CS388: Natural Language Processing

Lecture 13:
Dependency II

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Recall: Dependencies

- Dependency syntax: syntactic structure is defined by dependencies
- Head (parent, governor) connected to dependent (child, modifier)
- Each word has exactly one parent except for the ROOT symbol
- Dependencies must form a directed acyclic graph
Recall: Projectivity

- Projective $\leftrightarrow$ no “crossing” arcs

- Crossing arcs:

  - dogs in houses and cats
  - the dog ran to the house

credit: Language Log
Recall: Eisner’s Algorithm

- Left and right children are built independently, heads are edges of spans
- **Complete item**: all children are attached, head is at the “tall end”
- **Incomplete item**: arc from “tall end” to “short end”, may still expect children
Recall: Biaffine Neural Parsing

- Neural CRFs for dependency parsing: let $c = \text{LSTM embedding of } i$, $p = \text{LSTM embedding of parent}(i)$. $score(i, \text{parent}(i), x) = p^T U c$

- $score(\text{tree}) = \text{sum of edge scores}$

LSTM looks at words and POS

Dozat and Manning (2017)
Evaluating Dependency Parsing

- UAS: unlabeled attachment score. Accuracy of choosing each word’s parent \((n \text{ decisions per sentence})\)

- LAS: additionally consider label for each edge

- Log-linear CRF parser, decoding with Eisner algorithm: 91 UAS

- Higher-order features from Koo parser: 93 UAS

- Best English results with neural CRFs (Dozat and Manning): 95-96 UAS
Head-driven phrase structure grammar (HPSG): very complex grammar formalism which annotates large feature structures over tree.

Very little work on HPSG in NLP since no real treebank exists.

Joint model of constituency and dependency combining ideas from Dozat + Manning and Stern et al.

Zhou and Zhao (2019)
Slightly stronger results than Dozat + Manning, significantly better results on Chinese
This Lecture

- Transition-based (shift-reduce) dependency parsing
  - Approximate, greedy inference — fast, but a little bit weird!
Shift-Reduce Parsing
Shift-Reduce Parsing

- Similar to deterministic parsers for compilers
  - Also called transition-based parsing
- A tree is built from a sequence of incremental decisions moving left to right through the sentence
- Stack containing partially-built tree, buffer containing rest of sentence
- Shifts consume the buffer, reduces build a tree on the stack
Shift-Reduce Parsing

I ate some spaghetti bolognese

- Initial state: **Stack**: [ROOT]  **Buffer**: [I ate some spaghetti bolognese]
- Shift: top of buffer -> top of stack
  - Shift 1: **Stack**: [ROOT I]  **Buffer**: [ate some spaghetti bolognese]
  - Shift 2: **Stack**: [ROOT I ate]  **Buffer**: [some spaghetti bolognese]
Shift-Reduce Parsing

Let $\sigma$ denote the stack, $\sigma|_w=w_{-1}$ = stack ending in $w_{-1}$

"Pop two elements, add an arc, put them back on the stack"

State: Stack: [ROOT I ate] Buffer: [some spaghetti bolognese]

I ate some spaghetti bolognese

State: Stack: [ROOT ate] Buffer: [some spaghetti bolognese]
Arc-Standard Parsing

ROOT

I ate some spaghetti bolognese

Start: stack contains [ROOT], buffer contains [I ate some spaghetti bolognese]

Arc-standard system: three operations

- Shift: top of buffer -> top of stack
- Left-Arc: $\sigma|w_{-2}, w_{-1}$ $\rightarrow$ $\sigma|w_{-1}$, $w_{-2}$ is now a child of $w_{-1}$
- Right-Arc $\sigma|w_{-2}, w_{-1}$ $\rightarrow$ $\sigma|w_{-2}$, $w_{-1}$ is now a child of $w_{-2}$

End: stack contains [ROOT], buffer is empty []

How many transitions do we need if we have n words in a sentence?
Arc-Standard Parsing

ROOT

I ate some spaghetti bolognese

- Could do the left arc later! But no reason to wait
- Can’t attach ROOT <- ate yet even though this is a correct dependency!
Arc-Standard Parsing

I ate some spaghetti bolognese

S top of buffer -> top of stack
LA pop two, left arc between them
RA pop two, right arc between them

[ROOT ate]  [some spaghetti bolognese]
[ROOT ate some spaghetti] [bolognese]
[ROOT ate spaghetti] some [bolognese]
Arc-Standard Parsing

ROOT

I ate some spaghetti bolognese

[S top of buffer -> top of stack]

LA pop two, left arc between them

RA pop two, right arc between them

Stack consists of all words that are still waiting for right children, end with a bunch of right-arc ops

Final state:
Other Systems

- Arc-eager (Nivre, 2004): lets you add right arcs sooner and keeps items on stack, separate reduce action that clears out the stack

- Arc-swift (Qi and Manning, 2017): explicitly choose a parent from what’s on the stack

- Many ways to decompose these, which one works best depends on the language and features (nonprojective variants too!)
Building Shift-Reduce Parsers

[ROOT] [I ate some spaghetti bolognese]

- How do we make the right decision in this case?
- Only one legal move (shift)

[ROOT ate some spaghetti] [bolognese]

- How do we make the right decision in this case? (all three actions legal)
- Multi-way classification problem: shift, left-arc, or right-arc?

\[
\arg\max_{a \in \{S, LA, RA\}} w^\top f(\text{stack, buffer, } a)
\]
Features for Shift-Reduce Parsing

[ROOT ate some spaghetti]    [bolognese]

- Features to know this should left-arc?
- One of the harder feature design tasks!
- In this case: the stack tag sequence VBD - DT - NN is pretty informative — looks like a verb taking a direct object which has a determiner in it
- Things to look at: top words/POS of buffer, top words/POS of stack, leftmost and rightmost children of top items on the stack
Training a Greedy Model

\[
\text{argmax}_{a \in \{S, LA, RA\}} w^\top f(\text{stack, buffer, } a)
\]

- Can turn a tree into a decision sequence \(a\) by building an *oracle*
- Train a classifier to predict the right decision using these as training data
- Training data assumes you made correct decisions up to this point and teaches you to make the correct decision, but what if you screwed up...
Greedy training

- Greedy: 2n local training examples
- Non-gold states unobserved during training: consider making bad decisions but don’t condition on bad decisions
## Speed Tradeoffs

<table>
<thead>
<tr>
<th>Parser</th>
<th>Dev UAS</th>
<th>Dev LAS</th>
<th>Test UAS</th>
<th>Test LAS</th>
<th>Speed (sent/s)</th>
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<tbody>
<tr>
<td>standard</td>
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<td>88.7</td>
<td>89.7</td>
<td>88.3</td>
<td>51</td>
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<td>eager</td>
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<td>89.2</td>
<td>89.9</td>
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<td>Malt:sp</td>
<td>90.0</td>
<td>88.8</td>
<td>89.9</td>
<td>88.5</td>
<td>560</td>
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<tr>
<td>Malt:eager</td>
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<td>88.9</td>
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<td>535</td>
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<tr>
<td>MSTParser</td>
<td>92.1</td>
<td>90.8</td>
<td>92.0</td>
<td>90.5</td>
<td>12</td>
</tr>
<tr>
<td>Our parser</td>
<td><strong>92.2</strong></td>
<td><strong>91.0</strong></td>
<td><strong>92.0</strong></td>
<td><strong>90.7</strong></td>
<td><strong>1013</strong></td>
</tr>
</tbody>
</table>

- Many early-2000s constituency parsers were \(\sim5\) sentences/sec
- Using S-R used to mean taking a performance hit compared to graph-based, that’s no longer (quite as) true

Chen and Manning (2014)
Global Decoding
Global Decoding

Is it a problem that we make decisions greedily?

Correct: Right-arc, Shift, Right-arc, Right-arc
Global Decoding: A Cartoon

I gave him dinner

- Both wrong! Also both probably low scoring!

Correct, high scoring option
Global Decoding: A Cartoon

- Lookahead can help us avoid getting stuck in bad spots
- Global model: maximize sum of scores over all decisions
- Similar to how Viterbi works: we maintain uncertainty over the current state so that if another one looks more optimal going forward, we can use that one
I gave him dinner

Greedy: repeatedly execute

\[ a_{\text{best}} \leftarrow \text{argmax}_a w^\top f(s, a) \]
\[ s \leftarrow a_{\text{best}}(s) \]

Global: \[ \text{argmax}_{s, a} w^\top f(s, a) = \sum_{i=1}^{2n} w^\top f(s_i, a_i) \]
\[ s_{i+1} = a_i(s_i) \]

Can we do search exactly? How many states \( s \) are there?

No! Use beam search
Beam Search

- Maintain a beam of $k$ plausible states at the current timestep, expand each and only keep top $k$ best new ones.

- Example: POS

- Beam size of $k$, $n$ words, $s$ states, time complexity $O(nks \log(k))$
How good is beam search?

- $k=1$: greedy search

Choosing beam size:

- 2 is usually better than 1
- Usually don’t use larger than 50
- Depends on problem structure
Beam search gave us the lookahead to make the right decision.
Global Training

- If using global inference, should train the parser in a global fashion as well: use structured perceptron / structured SVM
- Model treats an entire derivation as something to featurize
- No algorithm like Viterbi for doing efficient parsing, so use beam search
State-of-the-art Transition-Based Parsers
Dependency Parsers

- 2005: Eisner algorithm graph-based parser was SOTA (~91 UAS)
- 2010: Koo’s 3rd-order parser was SOTA for graph-based (~93 UAS)
- 2012: Maltparser was SOTA was for transition-based (~90 UAS)
- 2014: Chen and Manning got 92 UAS with transition-based neural model
- 2016: Improvements to Chen and Manning
State-of-the-art Parsers

Configuration

Softmax layer:
\[ p = \text{softmax}(W_2 h) \]

Hidden layer:
\[ h = (W_1^w x^w + W_1^t x^t + W_1^l x^l + b_1)^3 \]

Input layer: \([x^w, x^t, x^l]\)

Chen and Manning (2014)
Parsey McParseFace (a.k.a. SyntaxNet)

- Close to state-of-the-art, released by Google publicly
- 94.61 UAS on the Penn Treebank using a global transition-based system with early updating (compared to 95.8 for Dozat, 93.7 for Koo in 2009)
- Additional data harvested via “tri-training”, form of self-training
- Feedforward neural nets looking at words and POS associated with words in the stack / those words’ children / words in the buffer
- Feature set pioneered by Chen and Manning (2014), Google fine-tuned it
- Shift-reduce parsers are often playing “catch-up”, hard to really push the SOTA with shift-reduce because it’s harder to design models

Andor et al. (2016)
Shift-Reduce Constituency

Can do shift-reduce for constituency as well, reduce operation builds constituents

Cross and Huang (2016)
Recap

- Shift-reduce parsing can work nearly as well as graph-based parsing
- Arc-standard system for transition-based parsing
- Purely greedy or more “global” approaches
- Next time: semantic parsing