TAG, Dynamic Programming, and the Perceptron for Efficent, Feature-Rich Parsing

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Discriminative Models for Parsing

Structured Prediction methods like CRF or Perceptron train linear models defined on factored representations of structures:

$$\text{Parse}(\mathbf{x}) = \underset{y \in \mathcal{Y}(\mathbf{x})}{\text{argmax}} \sum_{r \in y} \mathbf{f}(\mathbf{x}, r) \cdot \mathbf{w}$$

Main Advantage:

- Flexibility of feature definitions in $\mathbf{f}(\mathbf{x}, r)$

Critical Difficulty:

- Training algorithms repeatedly parse the training sentences. Efficient parsing algorithms are crucial.

A Feature-rich Consituent Parsing Model

We present a TAG-style model to recover constituent trees.

It defines feature vectors looking at:

- CFG-based structure
- Dependency relations between lexical heads
- Second-order dependency relations
  with sibling and grandparent dependencies

These can be combined with surface features of the sentence.

Efficient Coarse-to-fine Inference

We use a coarse-to-fine parsing strategy on dependency graphs:

- We use general versions of the Eisner algorithm to parse with the full TAG parser
- Simple first-order dependency models restrict the space of the full model, making parsing feasible

We train a parser with discriminative methods at full-scale.

TAG + Dynamic Programming + Perceptron

We use the Averaged Perceptron to train the parameters of our TAG model:

- $\mathbf{w} = 0$, $\mathbf{w}_a = 0$
- For $t = 1 \ldots T$
  - For each training example $(\mathbf{x}, y)$
    1. $z = \text{Parse}(\mathbf{x}; \mathbf{w})$
    2. if $y \neq z$ then
       $$\mathbf{w} = \mathbf{w} + \mathbf{f}(\mathbf{x}, y) - \mathbf{f}(\mathbf{x}, z)$$
    3. $\mathbf{w}_a = \mathbf{w}_a + \mathbf{w}$
- return $\mathbf{w}_a$

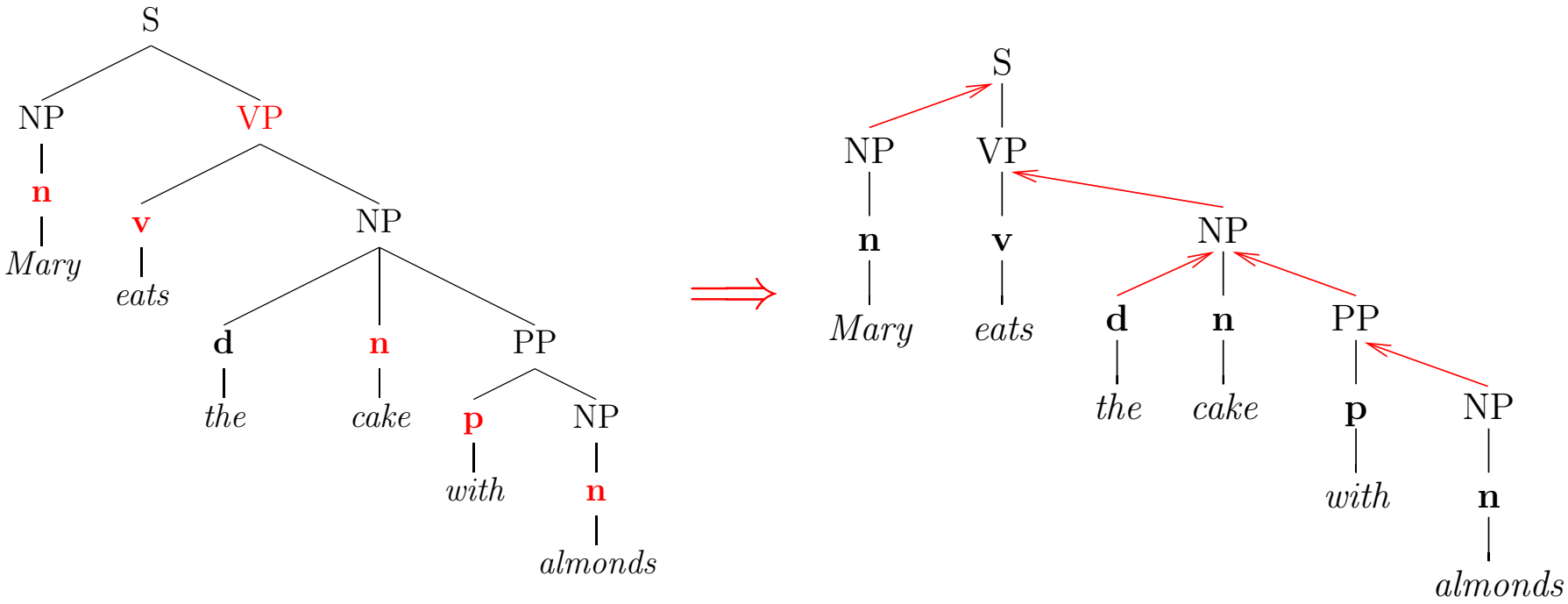
We obtain state-of-the-art results for English.

Outline

Tree-Adjoining Grammar (TAG)

- In TAG formalisms [Joshi et al. 1975]:
  - The basic elements are trees
  - Trees can be combined to form bigger trees
- There are many variations of TAG
- Here we present a simple TAG-style grammar:
  - Allows rich features
  - Allows efficient inference

Decomposing trees into spines and adjunctions

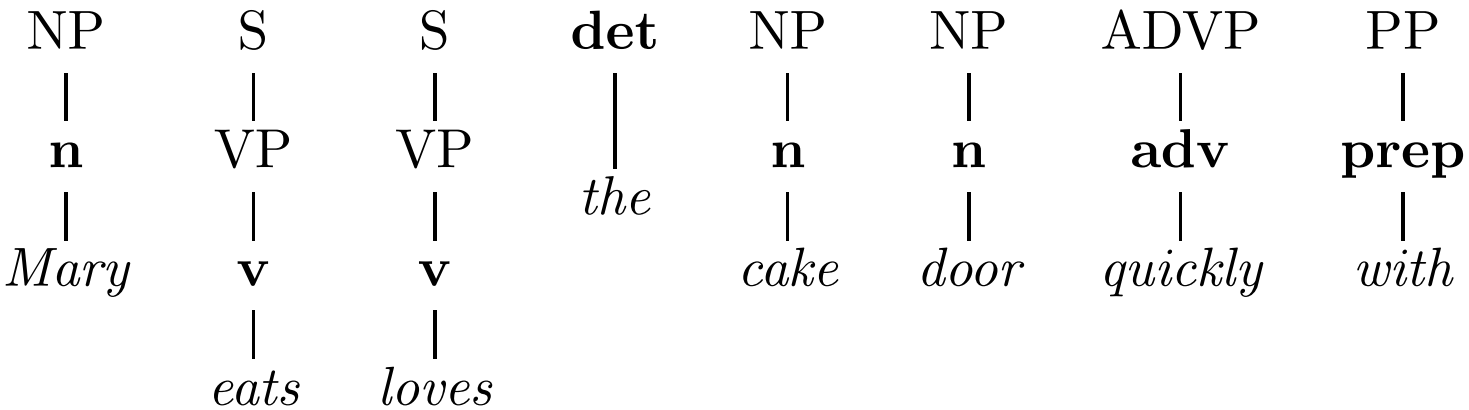


Syntactic constituents sit on top of their lexical heads.
The underlying structure looks like a dependency structure.

Spines

Spines are lexical units with a chain of unary projections.

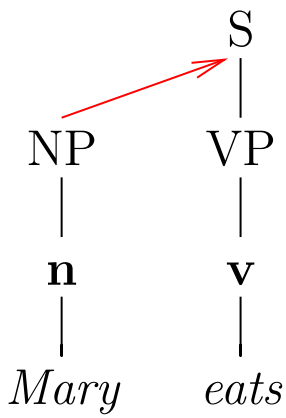
They are the elementary trees in our TAG.
(see also [Shen & Joshi 2005])



We build a dictionary of spines appearing in the WSJ.

Sister Adjunctions

Sister adjunctions are used to combine spines to form trees.



An adjunction operation attaches:

- A modifier spine
- To some position of a head spine

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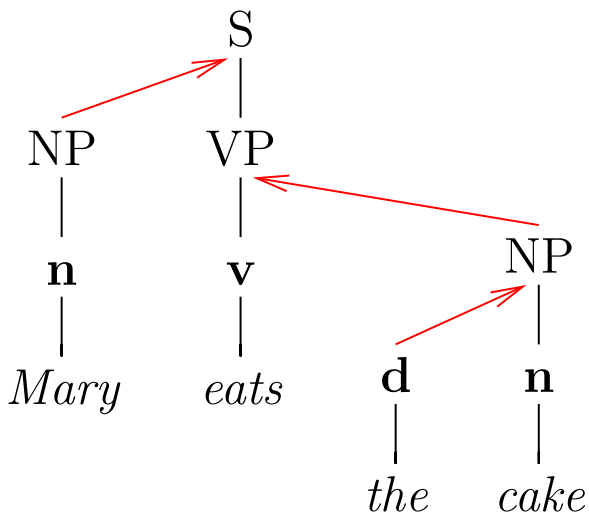

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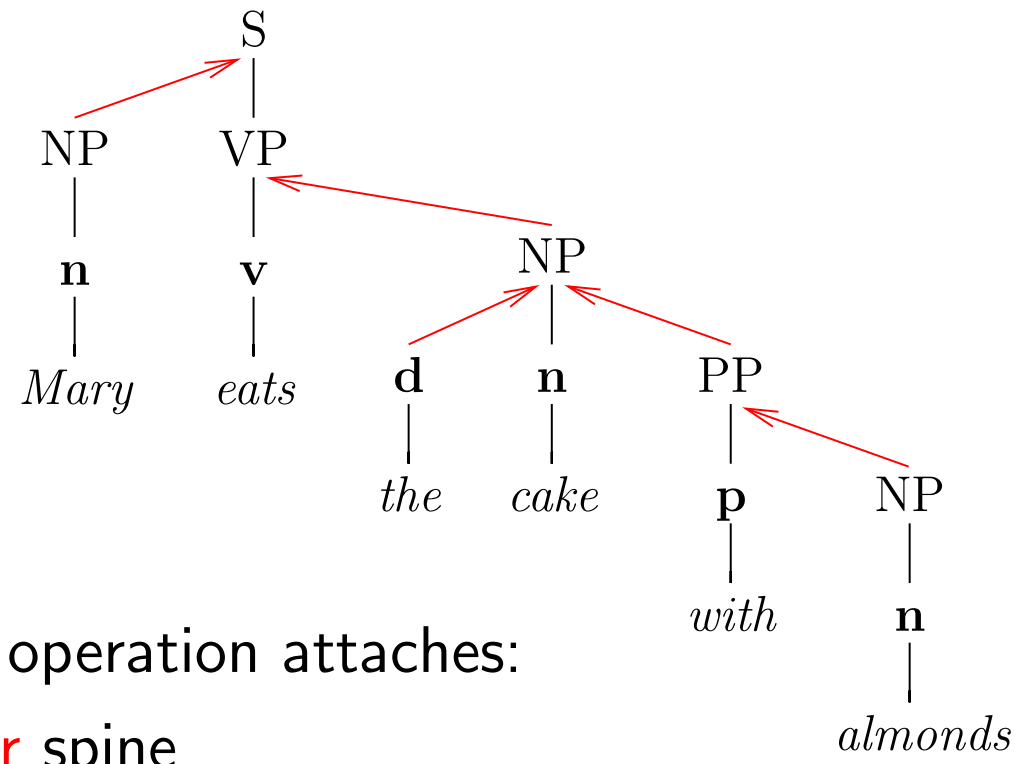

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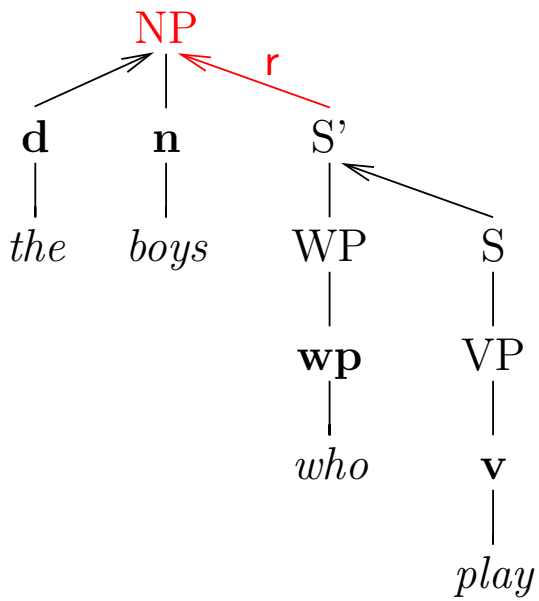
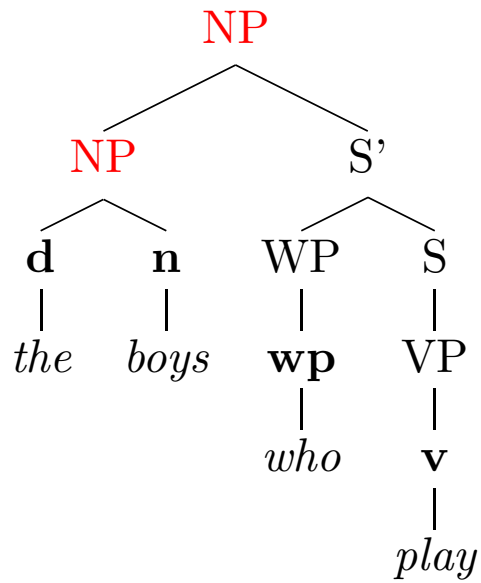
Regular Adjunctions

We also consider a regular adjunction operation.

It adds one level to the syntactic constituent it attaches to.



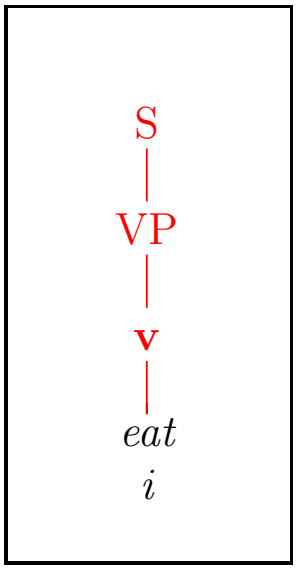


N.B.: This operation is simpler than adjunctions in classic TAG, resulting in more efficient parsing costs.

Derivations in our TAG

A tree is a set with two types of elements:

spines

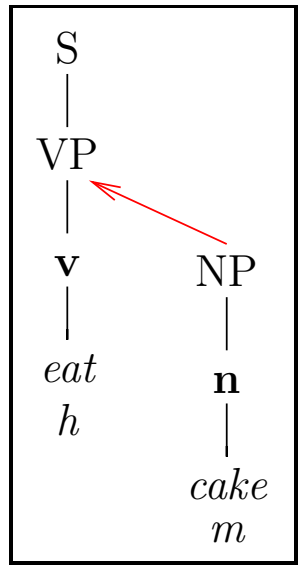


$\langle i, \sigma \rangle$

i : word position

σ : a spine

adjunctions



$\langle h, m, \sigma_h, \sigma_m, \texttt{POS}, \texttt{A} \rangle$

h m : head and modifier positions

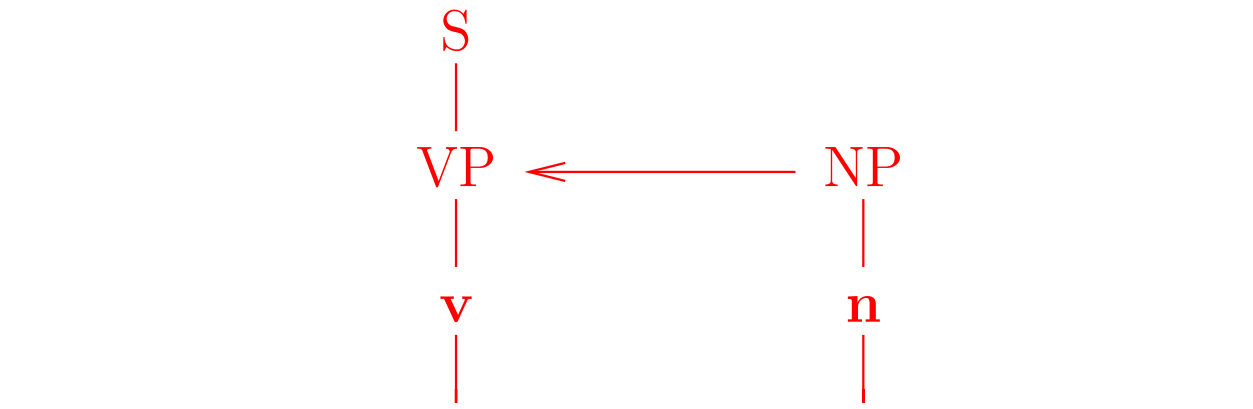
σ_h σ_m : spines of h and m

POS : the attachment position

A : sister or regular

A TAG-style Linear Model

$\mathbf{f_a}(\mathbf{x}, \langle h, m, \sigma_h, \sigma_m, \texttt{POS}, \texttt{A} \rangle)$



$$\text{Parser}(\mathbf{x}) = \text{argmax}_{y \in \mathcal{Y}(\mathbf{x})} \sum_{\langle i,\sigma \rangle \in S(y)} \mathbf{f_s}(\mathbf{x}, \langle i, \sigma \rangle) \cdot \mathbf{w} + \sum_{\langle h,m,\ldots \rangle \in A(y)} \mathbf{f_a}(\mathbf{x}, \langle h, m, \ldots \rangle) \cdot \mathbf{w}$$

Outline

Parsing with the Eisner Algorithms

- Our TAG structures are a general form of dependency graph:
  - Dependencies are adjunctions between spines
  - Labels include the type and position of the adjunction

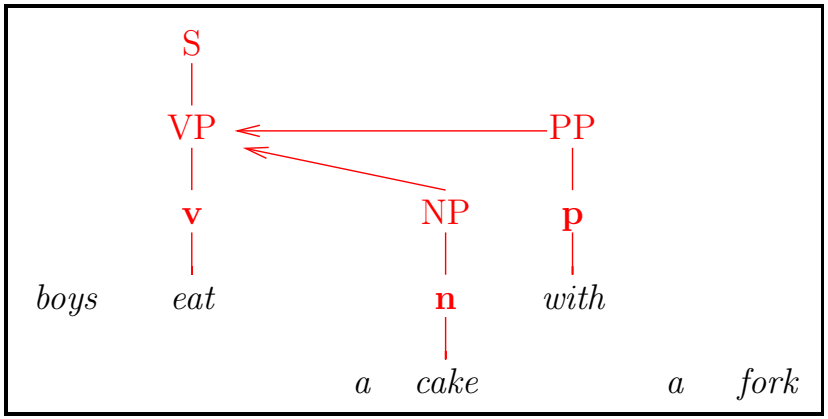
- Parsing can be done with the Eisner [1996,2000] algorithms
  - Applies to splittable dependency representations
    i.e., left and right modifiers are adjoined independently
  - Words in the dependency graph can have senses,
    like our spines
  - Parsing time is $O(n^3 G)$

- Can be extended to include second-order features.

Second-Order Features in our TAG

We incorporate recent extensions to the Eisner algorithm:

siblings

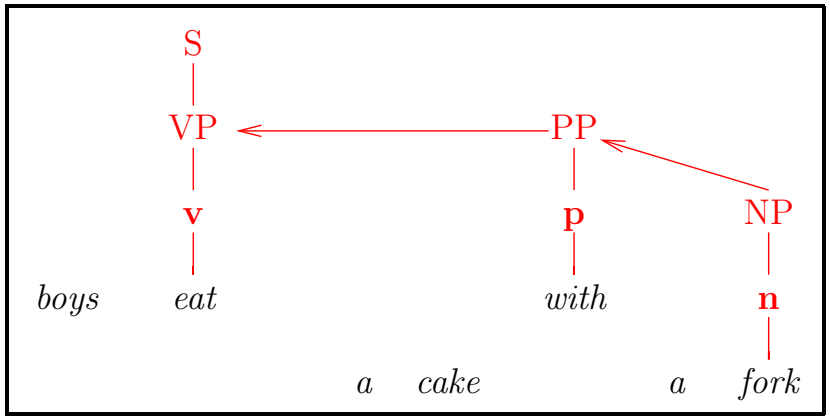


$O(n^3G)$

[Eisner 2000]

[McDonald & Pereira, 2006]

grandchildren



$O(n^4G)$

[Carreras, 2007]

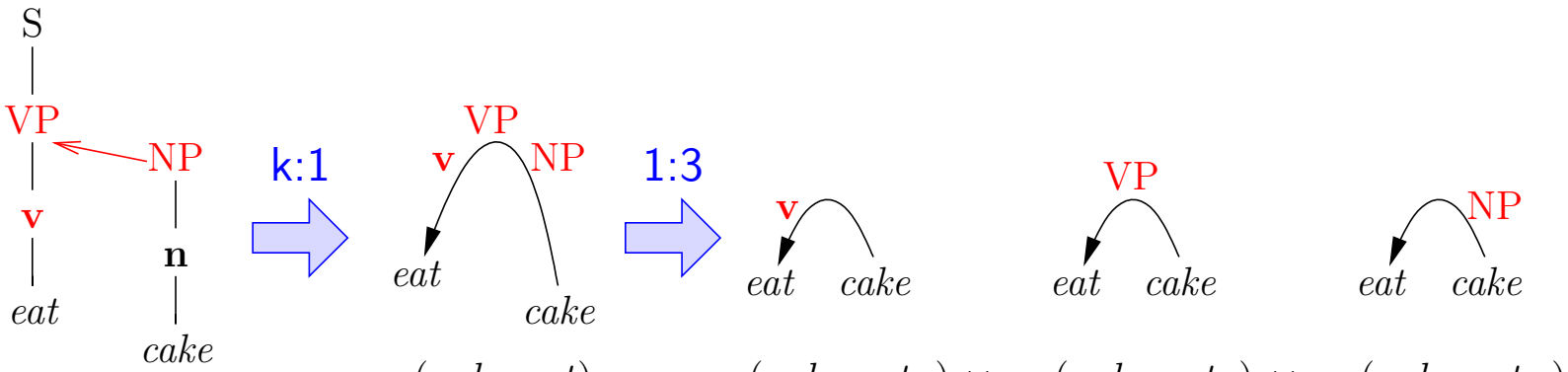
Exact Inference is Too Expensive

- Parsing time is at least $O(n^3 G)$.
  (it is $O(n^4 G)$ in our final model)

- The constant G is polynomial in the number of possible spines for any word, and the maximum height of any spine.
  This is prohibitive for real parsing tasks ($G > 5000$).

- *Solution:* Coarse-to-fine inference
  (e.g. [Charniak 97] [Charniak & Johnson 05] [Petrov & Klein 07])
  - Use simple dependency parsing models to restrict the space of possible structures of the full model.

A Coarse-to-fine Strategy for Fast Parsing



- First-order dependency models estimate conditional distributions of simple dependencies
- We build a beam of most likely dependencies:
  - Inside-Outside inference, in $O(n^3 H)$ with $H \sim 50$
  - We can discard 99.6 of dependencies and retain 98.5 of correct constituents
- The full model is constrained to the pruned space both at training and testing

A TAG-style Linear Model: Summary

A simple TAG-style model, based in spines and adjunctions:

- It allows a wide variety of features
- It's splittable, allowing efficient inference
  - $O(n^3G)$ for CFG-style, head-modifier and sibling features
  - $O(n^4G)$ for grandchildren dependency features
- The backbone dependency graph can be pruned with simple first-order dependency models

Other TAG formalisms have more expensive parsing algorithms [Chiang 2003] [Shen & Joshi 2005].

Outline

Parsing the WSJ Treebank

- Extraction of our TAG derivations from WSJ trees
  - Straighforward process using the head rules of [Collins 1999]
  - $\sim$300 spines, $\sim$20 spines/token
- Learning:
  - Train first-order models using EG [Collins et al. 2008]
    5 training passes, 5 hours per pass
  - Train TAG-style full model using Avg. Perceptron
    10 training passes, 12 hours per pass
- Parse test data and evaluate

Test results on WSJ data

Full Parsers	precision	recall	F_1
Charniak 2000	89.5	89.6	89.6
Petrov & Klein 2007	90.2	89.9	90.1
this work	**91.4**	**90.7**	**91.1**

Rerankers	precision	recall	F_1
Collins 2000	89.9	89.6	89.8
Charniak & Johnson 2005	·	·	91.4
Huang 2008	·	·	91.7

Evaluating Dependencies

- We look at the accuracy of recovering unlabeled dependencies
- We compare to state-of-the-art dependency parsing models using the same features and learner :

training structures	dependency accuracy
unlabeled dependencies (*)	92.0
labeled dependencies (*)	92.5
adjoined spines	**93.5**

(*) results from [Koo et al., ACL 2008]

constituent structure greatly helps parsing performance

Summary

A new efficient and expressive discriminative model for full consituent parsing:

- Represents phrase structure with a TAG-style grammar
- Has rich features combining phrase structure and lexical heads due to our spines being basic elements
- Parsing is efficient with the Eisner methods due to the splittable nature of our adjunctions

A very effective method to prune dependency-based graphs:

key to discriminative training at full scale

Thanks!