Using Left-corner Parsing to Encode Universal Structural Constraints in Grammar Induction

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Grammar induction is difficult

- Task: finding syntactic patterns without treebanks (supervision)

- We need a good *prior, or constraints*, to the grammars
  - Such constraints should be *universal* (language independent)

- Central question in this work:
  - Which constraint should we impose for better grammar induction across languages?
Previous work

- Many works incorporated *shorter dependency length* bias
  - Many dependency arcs are *short*

There are rumors about preparation by slum dwellers …

- Popular way is via initialization of EM (Klein and Manning, 2004)
  - used in most later approaches (Cohen and Smith (2009); Blunsom and Cohn (2010); Berg-kirkpatric et al. (2010); etc)
- Other work directly *parameterizes* length component
  e.g., Smith and Eisner (2005); Mareček and Žabokrtský (2012)
This work

- We explore the utility of *center-embedding avoidance* in languages.

- Languages tend to avoid nested, or center-embedded structures:
  - because it is difficult to comprehend for humans.

  ex:
  
  *The reporter who the senator who Mary met attacked ignored the president*  

- Intuition to our approach:
  - Our model tries to learn grammars with less center-embedding.
  - This is possible by formulating models on *left-corner parsing*.
Contributions

› Learning method to avoid deeper center-embedding
  • We detect center-embedded derivations in a chart efficiently using left-corner parsing

› Application to dependency grammar induction
  • We focus on dependency grammar induction since it is the most widely studied task

› Experiments on many languages in Universal Dependencies
  • We find that our approach shows different tendencies than the dependency length-based constraints
  • We give an analysis of this difference to characterize our approach
Approach and Model
Approach overview

› We assume a base generative model for dependency trees

\[ p_{\text{base}}( \text{a dog barks} ) = 0.023 \]

› We constraint the model by multiplying a penalty factor \( f \)

\[ p(t) = p_{\text{base}}(t) \times f(t) \]

› One such \( f \) that penalizes center-embedding is:

\[ f(t) = \begin{cases} 
0 & \text{if } t \text{ contains degree } \geq 2 \text{ center-embedding} \\
1 & \text{else} 
\end{cases} \]

› Smith and Eisner (2005) is the same approach with different \( f \)

› We only add a constraint during learning (EM)

• **Challenge:** how to efficiently compute \( f \) during EM in a chart?
Key tool: left-corner parsing

- There are several variants in left-corner parsing
  - We use one particular method by Schuler et al. (2010)

- A parsing algorithm on a stack
  - The stack size grows only when processing center-embedding
  - Stack depth = (degree of center-embedding) + 1

A degree-2 embedded tree

Following configuration occurs for this tree
EM on left-corner parsing

- Idea: we *keep the current stack depth* of left-corner parsing in each chart item in inside-outside.

- When we prohibit degree $\geq 2$ center-embedding, the above rule is eliminated.
Applying to dependency grammar induction

- The technique is quite general, and can be applied to any models on PCFG

- We apply the technique into DMV (Klein and Manning, 2004)
  - The most popular generative model for grammar induction
  - Since DMV can be formulated as a PCFG, we can apply the idea

- The time complexity of the naive implementation is $O(n^6)$ due to the need to remember additional index
  - We can improve it to $O(n^4)$ using head-splitting
Span-based constraints

- Motivation: many occurrences of center-embedding are due to embeddings of small chunks, not clauses

Example

... prepared the cat's dinner

- We will try the following constraints in experiments

\[ f(t) = \begin{cases} 
0 & \text{if } t \text{ contains embedded chunk of length } > \delta \\
1 & \text{else}
\end{cases} \]

- This can be done by changing (relaxing) the condition of increasing stack depth
Experiments
Universal Dependencies (UD)

- We use UD in our experiments (v. 1.2)

- Characteristics:
  - all languages are annotated with the **content-head** style

- Some settings:
  - 25 languages in total (remove small treebanks)
  - The inputs are universal POS tags
  - Training sentence length $\leq 15$
  - Test sentence length $\leq 40$

In principle, function words never have a child in a tree

Ivan is the best dancer
Evaluation is difficult in grammar induction

Issue on previous grammar induction research:
- The annotation styles of the gold treebank differ across languages (e.g., auxiliary head vs. main verb head)
- This obscures the contribution of a constraint in each language

Our evaluation setting to mitigate this issue:
- We use UD to best guarantee the consistencies across languages
- All models take the following additional constraint

\[ f(t) = \begin{cases} 
0 & \text{if a function word has a child on } t \\
1 & \text{else} 
\end{cases} \]

- This guarantees that all outputs will follow the UD-style annotation
Models (constraints)

- All models are formulated as $p_{DMV}(t) \times f(t)$

- Only differences between models are $f$ (at training)
  - **FUNC**: Baseline (function word constraint only)
  - **DEPTH**: In addition to **FUNC**, set the maximum stack depth
  - **ARCLen**: Equivalent to Smith and Eisner (2005), a soft bias to favor shorter dependency arcs

- We initialize all models uniformly
  - We found harmonic initialization does not work well
UD summary

For **DEPTH**, which maximum stack depth should we use?

- We use (UD-style) English WSJ as a development set
- NOTE: English data in UD is not WSJ, but Web treebank
- The best setting is *allowing embedded chunks of length ≤ 3*

Average scores across 25 languages (UAS)

![Score Chart]

**DEPTH** improves scores but is slightly less effective than **ArcLen**
Analysis on English

- Average scores are similar, but is there any characteristics in each constraint?
- We found an interesting difference in English data (Web)

**DEPTH**: good at detecting *constituent boundaries*

**ARCLEN**: good at detecting *VERB → NOUNs*, but bad at constituents
Hypothesis: \textsc{Depth} is better at finding \textit{correct constituent boundaries} in language than \textsc{ArcLen}

\begin{itemize}
  \item \ldots possibly because avoiding center-embedding is essentially a constraint to constituents (?)
\end{itemize}

Quantitative study:

\begin{itemize}
  \item We extract \textit{unlabelled} brackets from gold and output trees and calculate F1 score
\end{itemize}

English:

\begin{itemize}
  \item \textsc{Func}: 14.1
  \item \textsc{Depth}: 27.9
  \item \textsc{ArcLen}: 25.5
\end{itemize}

Average:

\begin{itemize}
  \item \textsc{Func}: 25.6
  \item \textsc{Depth}: 30.5
  \item \textsc{ArcLen}: 27.9
Adding constraints to the sentence root

- Results so far suggest **DEPTH** itself cannot resolve some core dependency arcs, e.g., VERB→NOUN

- Recent state-of-the-art systems rely on additional constraints, e.g., on root candidates (Bisk and Hockenmaier, 2013; Naseem et al, 2010)

- We follow this, and add the following constraint in all models
  - The sentence root must be a VERB or a NOUN
Results with the root constraint

Average UAS

<table>
<thead>
<tr>
<th></th>
<th>FUNC</th>
<th>DEPTH</th>
<th>ARCLEN</th>
<th>Naseem et al. (2010)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average UAS</td>
<td>45.9</td>
<td>50.1</td>
<td>48.2</td>
<td>50.2</td>
</tr>
</tbody>
</table>

- **DEPTH** works the best when the root constraint is added.
- Competitive with Naseem et al. (2010), which utilizes much richer prior linguistic knowledge on POS tags.
Conclusion

- Main result: avoiding center-embedding is a good constraint in grammar induction
  - In particular, it helps to find linguistically correct constituent structures, probably because it is the constraint on constituents

- Future work:
  - Grammar induction beyond dependency grammars
  - including traditional constituent structure induction, which has been failed due to the lack of good syntactic cues
  - Weakly-supervised grammar induction, e.g., Garrette et al. (2015)

Thank you!