TAG, Dynamic Programming, and the Perceptron for Efficient, 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:

\[
\text{Parse}(x) = \arg\max_{y \in \mathcal{Y}(x)} \sum_{r \in y} f(x, r) \cdot w
\]

Main Advantage:
- Flexibility of feature definitions in \( f(x, r) \)

Critical Difficulty:
- Training algorithms repeatedly parse the training sentences. Efficient parsing algorithms are crucial.
A Feature-rich Constituent 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.
We use the Averaged Perceptron to train the parameters of our TAG model:

\[
\begin{align*}
\text{w} &= 0, \text{w}_a = 0 \\
\text{For } t = 1 \ldots T \\
\quad \text{For each training example } (x, y) \\
\quad &1. \ z = \text{Parse}(x; \text{w}) \\
\quad &2. \ \text{if } y \neq z \text{ then} \\
\quad &\quad \text{w} = \text{w} + f(x, y) - f(x, z) \\
\quad &3. \ \text{w}_a = \text{w}_a + \text{w} \\
\end{align*}
\]

return \text{w}_a

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

A TAG-style Linear Model for Constituent Parsing
   Representation: Spines and Adjuncions
   Model and Features

Fast Inference with our TAG

Parsing the WSJ Treebank
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 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
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**
Sister adjunctions are used to combine spines to form trees.

An adjunction operation attaches:
- A *modifier* spine
- To some *position* of a *head* spine
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**

- $S$
- $VP$
- $v$
  - $eat$
  - $i$

$\langle i, \sigma \rangle$

- $i$: word position
- $\sigma$: a spine

**adjunctions**

- $S$
  - $VP$
    - $v$
      - $eat$
      - $h$
    - $m$
      - $cake$

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

- $h$ $m$: head and modifier positions
- $\sigma_h$ $\sigma_m$: spines of $h$ and $m$
- $\text{POS}$: the attachment position
- $A$: sister or regular
A TAG-style Linear Model

\[ f_a(x, \langle h, m, \sigma_h, \sigma_m, \text{POS}, A \rangle) \]

[Diagram of parse tree: S -> VP <- NP, with words the boys eat a cake with a]

\[ \text{Parser}(x) = \arg\max_{y \in \gamma(x)} \sum_{\langle i, \sigma \rangle \in S(y)} f_s(x, \langle i, \sigma \rangle) \cdot w + \sum_{\langle h, m, \ldots \rangle \in A(y)} f_a(x, \langle h, m, \ldots \rangle) \cdot w \]
Outline

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Parsing the WSJ Treebank
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 $O(n^3G)$

- 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 $O(n^3G)$. (it is $O(n^4G)$ 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

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  Representation: Spines and Adjunctions
  Model and Features

Fast Inference with our TAG

Parsing the WSJ Treebank
Parsing the WSJ Treebank

- Extraction of our TAG derivations from WSJ trees
  - Straightforward process using the head rules of [Collins 1999]
  - ~300 spines, ~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

<table>
<thead>
<tr>
<th><strong>Full Parsers</strong></th>
<th>precision</th>
<th>recall</th>
<th>F₁</th>
</tr>
</thead>
<tbody>
<tr>
<td>Charniak 2000</td>
<td>89.5</td>
<td>89.6</td>
<td>89.6</td>
</tr>
<tr>
<td>Petrov &amp; Klein 2007</td>
<td>90.2</td>
<td>89.9</td>
<td>90.1</td>
</tr>
<tr>
<td><strong>this work</strong></td>
<td><strong>91.4</strong></td>
<td><strong>90.7</strong></td>
<td><strong>91.1</strong></td>
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<tr>
<td>Collins 2000</td>
<td>89.9</td>
<td>89.6</td>
<td>89.8</td>
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<tr>
<td>Charniak &amp; Johnson 2005</td>
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<td>.</td>
<td>91.4</td>
</tr>
<tr>
<td>Huang 2008</td>
<td>.</td>
<td>.</td>
<td>91.7</td>
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</table>
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:

<table>
<thead>
<tr>
<th>Training Structures</th>
<th>Dependency Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>unlabeled dependencies (*)</td>
<td>92.0</td>
</tr>
<tr>
<td>labeled dependencies (*)</td>
<td>92.5</td>
</tr>
<tr>
<td><strong>adjoined spines</strong></td>
<td><strong>93.5</strong></td>
</tr>
</tbody>
</table>

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

constituent structure greatly helps parsing performance
Summary

A new efficient and expressive discriminative model for full constituent 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!