  - Use both annotated training data and un-annotated raw text

Local Training Examples

L: left link
R: right link
N: no link

- Given training data {(X, Y)}

local examples

Word-pair	Link-label	Instance_weight	Features
The-boy	L	1	W1_The, W2_boy, W1W2_The_boy, T1_DT, T2_NN, T1T2_DT_NN, Dist_1, …
boy-skipped	L	1	W1_boy, W2_skipped, …
skipped-school	R	1	W1_skipped, W2_ school, …
skipped-regularly	R	1	W1_skipped, W2_regularly, …
The-skipped	N	1	W1_The, W2_skipped, …
The-school	N	1	W1_The, W2_school, …
…			

Local Training Methods

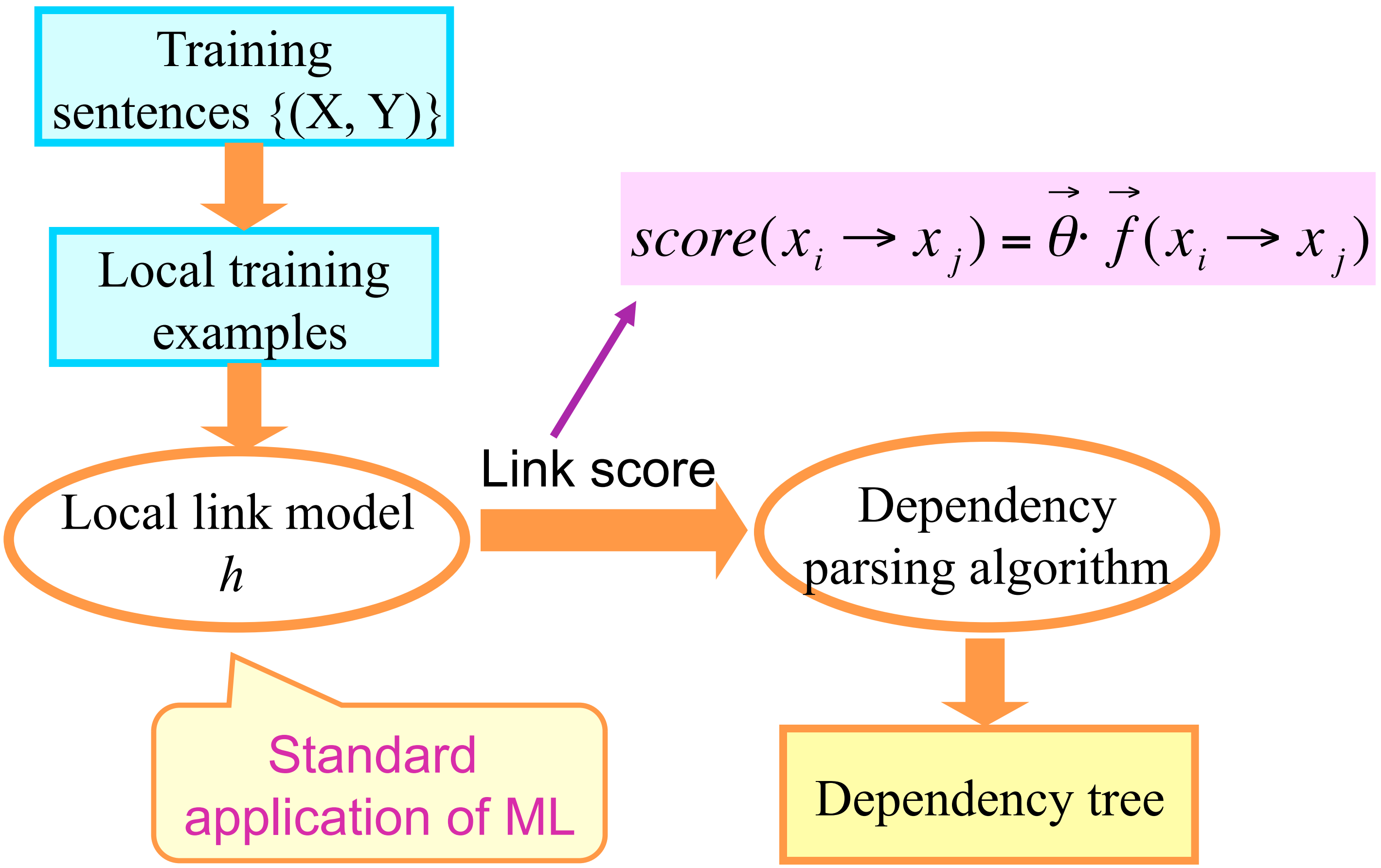
- Learn a local link classifier given a set of features defined on the local examples

- For each word pair in a sentence
  - No link, left link or right link ?
  - 3-class classification

- Efficient *O(n)* local training

- Any classifier can be used as a link classifier for parsing

Combine Local Training with a Parsing Algorithm



Parsing With a Local Link Classifier

- Learn the weight vector $\vec{\theta}$ over a set of features defined on the local examples
- Generative approaches
  - Maximum entropy models (Ratnaparkhi 99, Charniak 00)
- Discriminative approaches
  - Support vector machines (Yamada & Matsumoto 03)
  - Use a richer feature set!

- Each link is scored separately, instead of being computed in coordination with other links in a sentence

Global Training for Parsing

- Directly capture the relations between the links of an output tree

- Incorporate the effects of the parser directly into the training algorithm
  - Structured SVMs (Tsochantaridis et al. 04)
  - Max-Margin Parsing (Taskar et al. 04)
  - Improved large-margin training (Wang et al. 06)
  - Online large-margin training (McDonald et al. 05a)

Standard Large Margin Training

$$\min_{\theta} \frac{\beta}{2}\theta^T\theta + \sum_i \xi_i \qquad subject\ to$$

$$\xi_{i,Y} \geq L(Y_i, Y) - (score(X_i, Y_i) - score(X_i, Y))$$

$$for\ all\ i, Y \in \Phi(X_i)$$

Exponential constraints!

- Having been used for parsing
  - Tsochantaridis et al. 04, Taskar et al.04
- State of the art performance in dependency parsing
  - McDonald et at. 05a

Online Large-Margin Training (McDonald et al. 05a)

- For each training instance (X_i, Y_i)
  - Find current k best trees:
  - Create constraints using these k *best* ...
  - Small number of constraints for each QP

$$\theta = \arg\min_{\theta^*} \|\theta^* - \theta\|$$
$$s.t.\ score(X_i, Y_i) - score(X_i, Y) \geq L(Y_i, Y)$$
$$\forall\ Y \in k-best-trees(X_i)$$

Add *O(klogk)* (Huang& Chiang 05)

MIRA (crammer & Singer 03

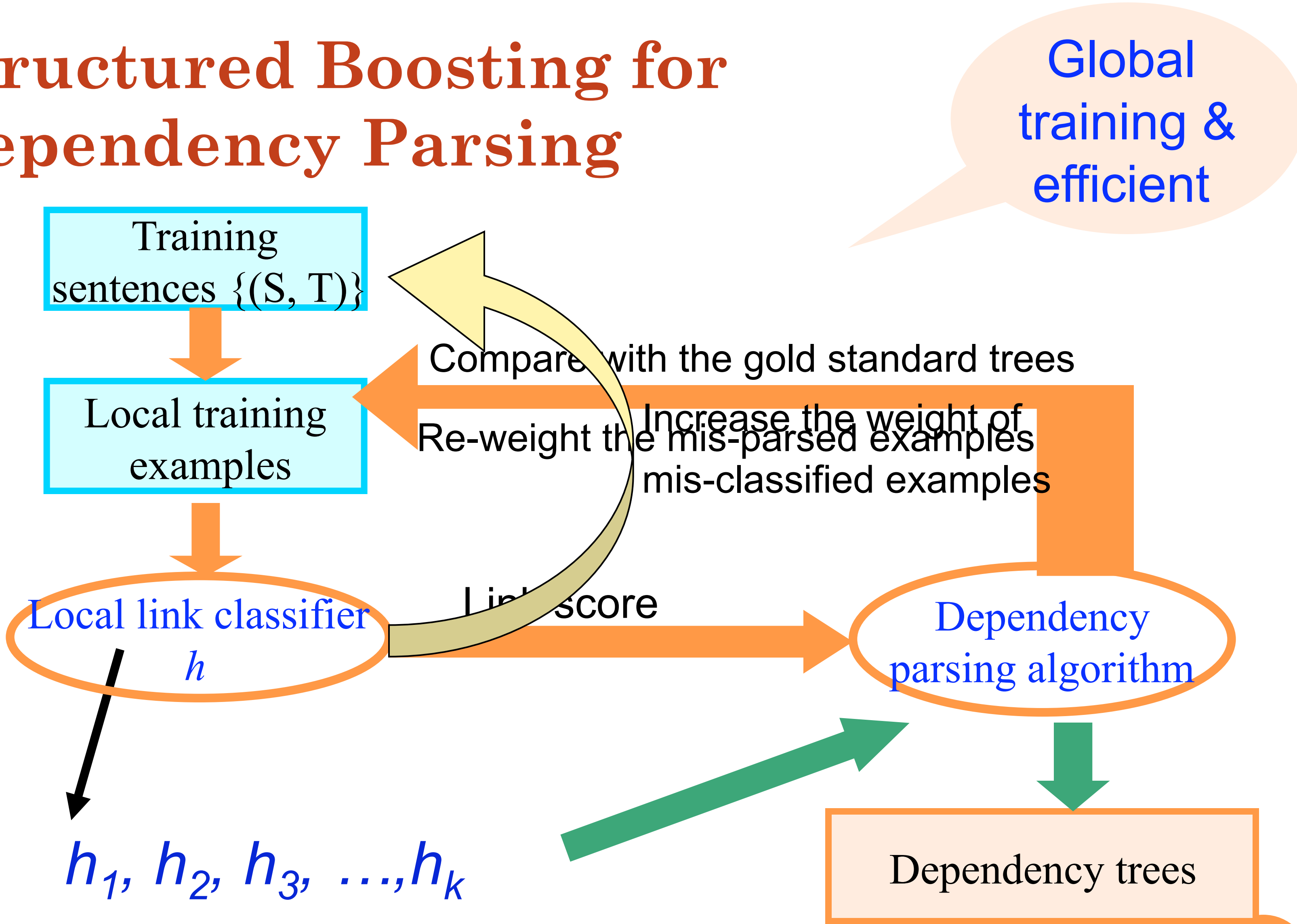
Only *k* constraints for each QP

Structured Boosting (Wang et al. 07)

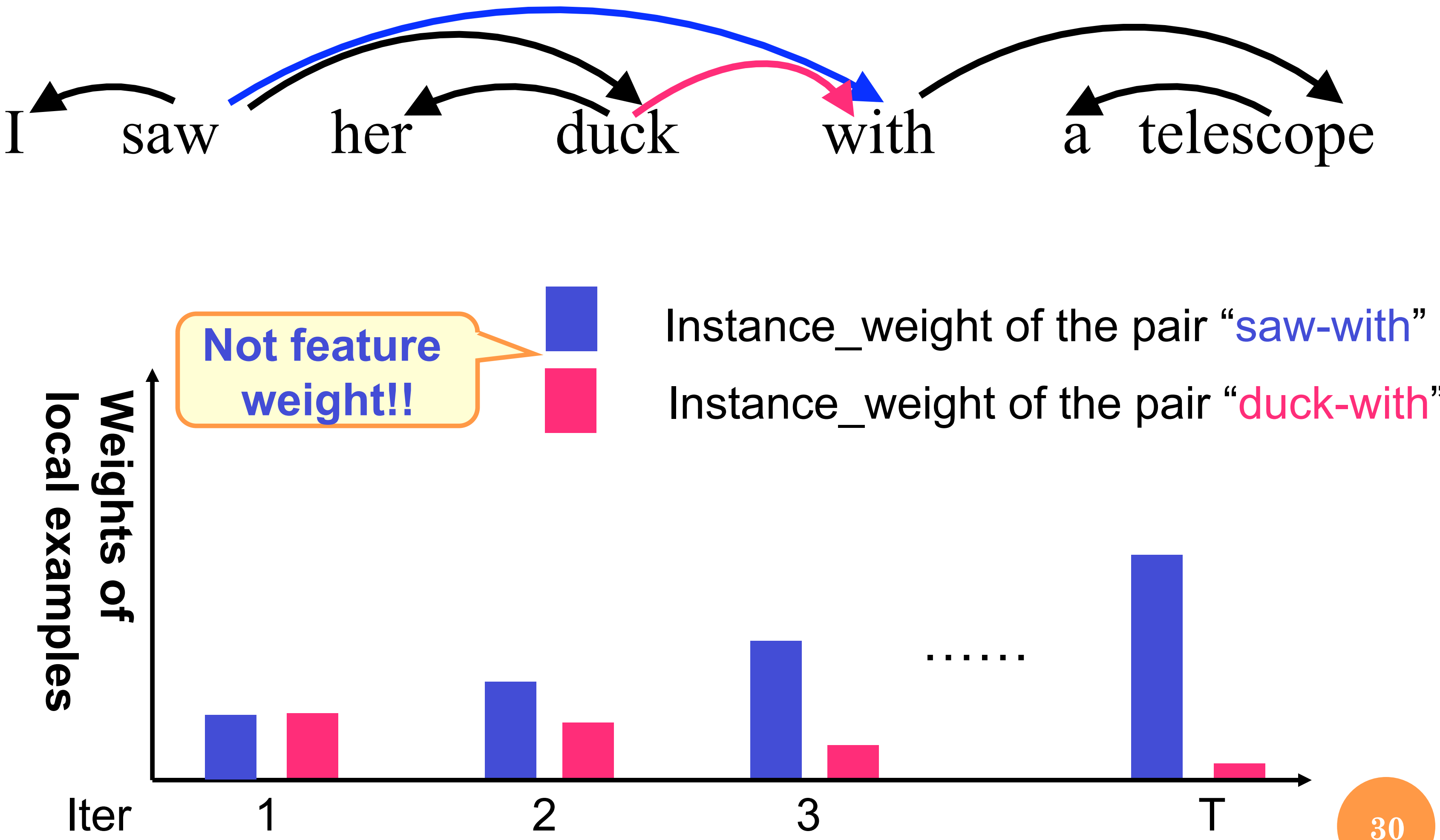
- A simple approach to training structured classifiers by applying a boosting-like procedure to standard supervised training methods
  - A simple variant of standard boosting algorithms Adaboost M1 (Freund & Schapire 97)

- Advantages
  - Global optimization
  - Simple, as efficient as local methods
  - General, can use any local classifier
  - Besides dependency parsing, it can be easily applied to other tasks

Structured Boosting for Dependency Parsing



Structured Boosting (An Example)



From Supervised to Semi/unsupervised learning

- The Penn Treebank
  - 4.5 million words
  - About 200 thousand sentences
  - A
    p
    s

Limited & Human-labor expensive!

- Raw text data
  - News wire
  - Wikipedia
  - Web resources
  -

Plentiful & Free!

Semi/unsupervised learning

Unsupervised/Semi-supervised learning approaches

- Self-training
  - Not very effective
  - Until recently (McClosky et al. 06a, McClosky et al. 06b)
- Generative models (EM)
  - Local optima
  - The disconnection between likelihood and accuracy
  - Same mistakes can be amplified at next iteration
- Semi-supervised Structured SVM (S^3VM)
  - Global optimum
  - Incorporate the effects of the parser directly into the training algorithm

Semi-supervised Structured SVM (S^3VM)

- The objective of the standard S^3VM is a combination of
  - Structured loss on labeled data (convex)
  - Structured loss on un-labeled data (non-convex)
- Convex + non-convex is non-convex
  - Local optima
- Complex and expensive to solve
  - Too complicated to apply it to parsing

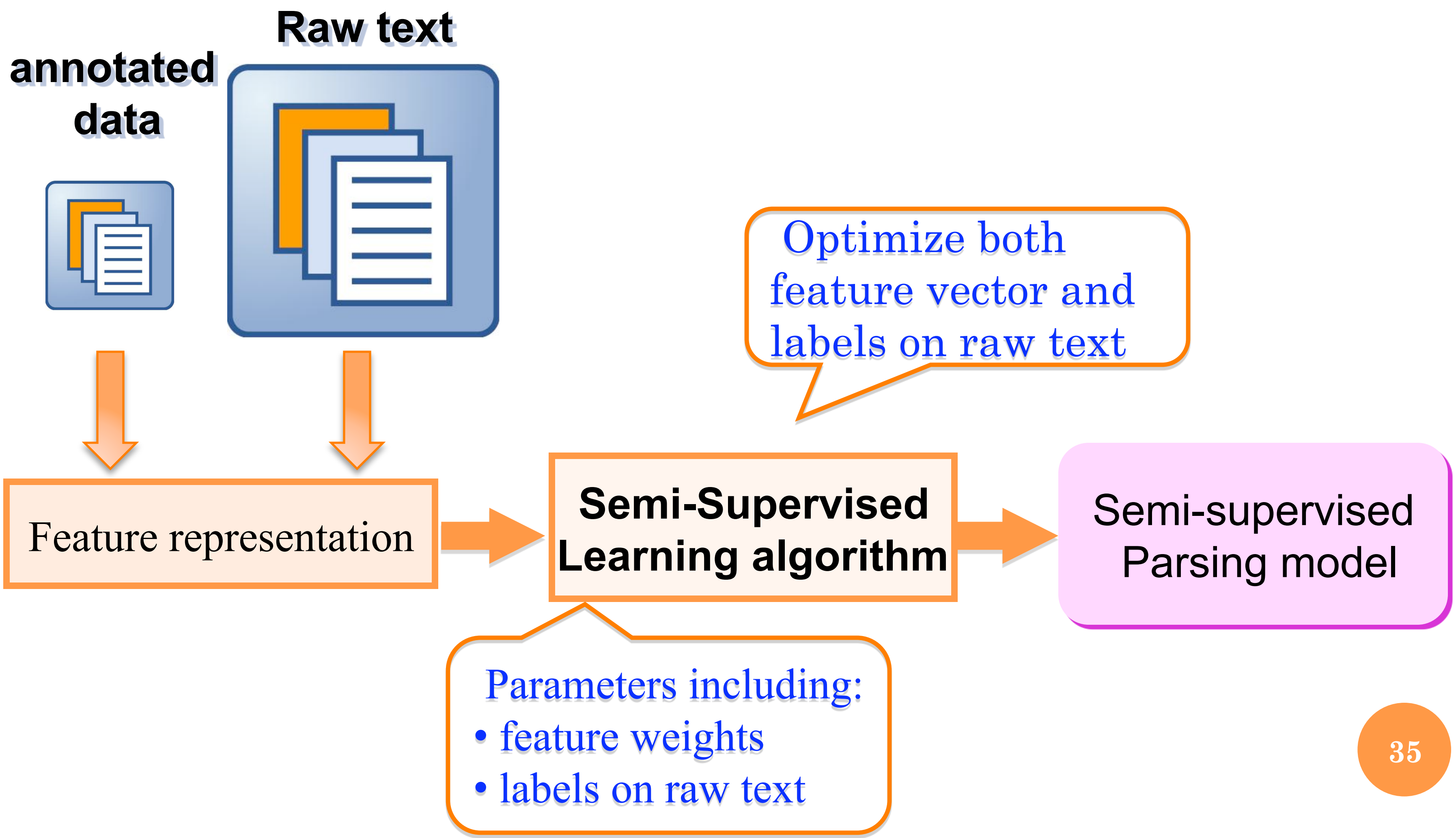
Semi-supervised Convex Training Dependency Parsing (Wang et al. 08)

- The objective is a combination of
  - Structured loss on labeled data (convex)
  - Least square loss on un-labeled data (convex)

convex + convex is convex

- Using a **stochastic gradient descent** approach
  - Parameters are updated locally on each sentence
  - Converge after a few iterations
- This convex training approach:
  - Focused on semi-supervised learning instead of feature engineering
  - Used only basic features due to the complexity issue

Semi-supervised Convex Training Dependency Parsing (Wang et al. 08)

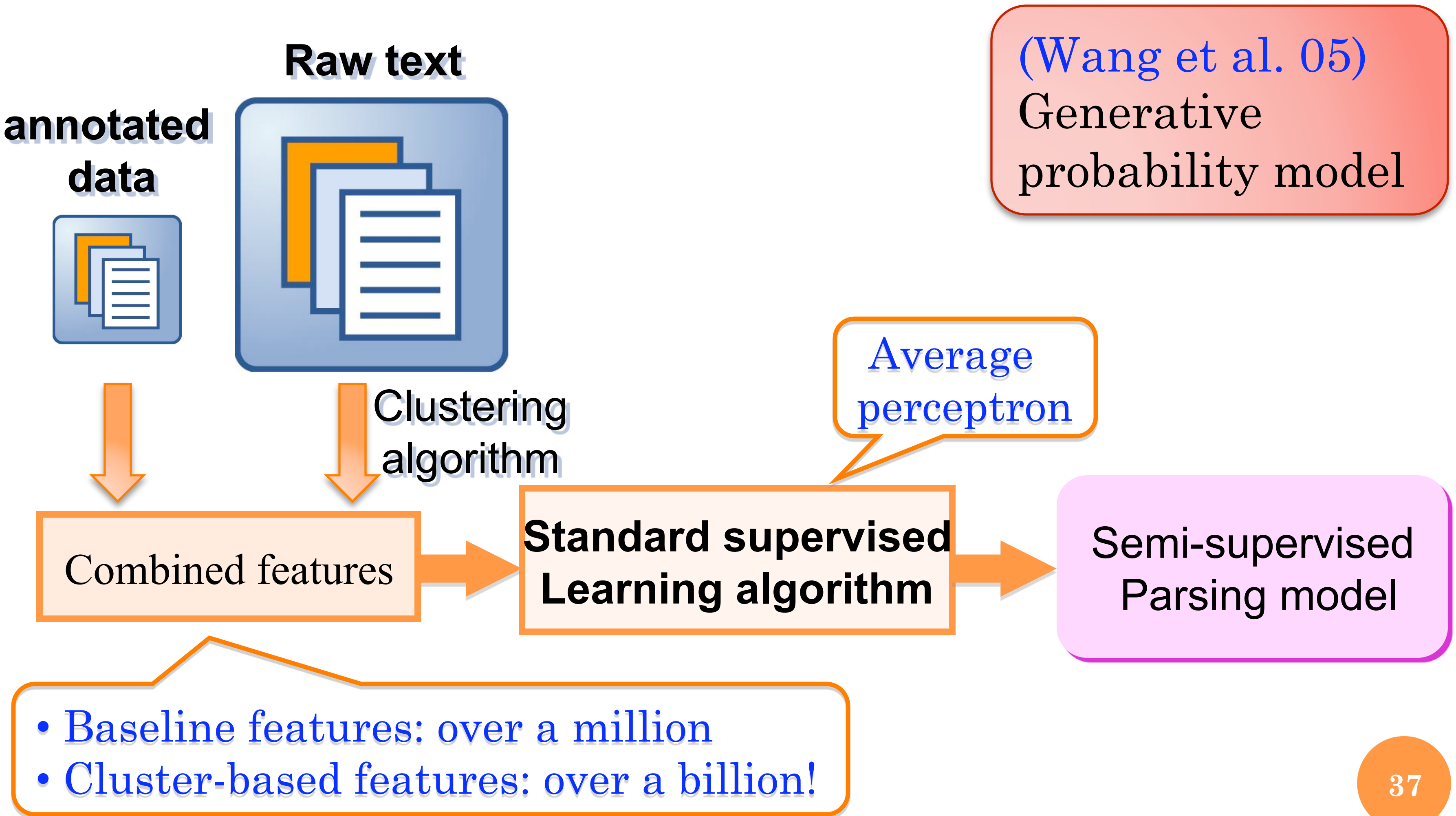


Simple Semi-supervised Dependency Parsing (Koo et al. 08)

- Extract features from unlabeled data
  - Instead of solving the complex S^3VM, add features derived from a large unannotated corpus

- Combining word clusters with discriminative learning (Miller et al. 04)
  - Incorporate word clusters derived from a large unannotated corpus via unsupervised learning
  - Using both the baseline and cluster-based features
  - Average perceptron learning algorithm (fast)
  - Achieve substantial improvement on dependency parsing over competitive baseline

Simple Semi-supervised Dependency Parsing (Koo et al. 08)



Summary – Graph-based Models

- Dependency parsing model
- Dependency parsing algorithms
- Features
- Learning algorithms

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Recent Advances in Dependency Parsing

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June 1, 2010

Part C: Transition-based Dependency Parsing Models

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NAACL Tutorial, Los Angeles
June 1, 2010

Outline

- Part A: introduction to dependency parsing
- Part B: graph-based dependency parsing models
- Part C: transition-based dependency parsing models
  - **Transition-based parsing processes**
  - Decoding algorithms
  - Learning algorithms and feature templates
- Part D: the integrated models
- Part E: other recent trends in dependency parsing

Overview

- Graph-based parsers
  - Enumerate all possible graphs
  - Score each candidate according to graph-based features
  - Choose the highest scored one
- Transition-based parsers
  - Build a candidate output using a stack and a set of actions
  - The stack used to hold partially-built parses
  - The input tokens are put into a queue

A transition-based parsing process

- Stack holds partially built parses
- Queue contains unprocessed words
- Transition-actions
  - Consume input words
  - Build output parse

I like playing table-tennis with her .

A transition-based parsing process

- Stack holds partially built parses
- Queue contains unprocessed words
- Transition-actions
  - Consume input words
  - Build output parse

I	like playing table-tennis with her .

A transition-based parsing process

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A transition-based parsing process

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- Queue contains unprocessed words
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  - Consume input words
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like playing table-tennis with her .

I

A transition-based parsing process

- Stack holds partially built parses
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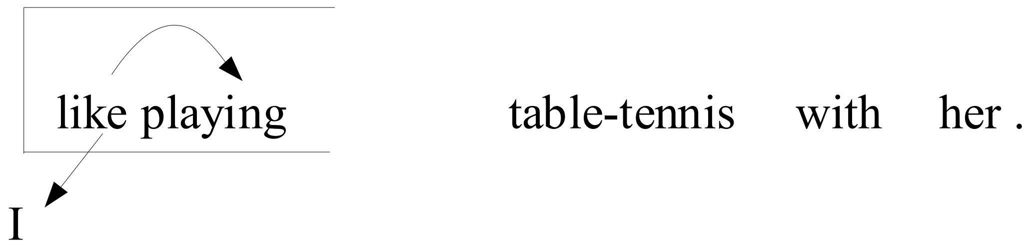
  - Consume input words
  - Build output parse



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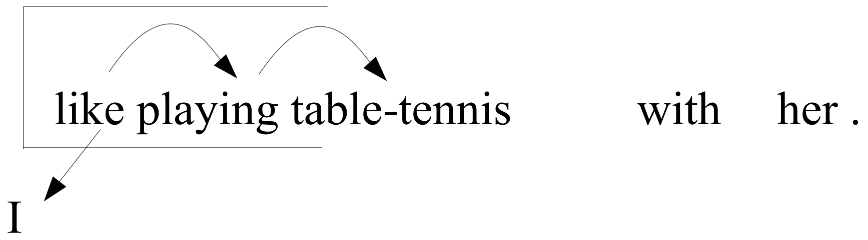

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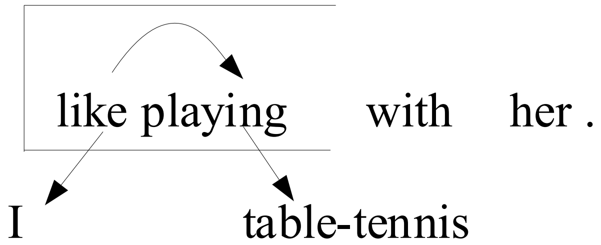

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...

A transition-based parsing process

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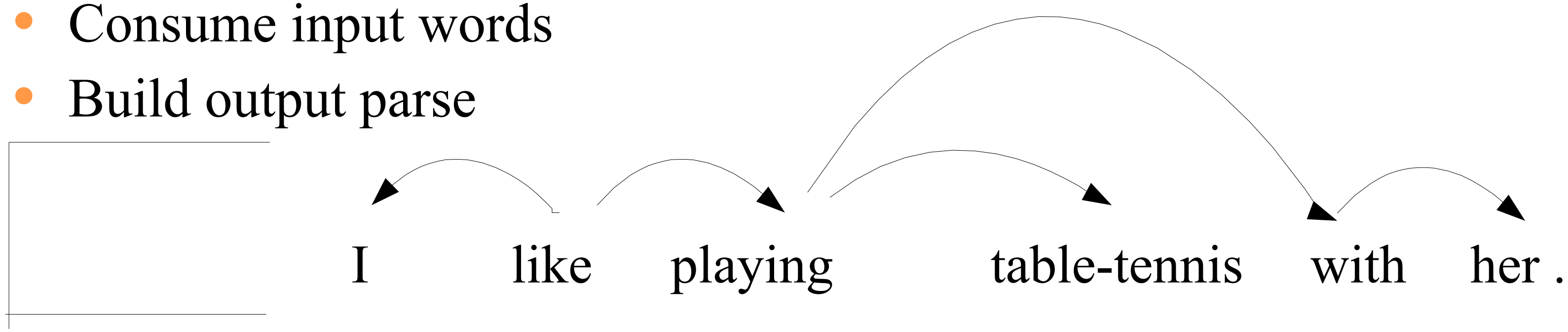
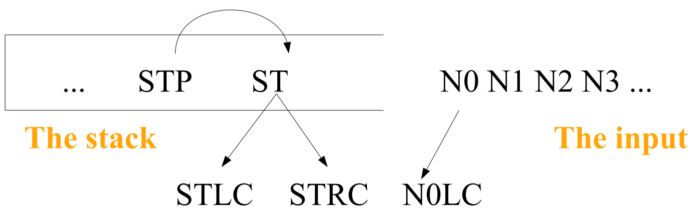


The arc-eager parser

- Arc-eager parser
  - A stack to hold partial candidates
  - A queue of next incoming words
  - Four transition-actions
    - SHIFT, REDUCE, ARC-LEFT, ARC-RIGHT
  - Examples
    - MaltParser (Nivre et al., 2006)
    - Johansson and Nugues (2007)
    - Zhang and Clark (2008)

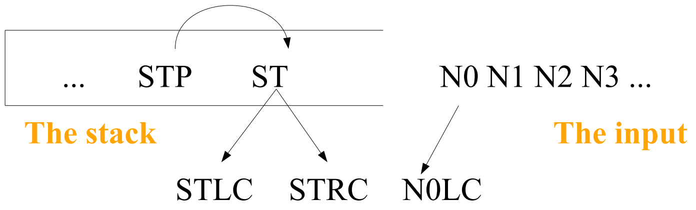
The arc-eager parser

- The context



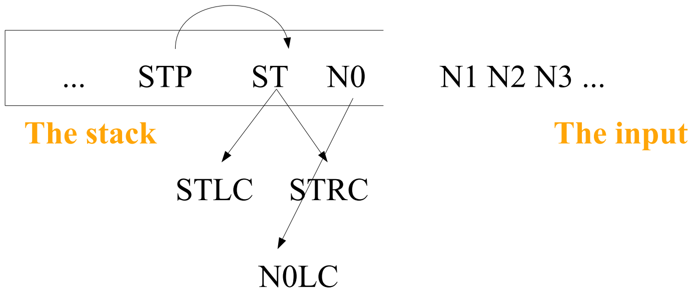
The arc-eager parser

- Transition actions
  - Shift



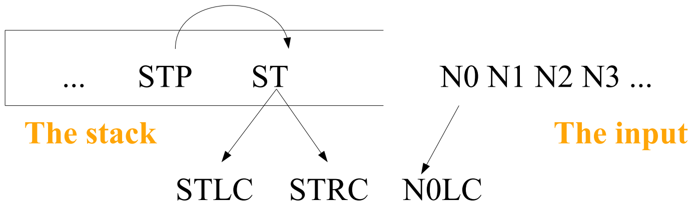
The arc-eager parser

- Transition actions
  - Shift
    - Pushes stack



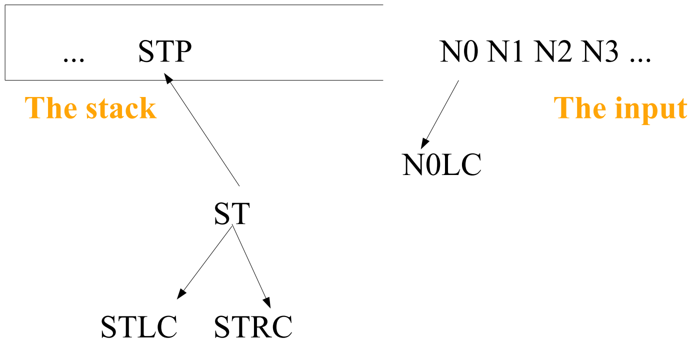
The arc-eager parser

- Transition actions
  - Reduce



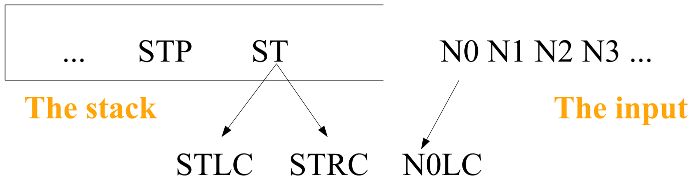
The arc-eager parser

- Transition actions
  - Reduce
    - Pops stack



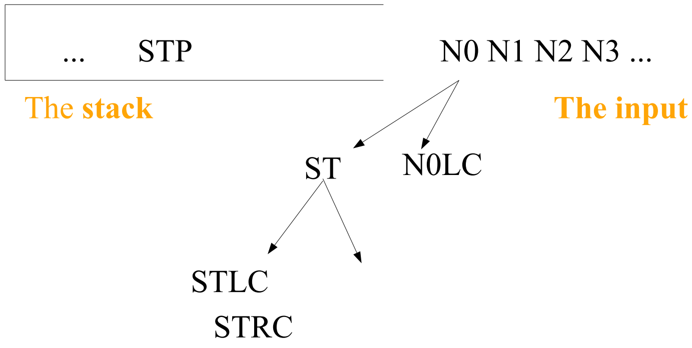
The arc-eager parser

- Transition actions
  - Arc-Left



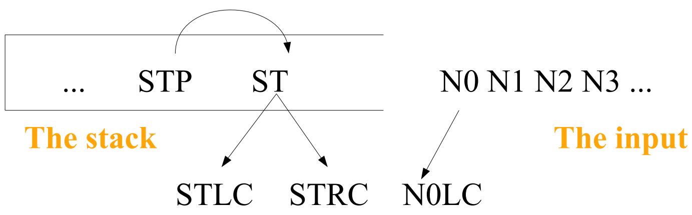
The arc-eager parser

- Transition actions
  - Arc-Left
    - Pops stack
    - Adds link



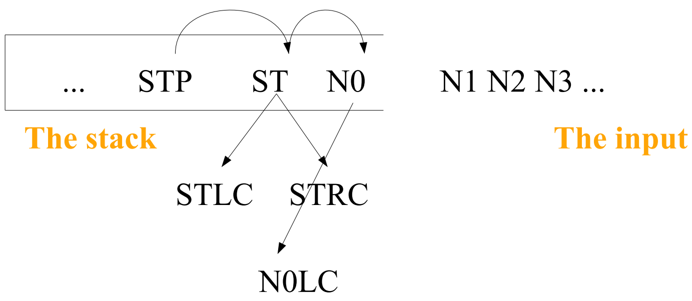
The arc-eager parser

- Transition actions
  - Arc-right



The arc-eager parser

- Transition actions
  - Arc-right
    - Pushes stack
    - Adds link



The arc-eager parser

- An example
  - S – Shift
  - R – Reduce
  - AL – ArcLeft
  - AR – ArcRight

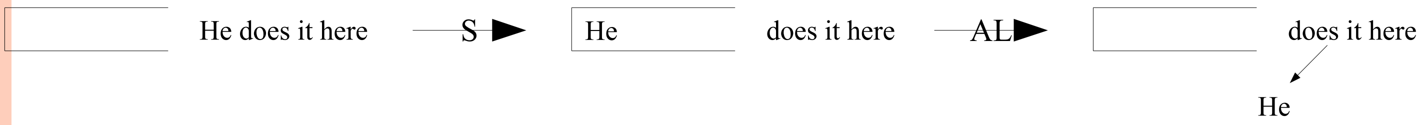
He does it here

The arc-eager parser

- An example
  - S – Shift
  - R – Reduce
  - AL – ArcLeft
  - AR – ArcRight

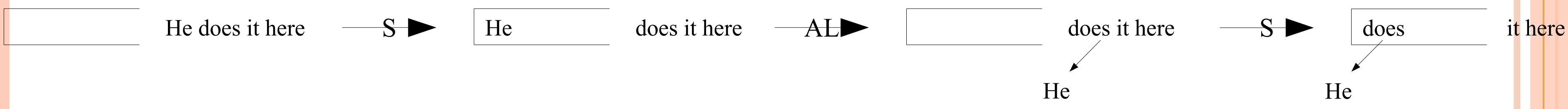
The arc-eager parser

- An example
  - S – Shift
  - R – Reduce
  - AL – ArcLeft
  - AR – ArcRight



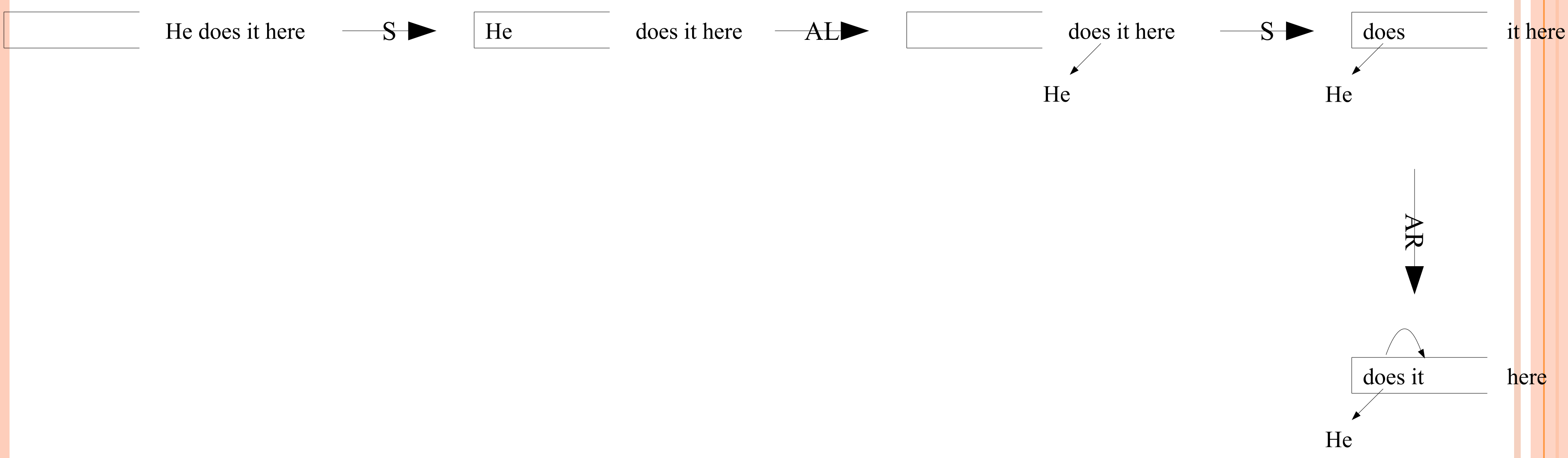
The arc-eager parser

- An example
  - S – Shift
  - R – Reduce
  - AL – ArcLeft
  - AR – ArcRight



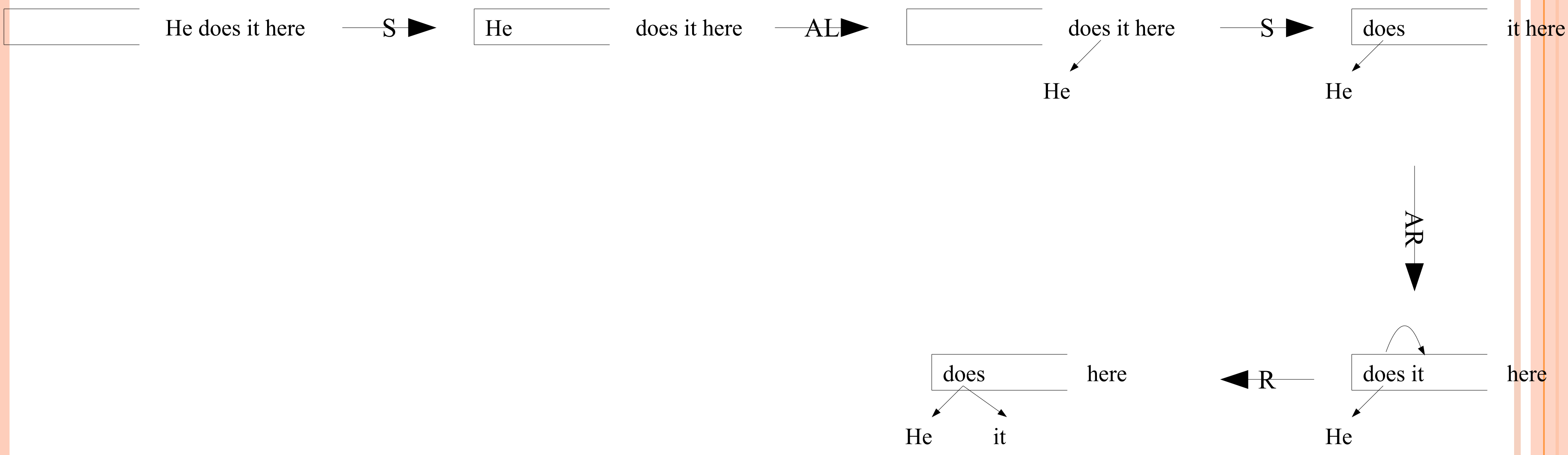
The arc-eager parser

- An example
  - S – Shift
  - R – Reduce
  - AL – ArcLeft
  - AR – ArcRight



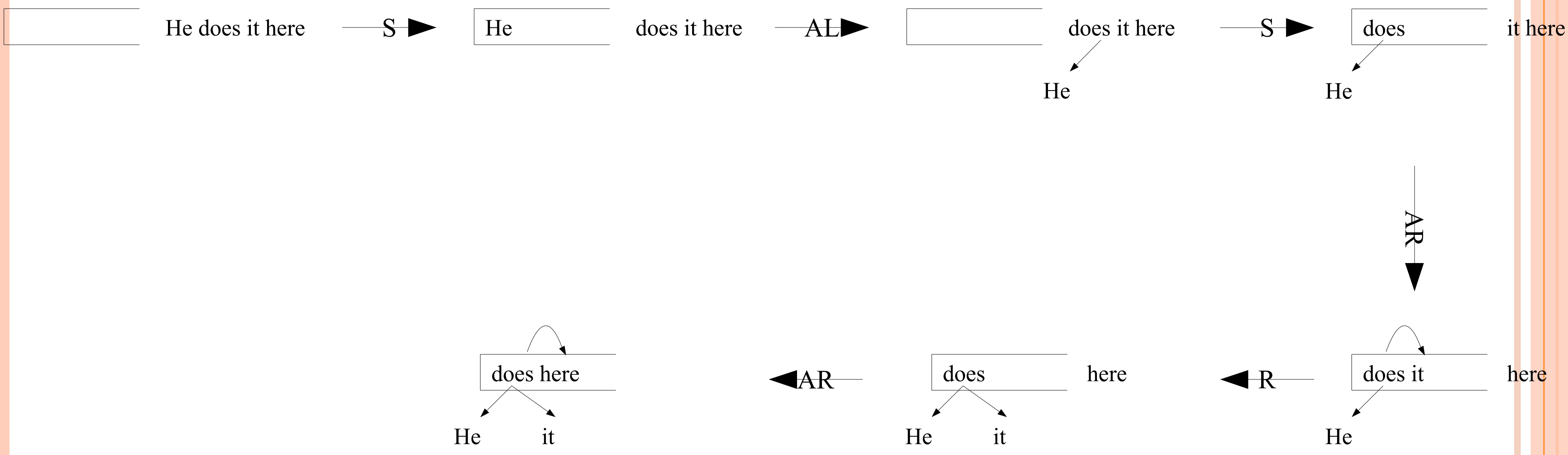
The arc-eager parser

- An example
  - S – Shift
  - R – Reduce
  - AL – ArcLeft
  - AR – ArcRight



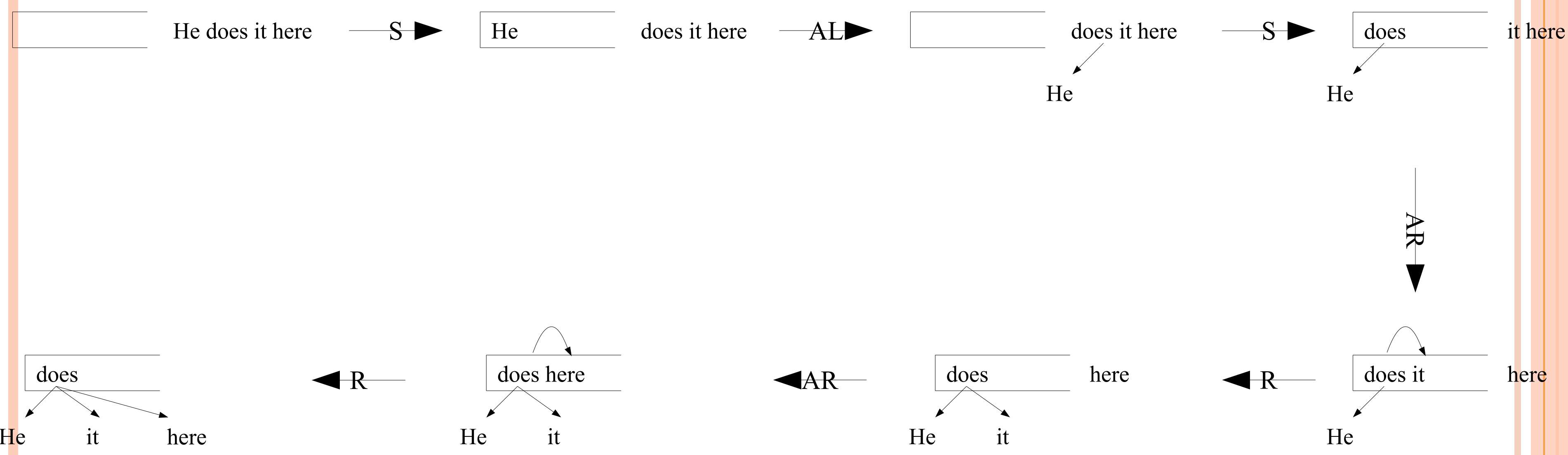
The arc-eager parser

- An example
  - S – Shift
  - R – Reduce
  - AL – ArcLeft
  - AR – ArcRight



The arc-eager parser

- An example
  - S – Shift
  - R – Reduce
  - AL – ArcLeft
  - AR – ArcRight



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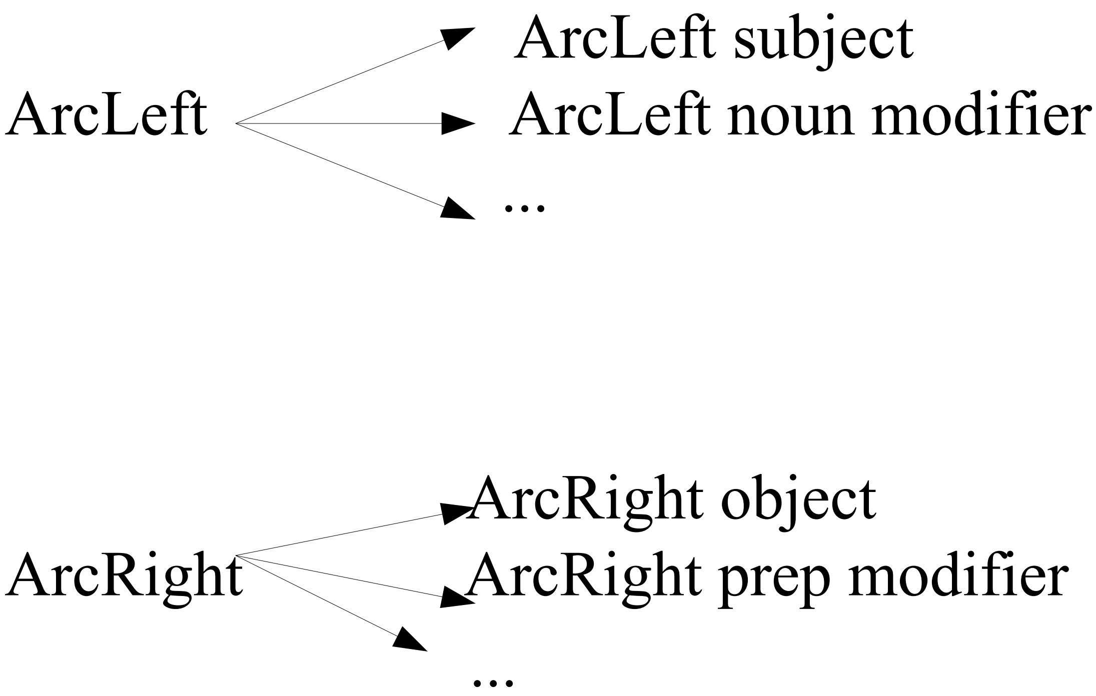
The arc-eager parser

- Arc-eager parser
  - Time complexity: linear
    - Every word is pushed once onto the stack
    - Every word except the root is popped once
  - Links are added between ST and N0
    - As soon as they are in place
    - 'eager'

The arc-eager parser

- Arc-eager parser
  - Labeled parsing?

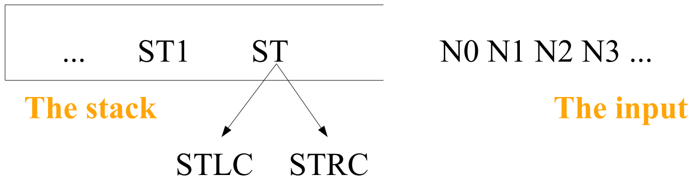


The arc-standard parser

- Arc-standard parser
  - Same as previously
    - A stack to hold partial candidates
    - A queue of next incoming words
  - Different from previously
    - Transition actions: SHIFT LEFT RIGHT
  - Examples
    - Yamada and Matsumoto (2003)
    - Huang et al. (2009)

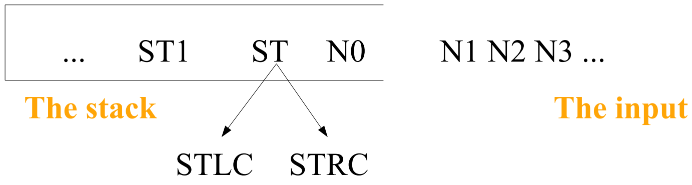
The arc-standard parser

- Transition actions
  - Shift



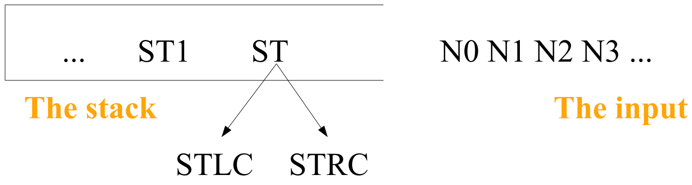
The arc-standard parser

- Transition actions
  - Shift
    - Pushes stack



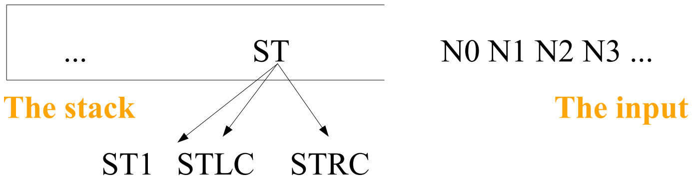
The arc-standard parser

- Transition actions
  - Left



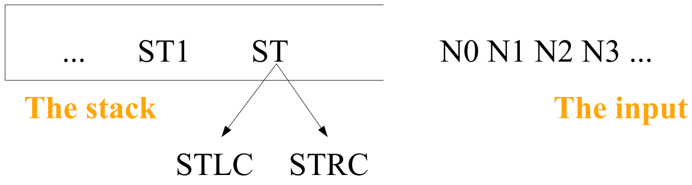
The arc-standard parser

- Transition actions
  - Left
    - Pops stack
    - Adds link



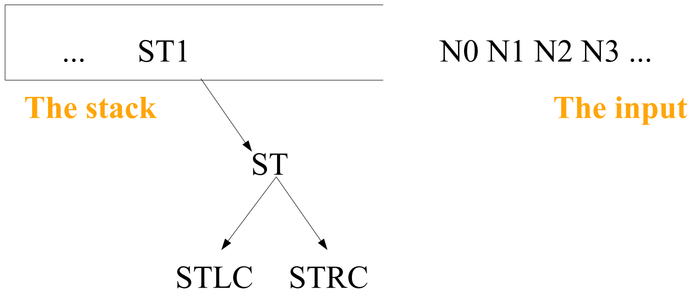
The arc-standard parser

- Transition actions
  - Right



The arc-standard parser

- Transition actions
  - Right
    - Pops stack
    - Adds link



The arc-standard parser

- Arc-standard parser
  - Time complexity: linear
    - Every word is pushed once onto the stack
    - Every word except the root is popped once
  - Links are added between ST and ST1
- Standard or eager?
  - empirical

The arc-standard parser

- Arc-standard parser
  - Similarity to shift-reduce phrase-structure parsing
    - Sagae and Lavie (2005)
    - Wang et al. (2006)
    - Zhang and Clark (2009)

Non-projectivity

- Problem

A meeting was scheduled for this today.

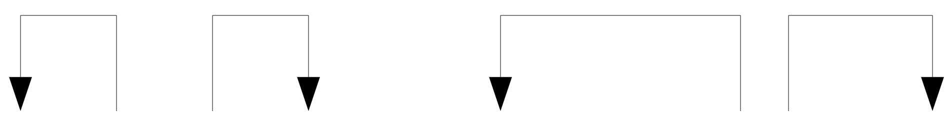
- Neither parsers solves it
  - Word orders are kept
  - Links added between neighbors (on stack)

Non-projectivity

- Problem

A meeting was scheduled for this today.

- One Solution



A meeting for this was scheduled today.

Non-projectivity

- Online reordering (Nivre 2009)
  - Add an extra action to the parser: swap
    - Pops the second word off stack
    - The other transitions are the same

Non-projectivity

- An extra transition action
  - swap

A meeting was scheduled for this today.

Non-projectivity

- An extra transition action
  - swap

A meeting was scheduled for this today.

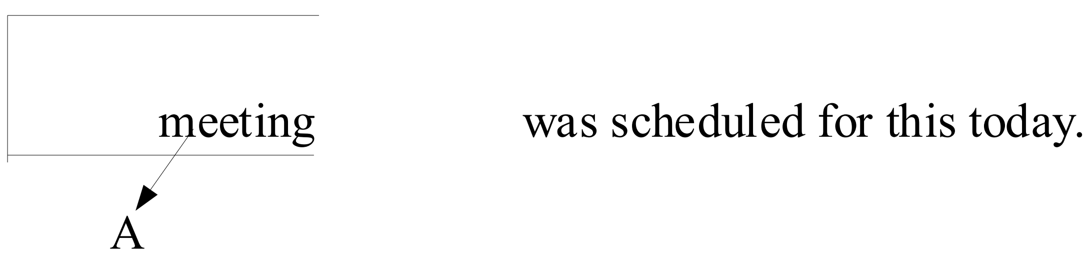
Non-projectivity

- An extra transition action
  - swap

A meeting was scheduled for this today.

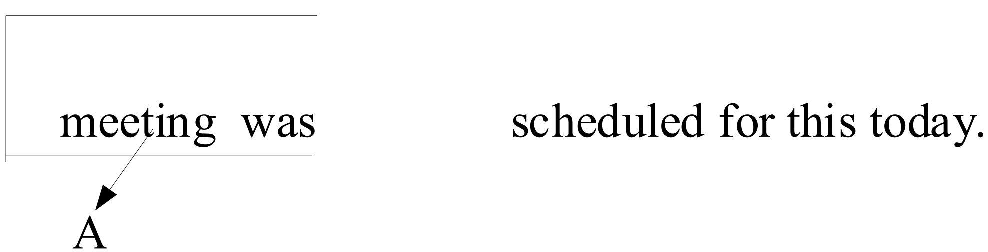
A transition-based parsing process

- An extra transition action
  - swap



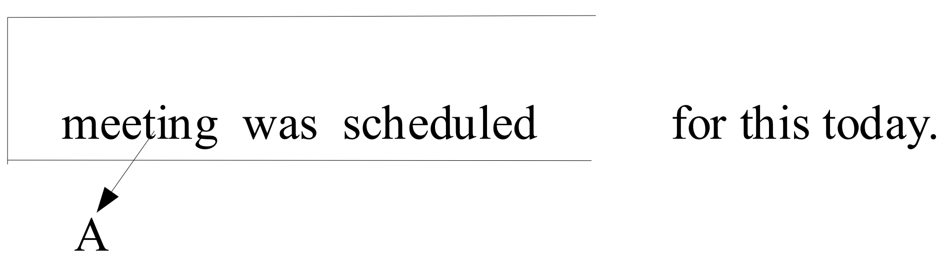
A transition-based parsing process

- An extra transition action
  - swap



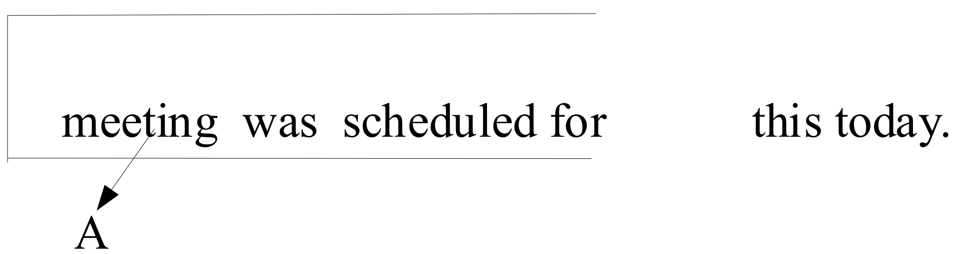
A transition-based parsing process

- An extra transition action
  - swap



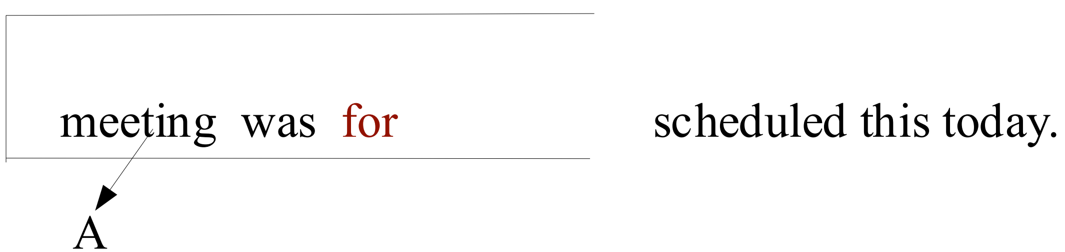
A transition-based parsing process

- An extra transition action
  - swap



A transition-based parsing process

- An extra transition action
  - **swap**



A transition-based parsing process

- An extra transition action
  - **swap**

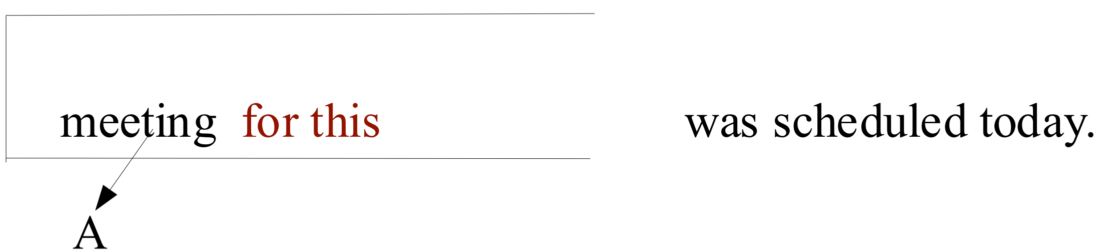
A transition-based parsing process

- An extra transition action
  - **Swap**

…

A transition-based parsing process

- An extra transition action
  - **swap**



Non-projectivity

- Online reordering (Nivre 2009)
  - Add an extra action to the parser: swap
  - Not linear any more
    - Can be N-square
    - Expected linear time

Transition-based parsing processes

- Summary
  - Build the output using
    - A stack
    - A set of transition actions
  - Different types
    - Arc-eager
    - Arc-standard
    - More?

Outline

- Part A: introduction to dependency parsing
- Part B: graph-based dependency parsing models
- Part C: transition-based dependency parsing models
  - Transition-based parsing processes
  - **Decoding algorithms**
  - Learning algorithms and feature templates
- Part D: the integrated models
- Part E: other recent trends in dependency parsing

Decoding algorithms

- Goal
  - Search for one sequence of transition-action to build the parse
  - Done by scoring transition action given context
  - Models talked about in the next section
- Comparison with graph-based
  - Search for one graph from candidates

Decoding algorithms

- Candidate item

  <S, G, Q>

Decoding algorithms

- Greedy local search
  - Initialize a start item

    S=empty, G=empty, Q=input sentence
  - Define a final item

    S=[root], G=tree, Q=[]
  - Pick up one transition-action at a time by score

Greedy local search

- Malt parser (Nivre et al., 2006)
  - Arc-eager transitions
    - Pushing actions: SHIFT, ARC-RIGHT
    - Popping actions: REDUCE, ARC-LEFT
    - Links are added with ARC-
  - Start state
    - Stack empty, no word has been processed by now
  - Finish state
    - Stack contains only root, all processed
  - Greedily picks up one transition action after another from start to finish

Score(action)

Greedy local search

- Malt parser

He does it here

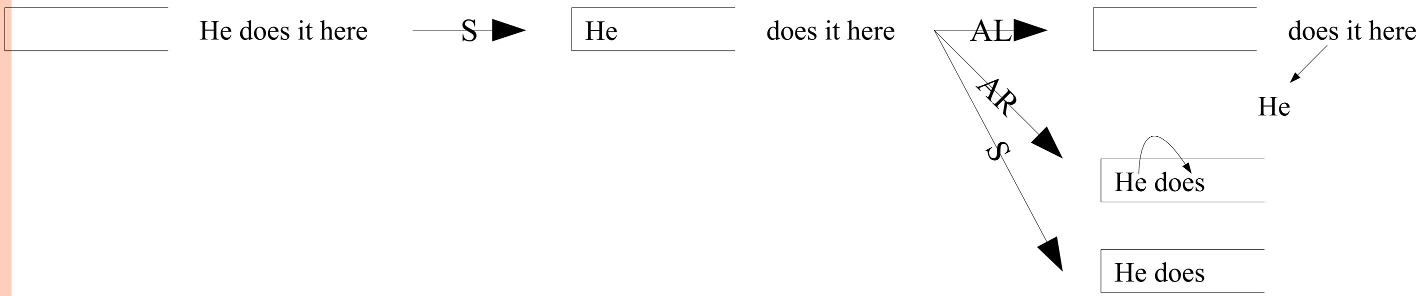
Greedy local search

- Malt parser

He does it here —S→ He | does it here

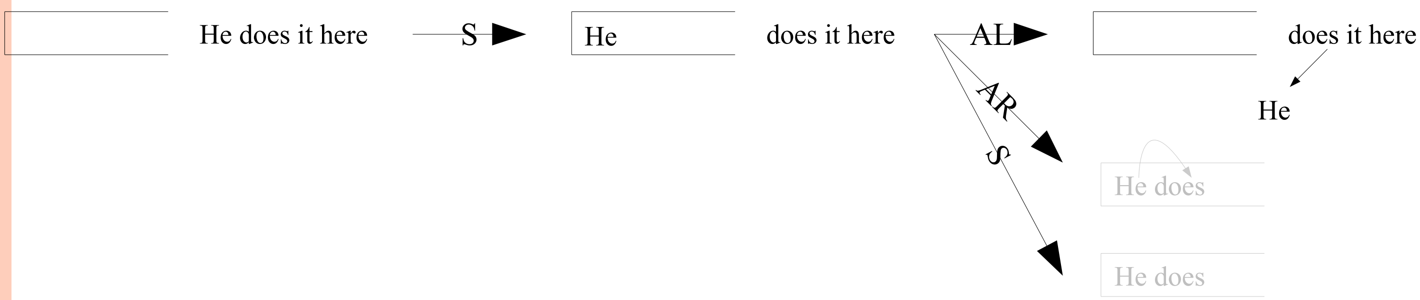
Greedy local search

- Malt parser



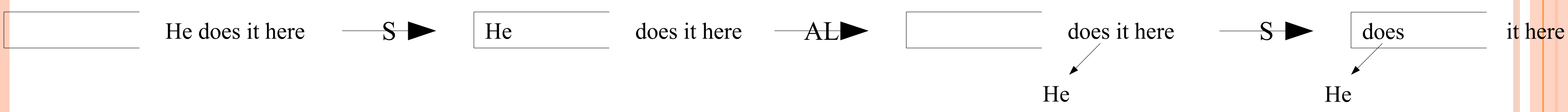
Greedy local search

- Malt parser



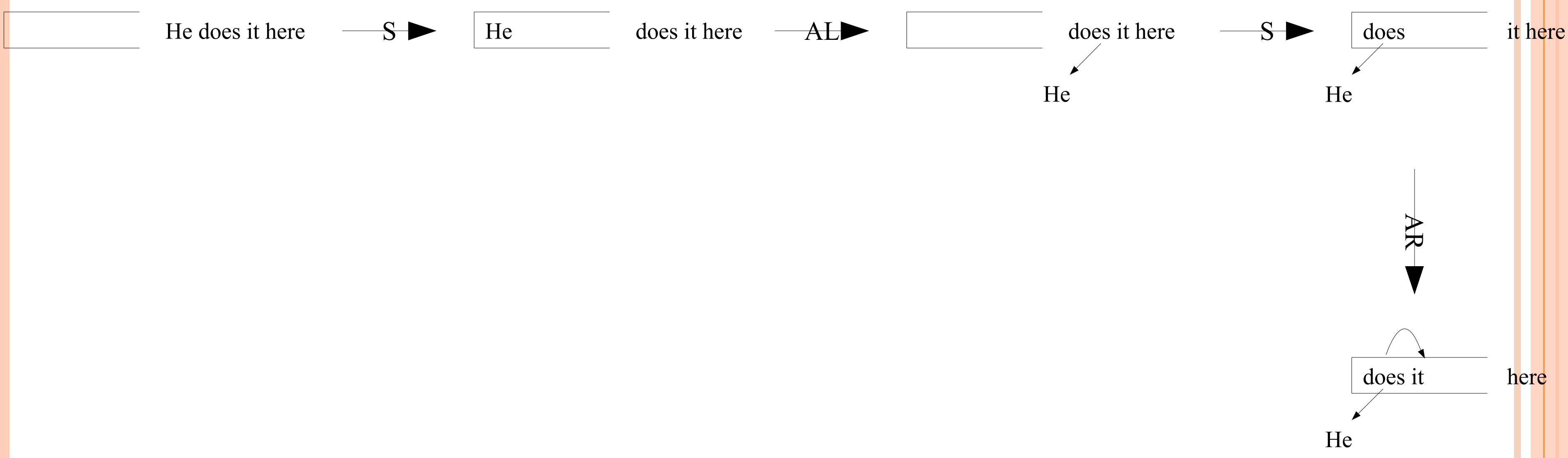
Greedy local search

- Malt parser



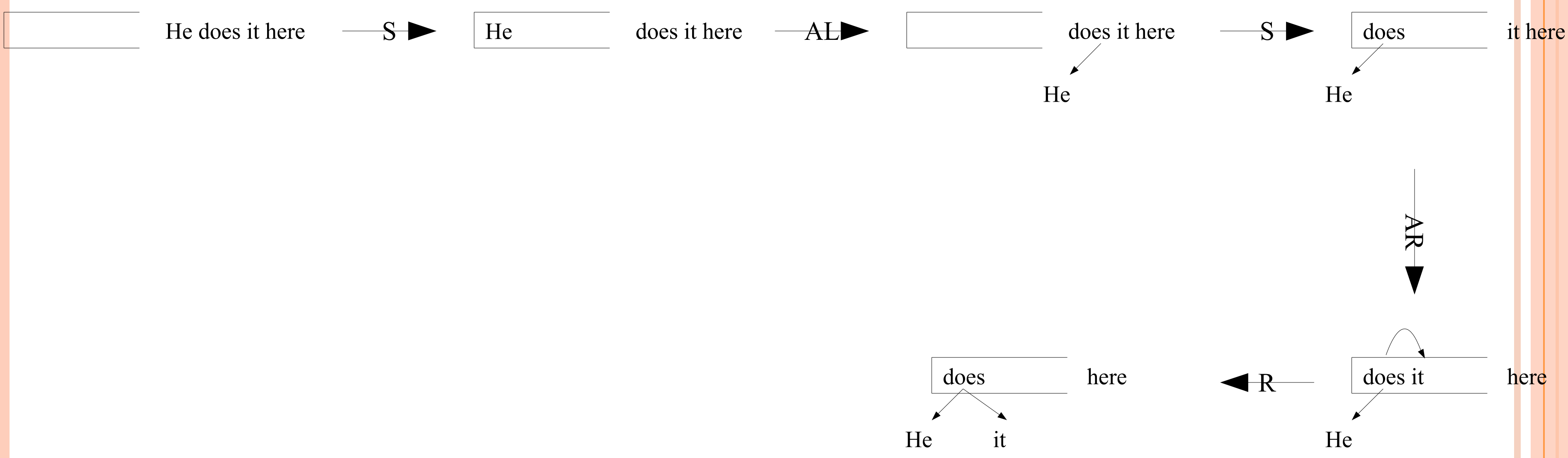
Greedy local search

- Malt parser



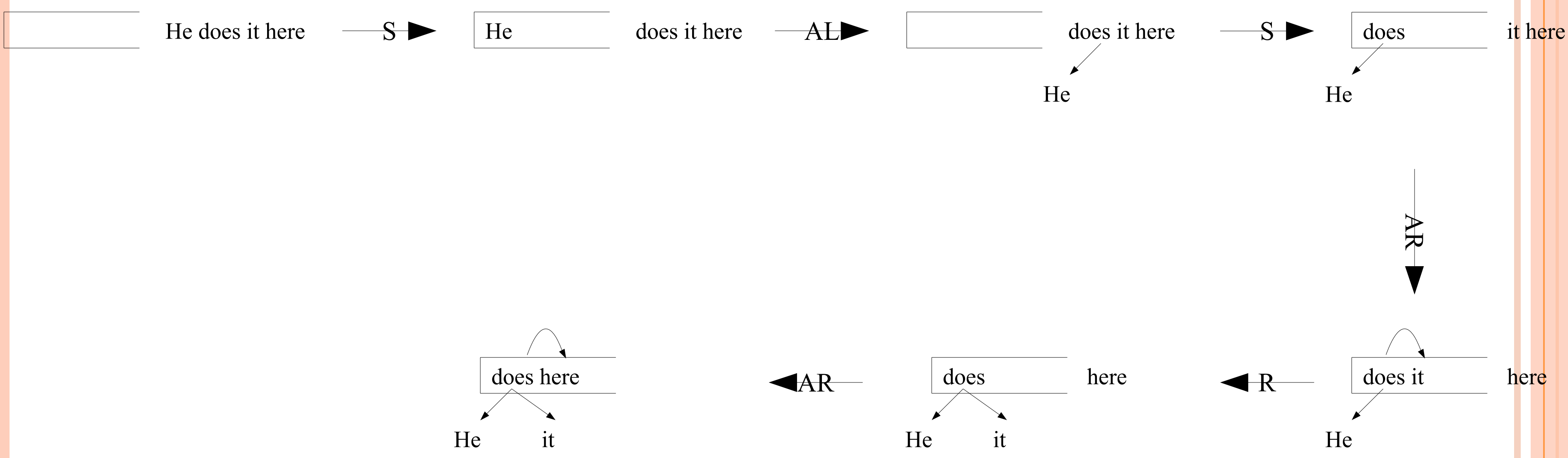
Greedy local search

- Malt parser



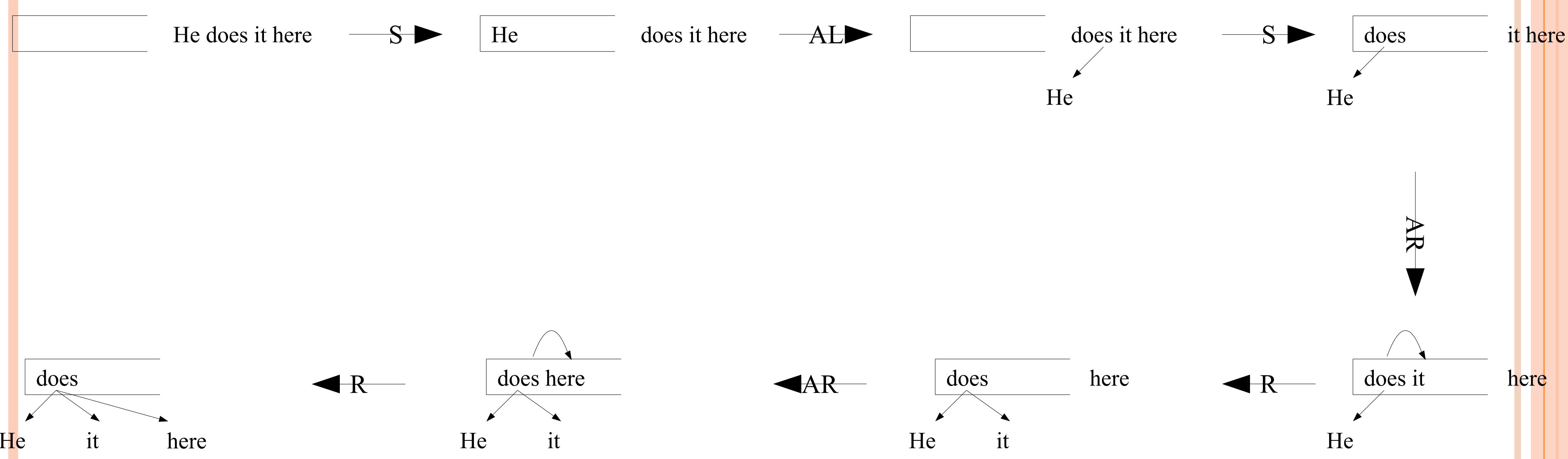
Greedy local search

- Malt parser



Greedy local search

- Malt parser



Decoding algorithms

- Greedy local search
  - Problem:
    one error leads to incorrect parse

Decoding algorithms

- Beam search

  - Keeps N different partial state items in agenda.
  - Use the total score of all actions to rank state items

$$Score(parse) = \sum_{action \in parse} Score(action)$$

  - Avoid error propagations from early decisions

Beam search

- Example work
  - Johansson and Nugues (2007)
  - Zhang and Clark (2008)

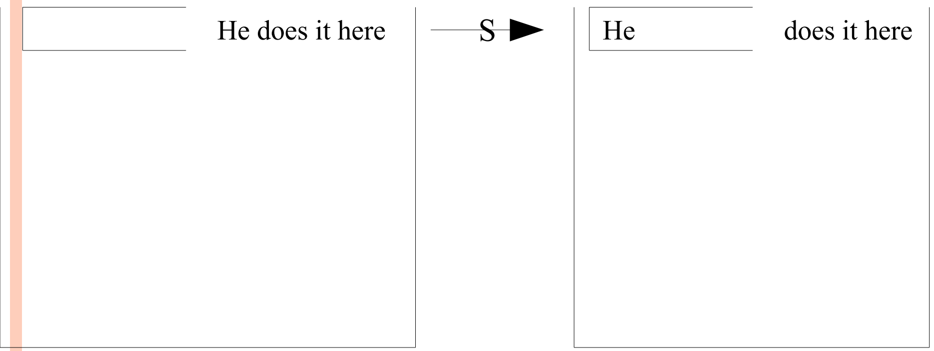
Beam search

- An example

He does it here

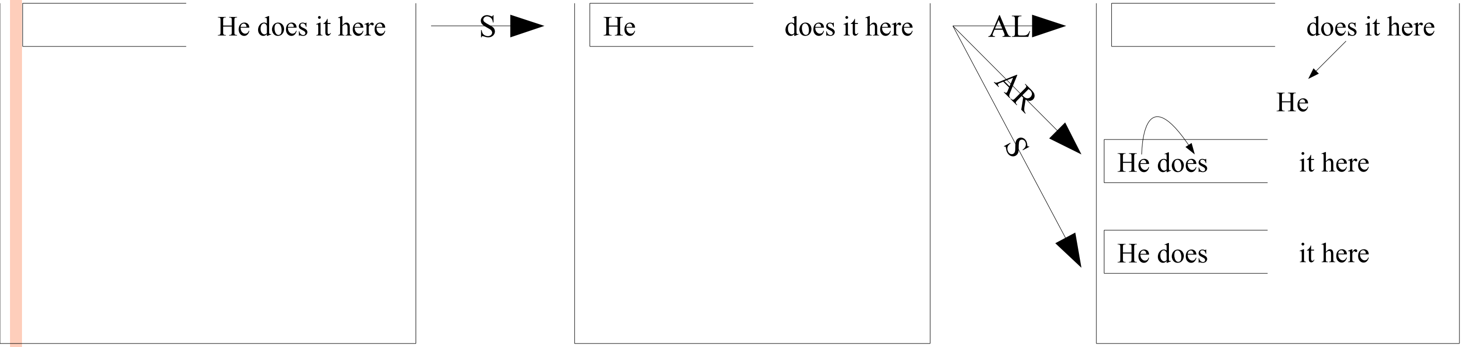
Beam search

- An example



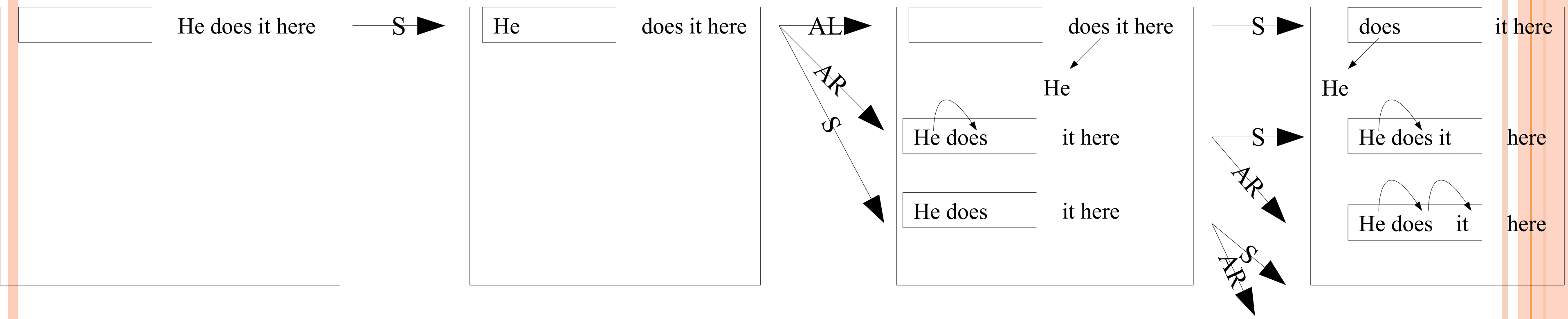
Beam search

- An example



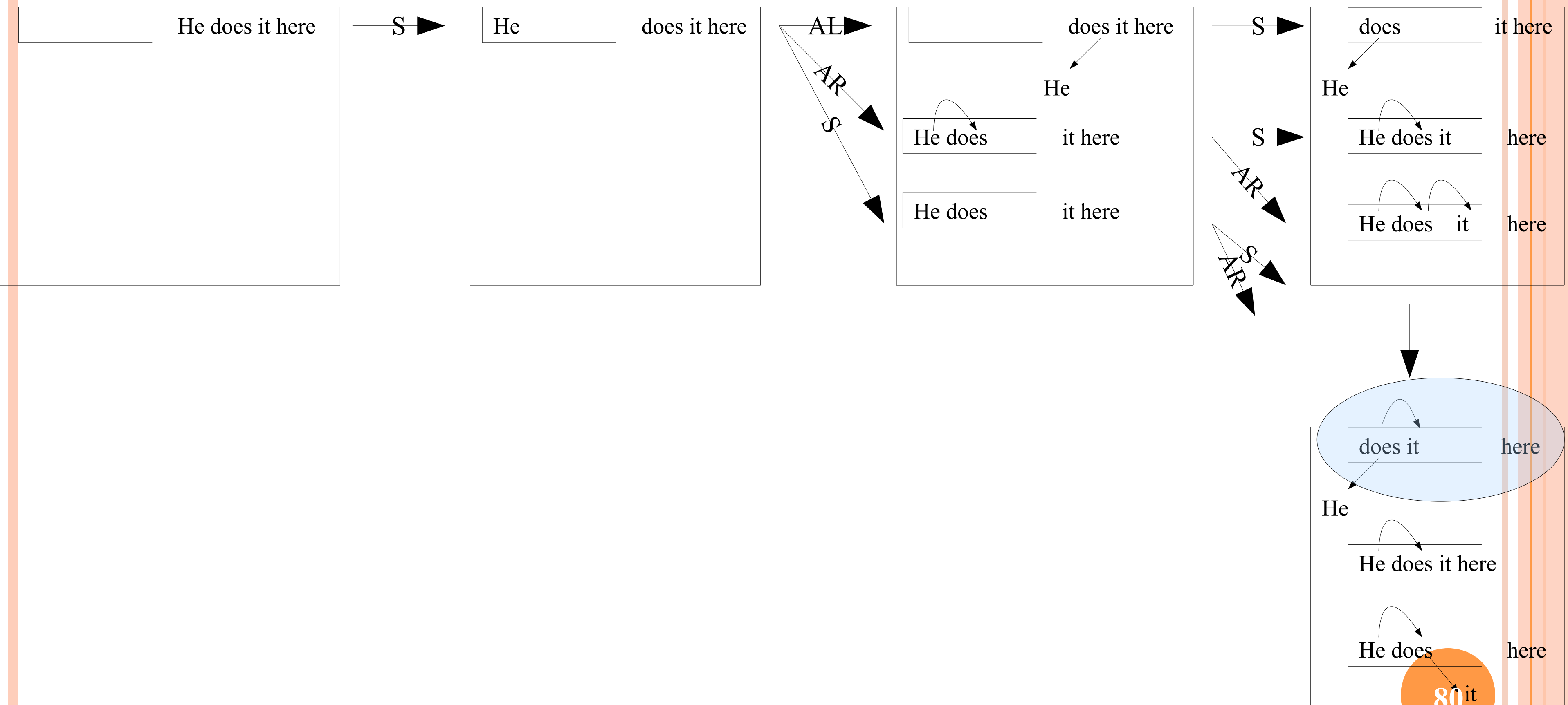
Beam search

- An example



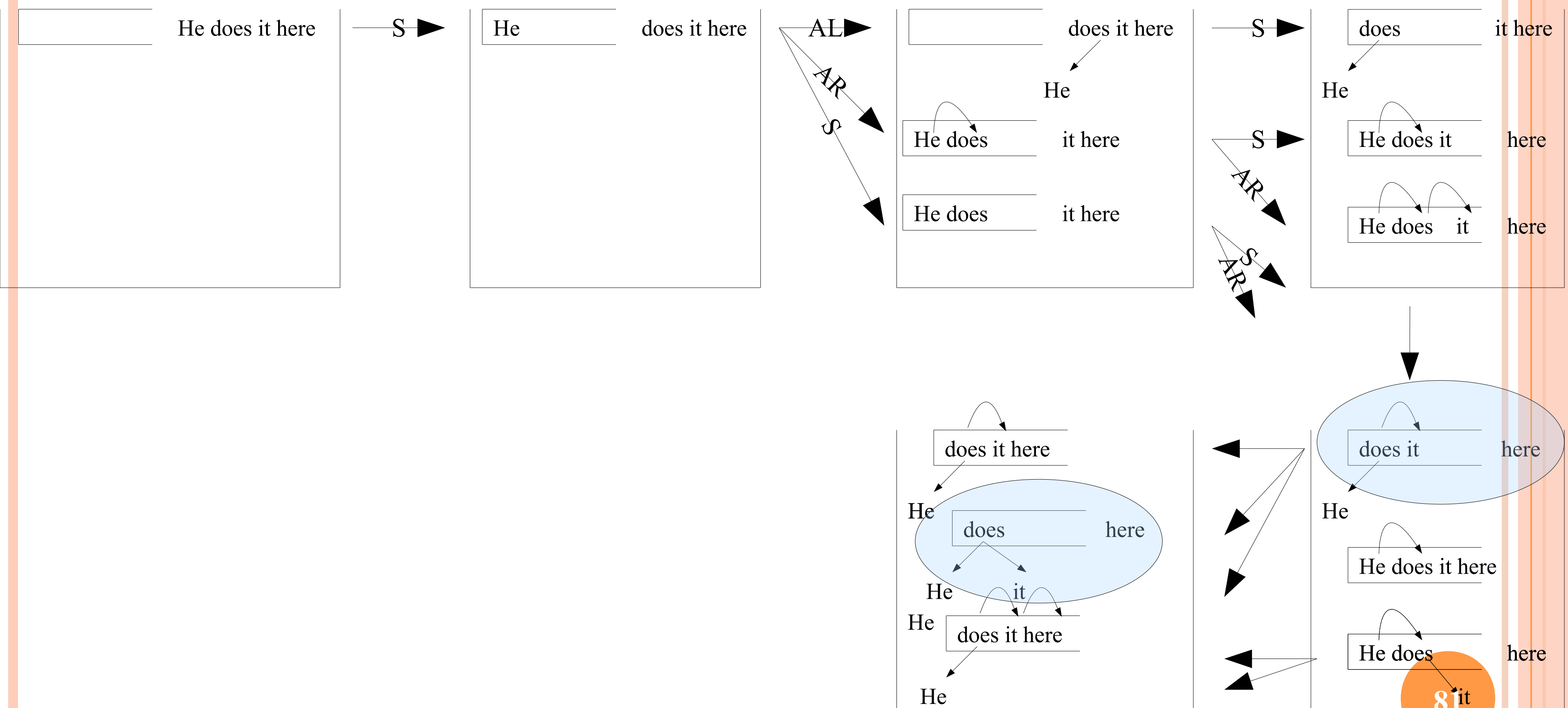
Beam search

- An example



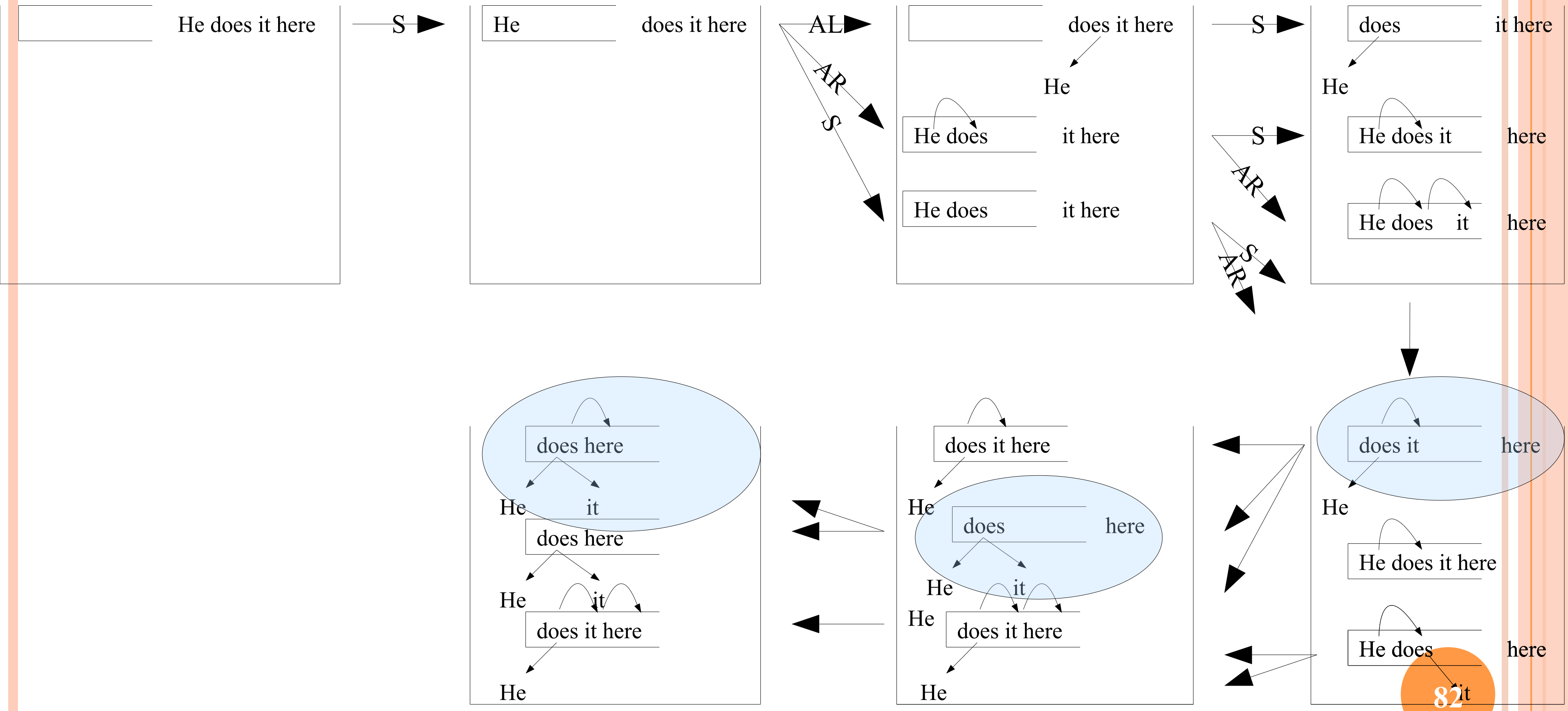
Beam search

- An example



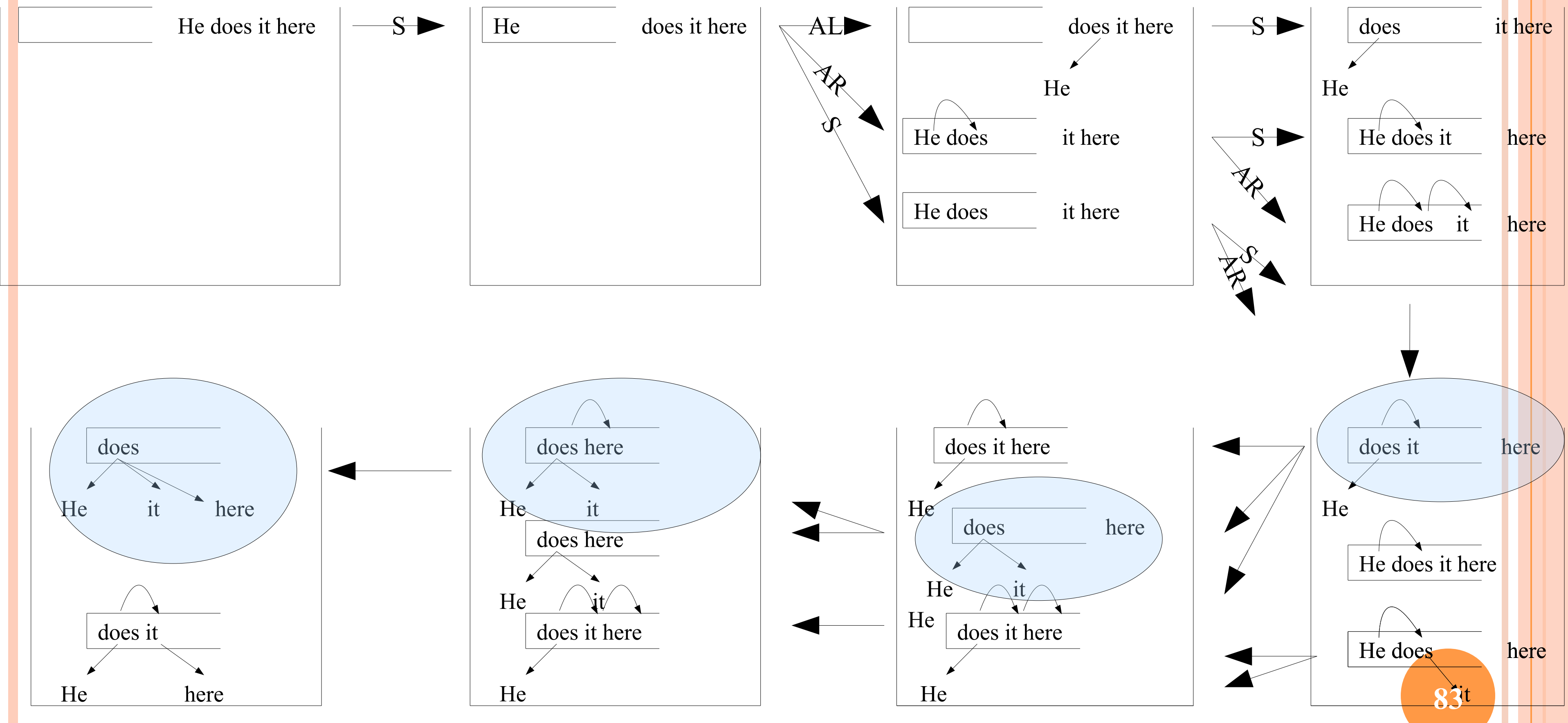
Beam search

- An example



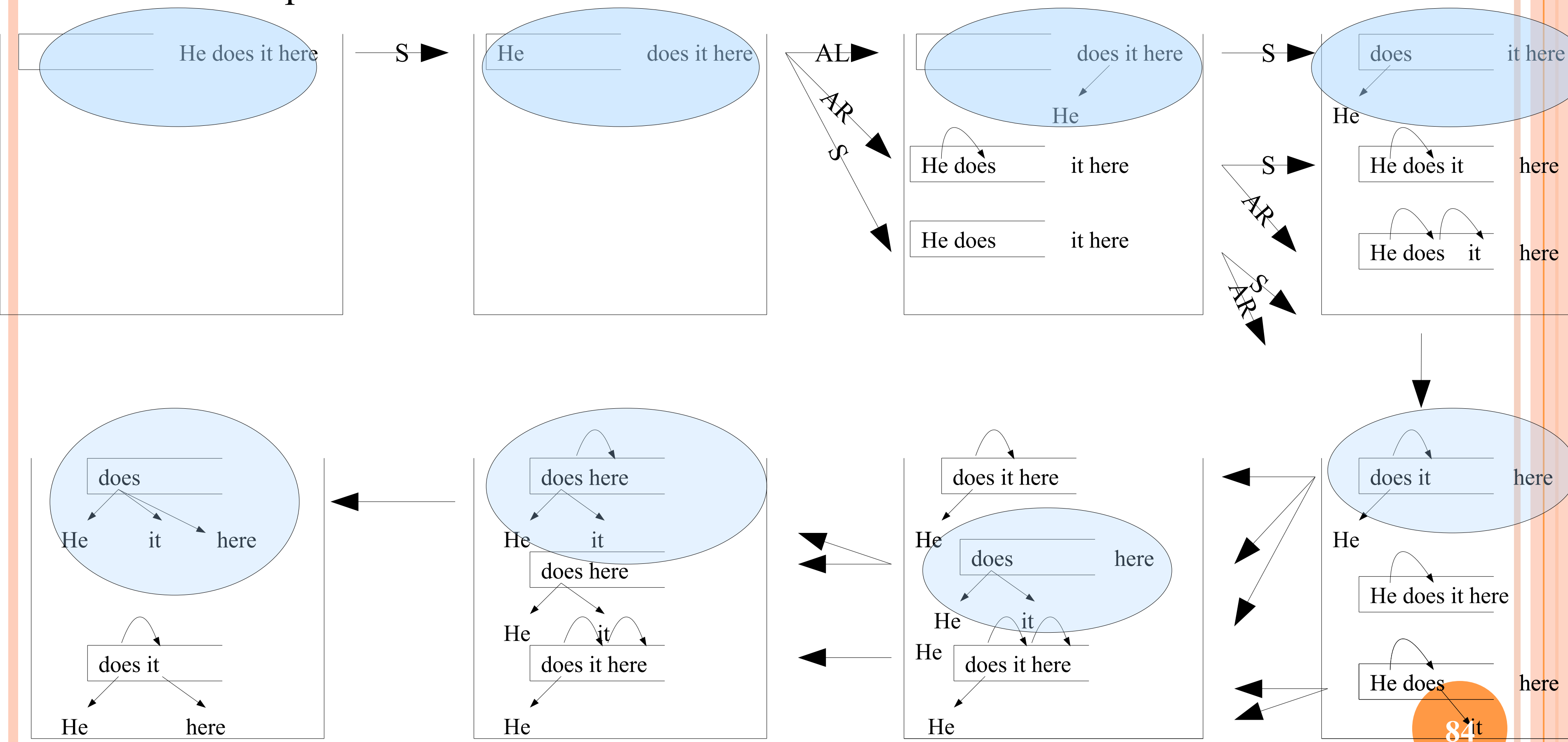
Beam search

- An example



Beam search

- An example



Parsing algorithms

- Search strategies
  - Greedy local search
  - Beam search
  - Best-first
    - Duan et al. (2007)

Parsing algorithms

- Search strategies
  - Greedy local search
  - Beam search
  - Best-first
  - Other strategies?
    - Huang and Sagae (2010)

Outline

- Part A: introduction to dependency parsing
- Part B: graph-based dependency parsing models
- Part C: transition-based dependency parsing models
  - Transition-based parsing processes
  - Decoding algorithms
  - **Learning algorithms and feature templates**
- Part D: the integrated models
- Part E: other recent trends in dependency parsing

Models

- The way we score transition actions
  - Linear models

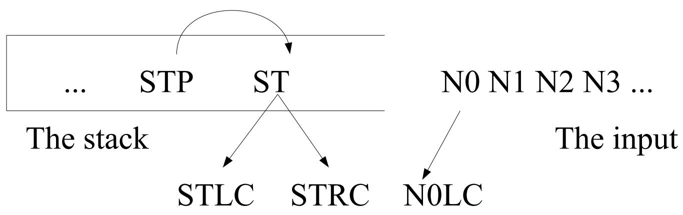
$$Score(action) = \sum_{feature \in features\ with\ context} feature \times weight(feature)$$

  - Non-linear models
    - SVM

      non-linear kernels

Learning algorithms

- Locally learn for each transition action
  - SVM

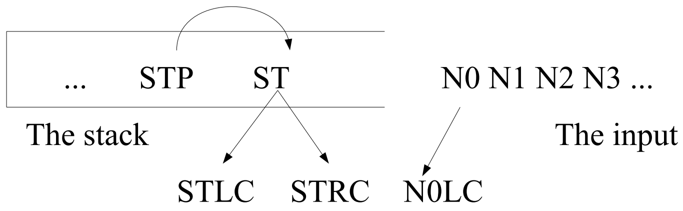


  - Examples
    - MaltParser (Nivre et al., 2006)
    - Johansson and Nugues (2007)
    - Duan (2007)

  - LIBSVM (http://www.csie.ntu.edu.tw/~cjlin/libsvm/)

Learning algorithms

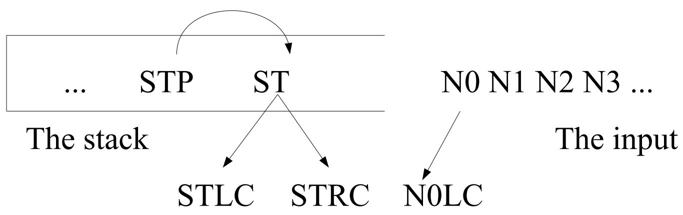
- Feature templates



- Example templates
  - STw, STp,
  - N0w, N0p,
  - ST N0 distance,
  - STLCw, STLCp,
  - N1w, N1p
  - ...

Learning algorithms

- Feature templates



- Example templates
  - STw, STp,
  - N0w, N0p,
  - ST N0 distance,
  - STLCw, STLCp,
  - N1w, N1p
  - …
- A second order polynomial kernel will combine individuals

Learning algorithms

- Globally learn the best sequence of actions
  - Linear model to score actions
  - Globally search for the best sequence of actions, globally learn

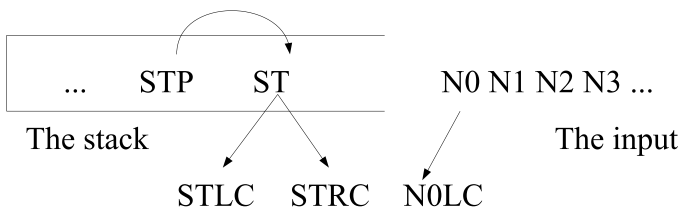
$$
\begin{aligned}
& Score(parse) \\
= \; & \sum_{action \in parse} Score(action) \\
= \; & \sum_{action \in parse} \sum_{feature \in status\ for\ action} feature \times weight(feature)
\end{aligned}
$$

Learning algorithms

- Globally learn the best sequence of actions
  - Zhang and Clark (2008)
  - Use the generalized perceptron learning algorithm (Collins, 2002)

Learning algorithms

- Feature templates



- Example templates
  - STw, STp,
  - N0w, N0p,
  - ST N0 distance,
  - STwSTp, STwN0w, STwpN0wp
  -
  - …
- Manual combination of information; linear model.

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Part D: The Combination of Different Models

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The combined models

- Motivation
  - Parsers make different mistakes, each having a particular strength
    - McDonald and Nivre (2007)
  - Combined parser lead to superior accuracies than individual parsers

Overview

- Part A: introduction to dependency parsing
- Part B: graph-based dependency parsing models
- Part C: transition-based dependency parsing models
- Part D: the integrated models
  - **The ensemble approach**
  - The stacking approach
  - The single-model approach
- Part E: other recent trends in dependency parsing

The ensemble method

- Sagae and Lavie (2006)
  - m parsers
  - Each different and trained separately

The ensemble method

- Sagae and Lavie (2006)
  - m parsers
  - Each different and trained separately

  - m parses for a single input
  - Combine all parses
    - Calculate link weights according to each parse
    - Add m numbers
    - Links from different parser outputs weighted equally or differently according to various configurations

The ensemble method

- Sagae and Lavie (2006)
  - m parsers
  - Each different and trained separately

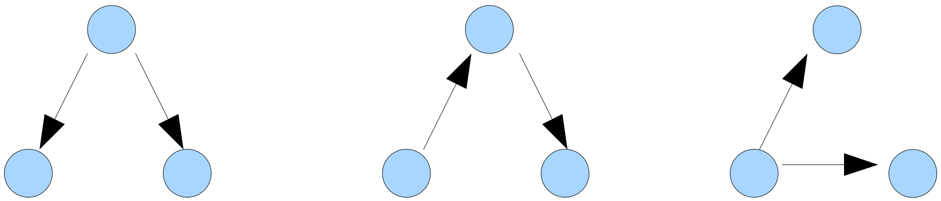
  - m parses for a single input
  - Combine all parses
    - Calculate link weights according to each parse
    - Add m numbers
    - Links from different parser outputs weighted equally or differently according to various configurations

  - Find the MST according to these weights

The ensemble method

- Sagae and Lavie (2006)
  - m parsers
  - Each different and trained separately

  - m parses for a single input



The ensemble method

- Sagae and Lavie (2006)
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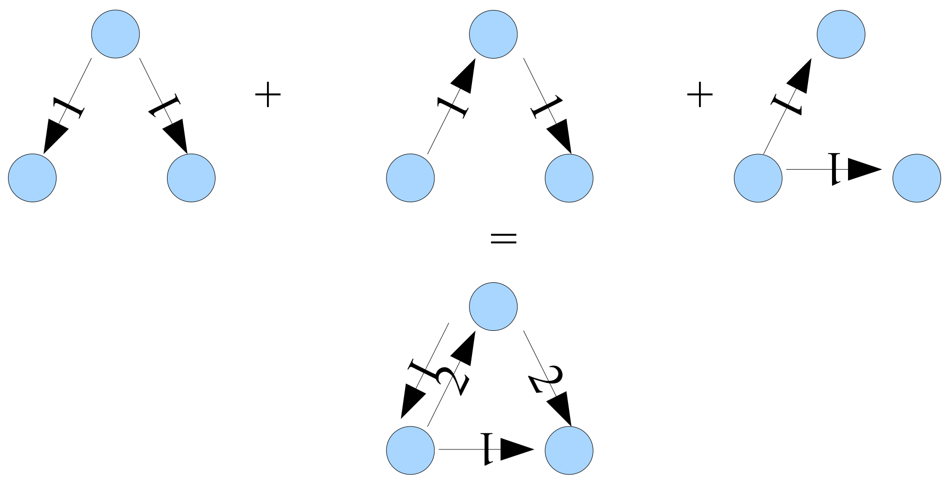
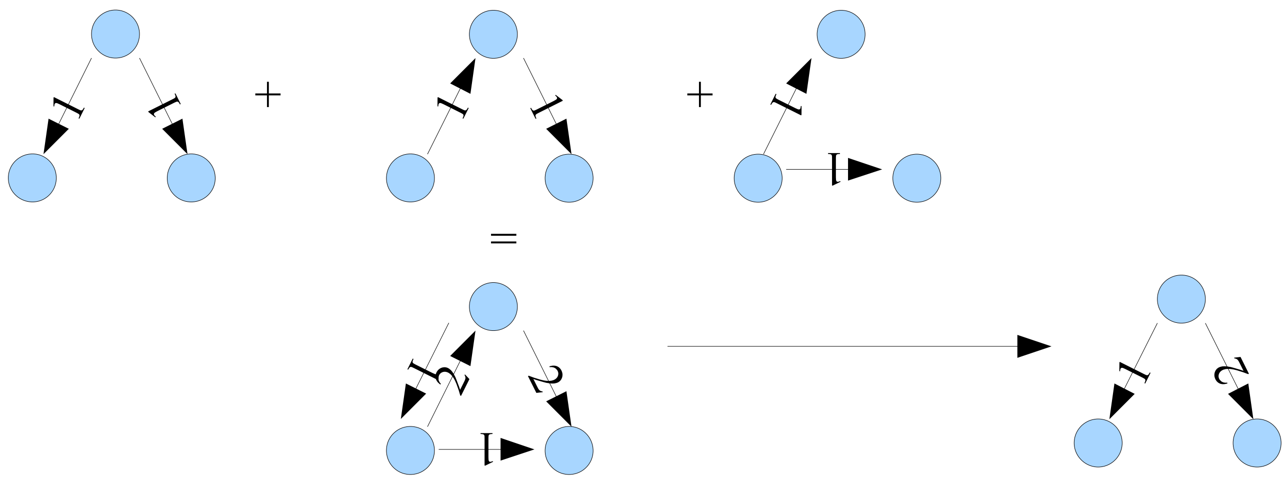
  - m parses for a single input
  - Combine all parses



The ensemble method

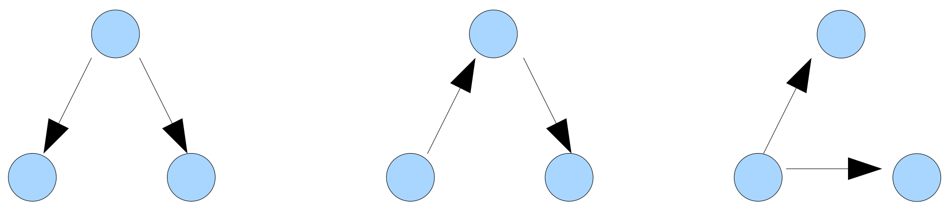
- Sagae and Lavie (2006)
  - m parsers
  - Each different and trained separately

  - m parses for a single input
  - Find MST



The ensemble method

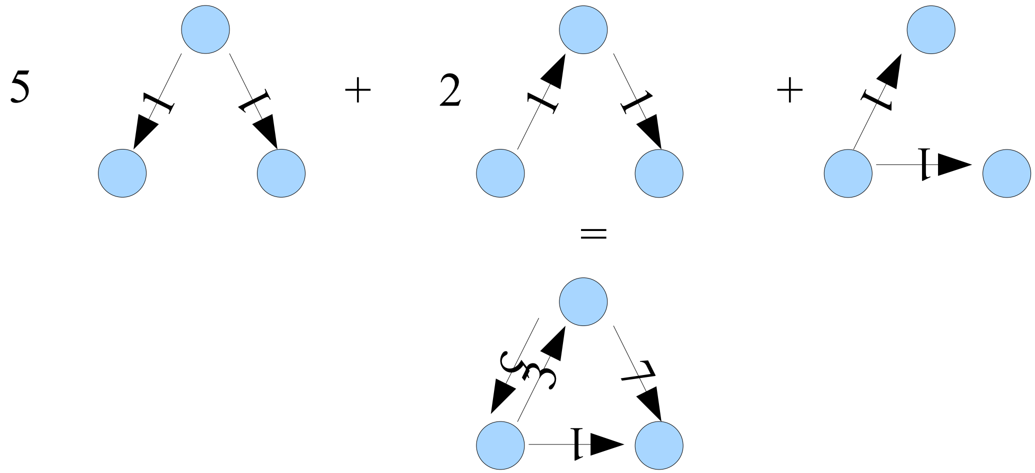
- Sagae and Lavie (2006)
  - m parsers
  - Each different and trained separately
  - m parses for a single input



The ensemble method

- Sagae and Lavie (2006)
  - m parsers
  - Each different and trained separately

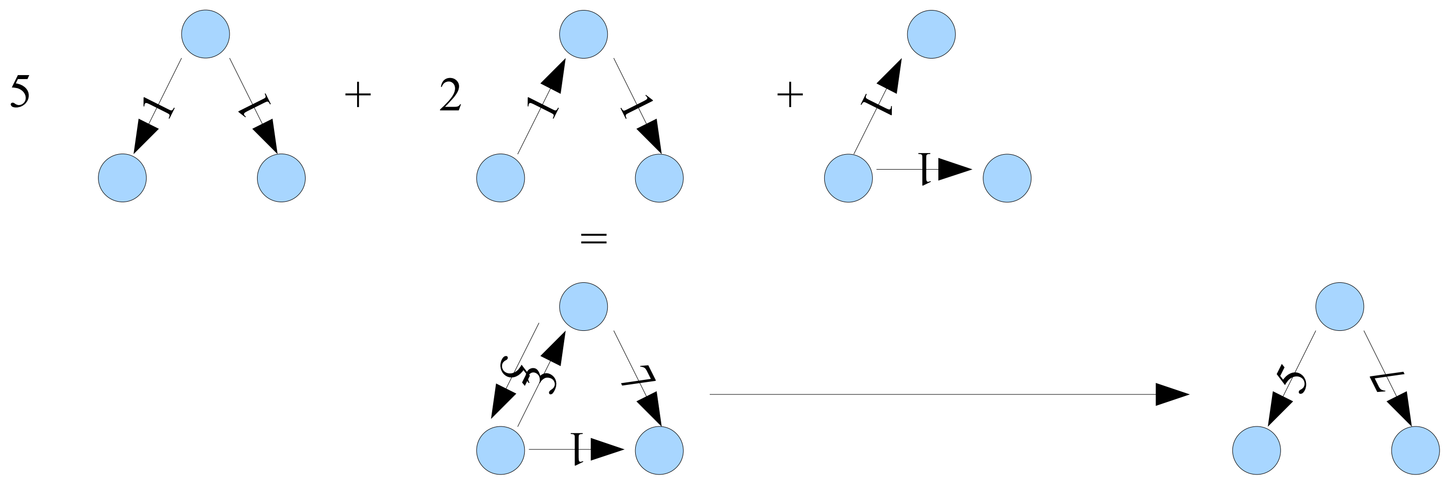
  - m parses for a single input
  - Combine all parses by weighted sum of them



The ensemble method

- Sagae and Lavie (2006)
  - m parsers
  - Each different and trained separately

  - m parses for a single input
  - Find the output



Overview

- Part A: introduction to dependency parsing
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  - The ensemble approach
  - **The stacking approach**
  - The single-model approach
- Part E: other recent trends in dependency parsing

The stacking method

- Nivre and McDonald (2008)
  - Combination of
    - Graph-based MSTParser
    - Transition-based MaltParser
  - Stacking

The stacking method

- Nivre and McDonald (2008)
  - Train one parser first
    - Parser1
  - Let the other parser (i.e. parser2) consult parser1 when it does parsing
  - Two resulting parsers (Malt-MST, and MST-Malt)

The stacking method

- Nivre and McDonald (2008)
  - During test
  - Use parser1 to parse input
  - Parser2 extract features from parser1 output
  - Take parser2 output as the result

The stacking method

- Nivre and McDonald (2008)
  - During training
  - Use parser1 to parse training data
  - Parser2 extract features from parser1 output
  - Train parser2 with the additional features

The stacking method

- Nivre and McDonald (2008)
  - During training
  - *Use parser1 to parse training data*
  - Parser2 extract features from parser1 output
  - Train parser2 with the additional features

The stacking method

- Nivre and McDonald (2008)
  - During training
  - *Use parser1 to parse training data*
    - Can't train parser1 on the training data (same set)
    - Solution
      - 10-fold cross-validation
      - Take a tenth of the training data as the "test" data
      - Use the other nine tenths to train parser1
      - Generate parser1 output for the "test" sent
      - Repeat 10 times to get parser1 output for all training sentences
  - Parser2 extract features from parser1 output
  - Train parser2 with the additional features

Overview

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  - The stacking approach
  - **The single-model approach**
- Part E: other recent trends in dependency parsing

The single-model method

- Zhang and Clark (2008)
  - Combine graph-based and transition-based parsers
    - Same as just now
  - Two parsers are treated equally
    - Graph-based and transition-based information in a single model
    - Trained together
    - Used together for decoding
  - They become one
    - single-model

The single-model method

- Zhang and Clark (2008)
  - Challenges:
    - Decoder combination
      - Graph-based parsers typically take dynamic programming
      - Transition-based features hard to be accommodated by DP at the same time
    - Model combination
      - How to use both kinds of information in a single model?
    - Training combination

The single-model method

MSTParser

Graph-based

Exact search

- Accurate
- Local features

MaltParser

Transition-based

Greedy (no search)

- Less accurate
- Non-local features

The single-model method

<u>MSTParser</u>

Graph-based

Exact search

- Accurate
- Local features

Beam search (approximate)

- Some search
- Non-local features

<u>MaltParser</u>

Transition-based

Greedy (no search)

- Less accurate
- Non-local features

The single-model method

MSTParser		MaltParser
Graph-based	Combine	Transition-based
Exact search	Beam search (approximate)	Greedy (no search)
Accurate	Some search	Less accurate
Local features	Non-local features	Non-local features

The single-model method

- Zhang and Clark (2008)
  - Decoder combination
    - The beam-search decoder for the transition-based parser
      - Provides transitions;
      - Provides graph (partial parse in candidate item <S, Q, G>);
      - Does not restrict features – we use non-local graph-features too.
  - Model combination
  - Training methods of the combined model

The single-model method

- Zhang and Clark (2008)
  - Decoder combination
  - Model combination (linear models)
    - $Score_{COMBINED}(parse) = Score_{GRAPH}(parse) + Score_{TRANSITION}(parse)$
    - $Score_{GRAPH}(parse) = \sum_{feature \in parse} feature \times weight(feature)$
    - $Score_{TRANSITION}(parse)$

$$= \sum_{action \in parse} Score(action)$$

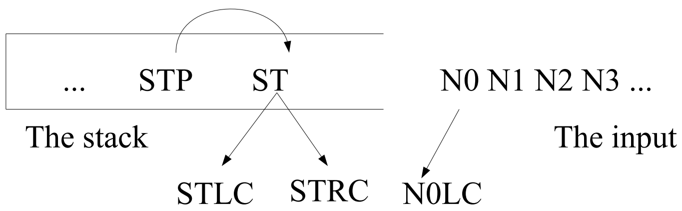
$$= \sum_{action \in parse} \sum_{feature \in status\ for action} feature \times weight(feature)$$

$$Score_{COMBINED}(parse) = \sum_{feature \in graph + action} feature \times weight(feature)$$

  - Training methods of the combined model

The single-model method

- Zhang and Clark (2008)
  - Decoder combination
  - Model combination



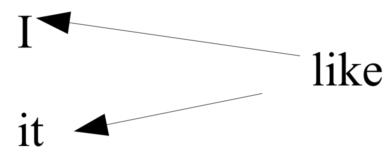
  - Transition feature templates (w – word, t – POS tag)
    - **Stack top**: STwt; STw; STt
    - **Current word**: N0wt; N0w; N0t
    - **Next word**: N1wt; N1w; N1t
    - **Stack top and current word**: STwtN0wt; STwtN0w; ...
    - **POS bigram**: N0tN1t
    - **POS trigrams**: N0tN1tN2t; STtN0tN1t; ...
    - **N0 word + POS bigrams**: N0wN1tN2t; STtN0wN1t; ...
  - Training methods of the combined model

The single-model method

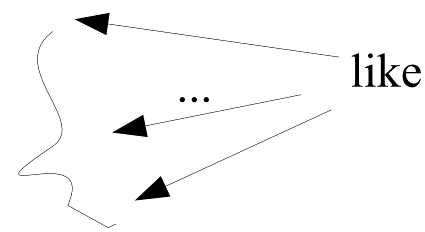
- Zhang and Clark (2008)
  - Decoder combination
  - Model combination
    - Graph feature templates
      - From MSTParser
        - **Head**: Head word, head tag, head word + tag
        - **Modifier**: Modifier word, modifier tag, modifier word + tag
        - **Head + modifier:** word / tag combinations
        - **Between**: Any tag between head and modifier
        - **Surrounding**: Tags on the left / right of head / modifier
        - **Sibling**: word / tag combinations
      - Extra features
        - **Two links**: Tags of parent, child and grandchild
        - **Arity** + head word / tag Transition feature templates (w – word, t – POS tag)
  - Training methods of the combined model

The single-model method

- Zhang and Clark (2008)
  - Decoder combination
  - Model combination
    - Graph feature templates
      - From MSTParser



      - Extra features



  - Training methods of the combined model

The single-model method

- Zhang and Clark (2008)
  - Decoder combination
  - Model combination
  - Training methods of the combined model
    - Perceptron – allowed by the linear model

The combined models

- Comparison
  - Ensemble method: decoding time combination
  - Stacking method: decoding and training time combination, but separately
  - Single method: complete combination
- One recent study about ensemble / stacking
  - Surdeanu and Manning (2010)

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Part E: Other Recent Trends in Dependency Parsing

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Outline

- Part A: introduction to dependency parsing
- Part B: graph-based dependency parsing models
- Part C: transition-based models
- Part D: the combined models
- Part E: other recent trends in dependency parsing
  - Explore higher order features
  - Use extra information source
  - Better parsing strategies

Other Recent Trends in Dependency Parsing

- Explore higher order features
- Use extra information sources
  - Raw data
  - Bilingual data
  - Linguistic rules
- Better parsing strategies

Explore Higher-Order Features (1)

- Dependency Parsing by Belief Propagation (Smith & Eisner, 08)
  - Has a first order baseline parser
  - Using a BP network to incorporate higher order features into this first order parser approximately

- Integration of graph-based and transition-based models (Zhang & Clark, 08)
  - Approximation by beam-search

Explore Higher-Order Features (2)

- Concise Integer Linear Programming Formulations for Dependency Parsing (Martins et al. 09)
  - Formulate dependency parsing as a polynomial-sized integer linear program
  - Integer linear programming in NLP tutorial this afternoon

Use Extra Information Source –Raw Data

- Improving dependency parsing with subtrees from auto-parsed data (W. Chen et al. 09)
  - Using a base parser to pare large scale unannotated data
  - Extract subtrees from the auto-parsed data
- Simple semi-supervised dependency parsing (Koo et al. 08)
- Semi-supervised convex dependency parsing (Wang et al. 08)

Use Extra Information Source – Bilingual Data

- Bilingually-constrained monolingual shift-reduce parsing (Huang et al. 09)
  - A novel parsing paradigm that is much simpler than bi-parsing
  - Enhance a shift-reduce dependency parser with alignment features to resolve shift-reduce conflicts

Use Extra Information Source – Linguistic Rules

- Semi-supervised Learning of Dependency Parsers using Generalized Expectation Criteria (Druck et al. 09)
  - Directly use linguistic prior knowledge as a training signal
  - Model parameters are estimated using a generalized expectation (GE) objective function that penalizes the mismatch between model predictions and linguistic expectation constraints.

Better Parsing Strategies

- Non-projective shift-reduce parsing (Nivre, 09)
  - Expected linear time
- Easy-First Non-Directional Dependency Parsing (Goldberg and Elhadad, 10)
  - Inspired by Shen et al. 07
  - Use an easy-first order instead, *O(nlogn)* complexity
  - Allows using more context at each decision
- Dynamic programming for incremental parsing (Huang & Sagae, 10)
  - Linear time

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Thanks!