Blocked Inference in Bayesian Tree Substitution Grammars

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Overview

• Builds on work of Cohn, Goldwater, & Blunsom (2009)
  • Infinite Bayesian model for learning a tree substitution grammar from parsed corpus.
  • There: used a Gibbs sampler for inference.
    • Samples a single variable at a time.
    • Simple, but slow to converge.
  • Here: develop a blocked Metropolis-Hastings sampler.
    • Samples groups of variables at a time.
    • Technical challenges, but faster convergence and better F1.

• General point: in models with strong dependencies between variables (e.g. structured models), need to sample groups of variables together.
Task: supervised TSG parsing

Training input:

Inferred TSG:
Task: supervised TSG parsing

Training input:

Inferred TSG:

Elementary trees
Task: supervised TSG parsing

Training input:

```
S
  NP
  | George
VP
  V
  | hates
  NP
  | broccoli
```

Inferred TSG:

```
S
  NP
  | George
VP
  V
  | hates
  NP
  | broccoli
```

Substitution site
Model: probabilistic TSG

- Weighted grammar; productions are elementary trees.
- Infinite model uses Dirichlet process prior over productions for each non-terminal $c$.
  - For elementary trees $e_1...e_n$:

\[
P(e_i \mid e_1...e_{i-1}, c, \alpha_c, P_0) \propto n_{e_i,c} + \alpha_c P_0(e_i \mid c)
\]

(Cohn, Goldwater, & Blunsom, NAACL ’09; also Post & Gildea ’09, O’Donnell, Goodman, & Tenenbaum ’09)
Model: probabilistic TSG

- Weighted grammar; productions are elementary trees.
- Infinite model uses Dirichlet process prior over productions for each non-terminal $c$.
  - For elementary trees $e_1...e_n$:
    \[
P(e_i | e_1...e_{i-1}, c, \alpha_c, P_0) \propto n_{e_i,c} + \alpha_c P_0(e_i | c)
    \]
    previous # of $e_i$ rooted at $c$

Prob. of elem. tree roughly proportional to # of previous occurrences.
Model: probabilistic TSG

- Weighted grammar; productions are elementary trees.
- Infinite model uses Dirichlet process prior over productions for each non-terminal $c$.
  - For elementary trees $e_1...e_n$:
    
    $$ P(e_i \mid e_1...e_{i-1}, c, \alpha_c, P_0) \propto n_{e_i,c} + \alpha_c P_0(e_i \mid c) $$

base distribution over all possible elem. trees

But all elem. trees have non-zero prob. ($P_0$ uses PCFG rules to generate elem. trees)
Inference

• Segment treebank into high probability $e_1 ... e_n$:
  • Which nodes are substitution sites?
Inference

• Use Markov Chain Monte Carlo.
  • Sample a few hidden variables (nodes) at a time, conditioned on values of all others.
  • Iterate to convergence: Samples from posterior $P(e_1...e_n|d)$. 
Inference

- Use Markov Chain Monte Carlo.
  - Sample a few hidden variables (nodes) at a time, conditioned on values of all others.
  - Iterate to convergence: Samples from posterior $P(e_1...e_n|d)$.
- Easy method: Gibbs sampler.
- But: poor mixing!
Inference

• Use Markov Chain Monte Carlo.
  • Sample a few hidden variables (nodes) at a time, conditioned on values of all others.
  • Iterate to convergence: Samples from posterior $P(e_1...e_n|d)$.
• Better method: blocked sampler.

• But: tricky to compute!
Problems with blocked sampling

- Exponentially many segmentations of each tree.

- Dynamic programming is possible using Metropolis-Hastings sampler (Johnson et al., 2007).
  - ...But only for finite PCFG.

![Diagram of a parse tree with labeled nodes: S, NP, VP, V, NP, George, hates, broccoli.]
MH for Bayesian TSG

• TSG model is infinite; how to apply dynamic programming?

\[ P(e_i \mid e_1...e_{i-1}, c, \alpha_c, P_0) \propto n_{e_i,c} + \alpha_c P_0(e_i \mid c) \]

Non-zero prob. for any tree generated by PCFG rules.

• Key insight: Infinite grammar can be represented as a finite PCFG!
Grammar transform

- Convert infinite TSG to finite PCFG:
  - Sub-grammar A contains PCFG productions for all elem. trees with count > 0.
  - Sub-grammar B is a PCFG representing $P_0$.
  - Rule with prob. proportional to $\alpha_c$ connects the two sub-grammars.

\[
P(e_i | e_1...e_{i-1}, c, \alpha_c, P_0) \propto n_{e_i,c} + \alpha_c P_0(e_i | c)
\]
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$$P(e_i \mid e_1 \ldots e_{i-1}, c, \alpha_c, P_0) \propto n_{e_i,c} + \alpha_c P_0(e_i \mid c)$$
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• Now can use MH for Bayesian PCFG.

• Bonus: can use for unsupervised training.
Faster convergence

(Penn WSJ, Sec. 2)
Higher parsing accuracy

- Improved F-score on small and large training sets:

<table>
<thead>
<tr>
<th>Training set</th>
<th>'09 best</th>
<th>New best</th>
</tr>
</thead>
<tbody>
<tr>
<td>WSJ sec. 2</td>
<td>77.6</td>
<td>78.4</td>
</tr>
<tr>
<td>WSJ sec. 2-21</td>
<td>84.0</td>
<td>85.3</td>
</tr>
</tbody>
</table>
Conclusions

- Local Gibbs sampling mixes poorly for structured prediction models; better to use blocked sampling.
- Grammar transform represents infinite TSG as finite PCFG, making blocked sampling possible.
- Blocked sampler: faster training and better parsing.
- See poster or paper for more details/results.

- Future extensions:
  - Use Pitman-Yor process instead of Dirichlet process.
  - Unsupervised dependency grammar TSG induction.