CS388: Natural Language Processing

Lecture 17:
Syntax II: Dependency Parsing

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Administrivia

- Project 3 graded soon
Recall: Constituency

- Tree-structured syntactic analyses of sentences
- Nonterminals (NP, VP, etc.) as well as POS tags (bottom layer)
- Structured is defined by a CFG
Recall: PCFGs

<table>
<thead>
<tr>
<th>Grammar (CFG)</th>
<th>Lexicon</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ROOT → S</strong></td>
<td><strong>NN → interest</strong></td>
</tr>
<tr>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td><strong>S → NP VP</strong></td>
<td><strong>NNS → raises</strong></td>
</tr>
<tr>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td><strong>NP → DT NN</strong></td>
<td><strong>VBP → interest</strong></td>
</tr>
<tr>
<td>0.2</td>
<td>1.0</td>
</tr>
<tr>
<td><strong>NP → NN NNS</strong></td>
<td><strong>VBZ → raises</strong></td>
</tr>
<tr>
<td>0.5</td>
<td>1.0</td>
</tr>
<tr>
<td><strong>NP → NP PP</strong></td>
<td><strong>VP → VBP NP</strong></td>
</tr>
<tr>
<td>0.3</td>
<td>0.7</td>
</tr>
<tr>
<td><strong>VP → VBP NP PP</strong></td>
<td><strong>NP → PP</strong></td>
</tr>
<tr>
<td>0.3</td>
<td>1.0</td>
</tr>
<tr>
<td><strong>PP → IN NP</strong></td>
<td><strong>NP → IN NP</strong></td>
</tr>
<tr>
<td>1.0</td>
<td>1.0</td>
</tr>
</tbody>
</table>

- Context-free grammar: symbols which rewrite as one or more symbols
- Lexicon consists of “preterminals” (POS tags) rewriting as terminals (words)
- CFG is a tuple (N, T, S, R): N = nonterminals, T = terminals, S = start symbol (generally a special ROOT symbol), R = rules
- PCFG: probabilities associated with rewrites, normalize by source symbol
Recall: CKY

- Find \( \text{argmax} \, P(T|x) = \text{argmax} \, P(T, x) \)

- Dynamic programming: chart maintains the best way of building symbol \( X \) over span \((i, j)\)

- Loop over all split points \( k \), apply rules \( X \rightarrow Y \, Z \) to build \( X \) in every possible way

Cocke-Kasami-Younger
Outline

‣ Dependency representation, contrast with constituency

‣ Graph-based dependency parsers

‣ Transition-based (shift-reduce) dependency parsers

‣ State-of-the-art parsers
Dependency Representation
Dependency Parsing

- Dependency syntax: syntactic structure is defined by these arcs
- 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

- POS tags same as before, usually run a tagger first as preprocessing
Still a notion of hierarchy! Subtrees often align with constituents
Constituency: several rule productions need to change
Dependency vs. Constituency: PP Attachment

- Dependency: one word (with) assigned a different parent

  the children ate the cake with a spoon

- More predicate-argument focused view of syntax

- “What’s the main verb of the sentence? What is its subject and object?” — easier to answer under dependency parsing
Dependency vs. Constituency: Coordination

- Constituency: ternary rule NP -> NP CC NP
Dependency vs. Constituency: Coordination

- Dependency: first item is the head

- Coordination is decomposed across a few arcs as opposed to being a single rule production as in constituency

- Can also choose *and* to be the head

- In both cases, headword doesn’t really represent the phrase — constituency representation makes more sense
Stanford Dependencies

- Designed to be practically useful for relation extraction

Bills on ports and immigration were submitted by Senator Brownback, Republican of Kansas
Dependency vs. Constituency

- Dependency is often more useful in practice (models predicate argument structure)
- Slightly different representational choices:
  - PP attachment is better modeled under dependency
  - Coordination is better modeled under constituency
- Dependency parsers are easier to build: no “grammar engineering”, no unaries, easier to get structured discriminative models working well
- Dependency parsers are usually faster
- Dependencies are more universal cross-lingually: Czech was one of the first languages for dep parsing in NLP due to its free word order
Universal Dependencies

- Annotate dependencies with the same representation in many languages

English

1. DET det NOUN dog AUX aux:pass VERB chased ADP by DET det NOUN cat

Bulgarian

2. NOUN postposition PRON expl:pass VERB nsubj:pass obli punct case

Czech

3. NOUN postposition AUX aux:pass VERB nsubj:pass obli punct case

Swiss

4. NOUN nsubj:pass VERB obli punct PUNCT

http://universaldependencies.org/
Graph-Based Parsing
Defining Dependency Graphs

- Words in sentence $\mathbf{x}$, tree $T$ is a collection of directed edges $(\text{parent}(i), i)$ for each word $i$
  - Parsing = identify $\text{parent}(i)$ for each word
  - Each word has exactly one parent. Edges must form a projective tree

- Log-linear CRF (discriminative): $P(T|\mathbf{x}) = \exp \left( \sum_i w^\top f(i, \text{parent}(i), \mathbf{x}) \right)$

- Example of a feature = $I[\text{head}=to \text{ & modifier}=house]$

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

LSTM looks at words and POS

Dozat and Manning (2017)
Generalizing CKY

- DP chart with three dimensions: start, end, and head, start \(\leq\) head < end
- new score = \(\text{chart}(2, 5, 4) + \text{chart}(5, 7, 5) + \text{edge score}(4 \rightarrow 5)\)
- \(\text{score}(2, 7, 4) = \max(\text{score}(2, 7, 4), \text{new score})\)
- Many *spurious derivations*: can build the same tree in many ways...need a better algorithm
- Eisner’s algorithm is cubic time

[Diagram showing a pyramid with labeled nodes: 2, 4, 5, 7. The node 4 labeled “wrote,” 5 labeled “a long report,” 7 labeled “on Mars.”]
Evaluating Dependency Parsing

- UAS: unlabeled attachment score. Accuracy of choosing each word’s parent ($n$ 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
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

I ate some spaghetti bolognese

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

- Left-arc (reduce): Let $\sigma$ denote the stack, $\sigma|w_{-1} = \text{stack ending in } w_{-1}$
  - “Pop two elements, add an arc, put them back on the stack”
    $$\sigma|w_{-2}, w_{-1} \rightarrow \sigma|w_{-1}$$
    $w_{-2}$ is now a child of $w_{-1}$

- **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

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

[ROOT]       [I ate some spaghetti bolognese]
[ROOT I]     [ate some spaghetti bolognese]
[ROOT I ate]  [some spaghetti bolognese]
[ROOT 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!
I ate some spaghetti bolognese
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:

[root]
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

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

- 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>
</tr>
</thead>
<tbody>
<tr>
<td>standard</td>
<td>89.9</td>
<td>88.7</td>
<td>89.7</td>
<td>88.3</td>
<td>51</td>
</tr>
<tr>
<td>eager</td>
<td>90.3</td>
<td>89.2</td>
<td>89.9</td>
<td>88.6</td>
<td>63</td>
</tr>
<tr>
<td>Malt:sp</td>
<td>90.0</td>
<td>88.8</td>
<td>89.9</td>
<td>88.5</td>
<td>560</td>
</tr>
<tr>
<td>Malt:eager</td>
<td>90.1</td>
<td>88.9</td>
<td>90.1</td>
<td>88.7</td>
<td>535</td>
</tr>
<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>92.2</td>
<td>91.0</td>
<td>92.0</td>
<td>90.7</td>
<td>1013</td>
</tr>
</tbody>
</table>

- Many early-2000s constituency parsers were \(\sim 5\) 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)
Shift-Reduce Constituency

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

Cross and Huang (2016)
“Tetra tagging”: four possible tags to get unlabeled binary trees

- “↗”: This terminal node is a left-child.
- “↘”: This terminal node is a right-child.
- “├”: The shortest span crossing this fence-post is a left-child.
- “╰”: The shortest span crossing this fence-post is a right-child.

<table>
<thead>
<tr>
<th></th>
<th>Sents/s</th>
<th>Hardware</th>
<th>F1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vilares et al. (2019)</td>
<td>942</td>
<td>1x GPU</td>
<td>91.13</td>
</tr>
<tr>
<td>Kitaev et al. (2019)*</td>
<td>39</td>
<td>1x GPU</td>
<td>95.59</td>
</tr>
<tr>
<td>Zhou and Zhao (2019)*</td>
<td>–</td>
<td>–</td>
<td>95.84</td>
</tr>
<tr>
<td>This work*</td>
<td>1200</td>
<td>1x TPU v3-8</td>
<td>95.44</td>
</tr>
</tbody>
</table>

Kitaev and Klein (2020)
State-of-the-art Dependency 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
Shift-Reduce with FFNNs

Softmax layer:
\[ p = \text{softmax}(W_2h) \]

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

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

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

- 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

Andor et al. (2016)
Challenges in other languages

- Swiss German example: note that the arcs cross, unlike in our English examples, which were almost entirely projective.
- (Swiss German also has famous non-context-free constructions)
- As a result: some different transition-based algorithms are needed

credit: Pitler et al. (2013)
Multilingual Parsing

- Interest in multilingual dependency parsing as far back as CoNLL 2006 shared task
- Now: can parse many languages with one pre-trained model

Üstün et al. (2020)
Reflections on Structure

‣ What is the role of it now?

‣ Systems still make these kinds of judgments, just not explicitly

‣ To improve systems, do we need to understand what they do?
Recap

- Shift-reduce parsing can work nearly as well as graph-based

- Arc-standard system for transition-based parsing

- Strong learning-based parsers, including multilingual parsers