Delexicalized Parsing

Daniel Zeman, Rudolf Rosa

April 16, 2021
What if we feed the parser with tags instead of words?

- Ændringer i listen i bilaget offentliggøres og meddeles på samme måde.
- NNS IN NN IN NN VB CC VB IN DT NN
- NNS IN NN MD VB CC VB IN DT NN
- Förändringar i förteckningen skall offentliggöras och meddelas på samma sätt.
- What if we feed the parser with tags instead of words?
  - Ændringer i listen i bilaget offentliggøres og meddeles på samme måde.
  - ((NNS (IN NN (IN NN))) ((VB CC VB) (IN (DT NN))))
  - ((NNS (IN NN)) ((MD (VB CC VB)) (IN (DT NN))))
  - Förändringar i förteckningen skall offentliggöras och meddelas på samma sätt.
Danish – Swedish Setup

  - In IJCNLP 2008 Workshop on NLP for Less Privileged Languages, pp. 35–42, Hyderabad, India
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- CoNLL 2006 treebanks (dependencies)
  - Danish Dependency Treebank
  - Swedish Talbanken05

- Two constituency parsers:
  - “Charniak”
  - “Brown” (Charniak N-best parser + Johnson reranker)

- Other resources
  - (JRC-Acquis parallel corpus)
  - Hajič tagger for Swedish (PAROLE tagset)
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Treebank Normalization

Danish
- DET governs ADJ
  ADJ governs NOUN

Swedish
- NOUN governs both DET and ADJ
Treebank Normalization

Danish
- DET governs ADJ
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- NUM governs NOUN

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- NOUN governs both DET and ADJ
- NOUN governs NUM
Treebank Normalization

Danish

- DET governs ADJ
  ADJ governs NOUN
- NUM governs NOUN
- GEN governs NOM

Ruslands vej
Russia’s way

Swedish

- NOUN governs both DET and ADJ
- NOUN governs NUM
- NOM governs GEN

års inkomster
year’s income
Treebank Normalization

**Danish**
- DET governs ADJ
  ADJ governs NOUN
- NUM governs NOUN
- GEN governs NOM
  *Ruslands vej*
  *Russia’s way*
- COORD: last member on conjunction, everything else on first member

**Swedish**
- NOUN governs both DET and ADJ
- NOUN governs NUM
- NOM governs GEN
  *års inkomster*
  *year’s income*
- COORD: member on previous member, commas and conjs on next member
Treebank Preparation

- Transform Danish to Swedish tree style
  - A few heuristics
  - Only for evaluation! Not needed in real world.
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- DA/SV tagset converted to Penn Treebank tags
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- Nonterminal labels:
  - derived from POS tags
  - then translated to the Penn set of nonterminals

- Make the parser feel it works with the Penn Treebank
  - (Although it could have been configured to use other sets of labels.)
Unlabeled F Scores

- da-da lexicalized: Charniak = 78.16, Brown = 78.24
  - (CoNLL train 94K words, test 5852 words)
- sv-sv lexicalized: Charniak = 77.81, Brown = 78.74
  - (CoNLL train 191K words, test 5656 words)
- da-sv lexicalized: Charniak = 43.28, Brown = 41.84
  - (no morphology tweaking)
- da-da delexicalized: Charniak = 79.62, Brown = 80.20 (!)
  - (hybrid sv-da Hajič-like tagset = "words", Penn POS = "tags")
- sv-sv delexicalized: Charniak = 76.07, Brown = 77.01
- da-sv delexicalized: Charniak = 65.50, Brown = 66.40
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How Big Swedish Treebank Yields Similar Results?

Unlabeled $F_1$-score

Delexicalized Parsing
Delexicalized Dependency Parsing

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- No tree structure harmonization
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  - Gold-standard (just converted)
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- UAS (unlabeled attachment score)

- No tree structure harmonization
  - “Danish is the worst possible source language for Swedish.”
Multi-Source Transfer (McDonald et al., 2011)

<table>
<thead>
<tr>
<th>Target Test Language</th>
<th>da</th>
<th>de</th>
<th>el</th>
<th>en</th>
<th>es</th>
<th>it</th>
<th>nl</th>
<th>pt</th>
<th>sv</th>
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<tbody>
<tr>
<td>da</td>
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<td>45.2</td>
<td>44.0</td>
<td>45.9</td>
<td>45.0</td>
<td>48.6</td>
<td>46.1</td>
<td>48.1</td>
<td>47.8</td>
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<tr>
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<td>83.9</td>
<td>53.2</td>
<td>47.2</td>
<td>45.8</td>
<td>53.4</td>
<td>55.8</td>
<td>55.5</td>
<td>46.2</td>
</tr>
<tr>
<td>el</td>
<td>33.3</td>
<td>52.5</td>
<td>77.5</td>
<td>63.9</td>
<td>41.6</td>
<td>59.3</td>
<td>57.3</td>
<td>58.6</td>
<td>47.5</td>
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<tr>
<td>en</td>
<td>34.4</td>
<td>37.9</td>
<td>45.7</td>
<td>82.5</td>
<td>28.5</td>
<td>38.6</td>
<td>43.7</td>
<td>42.3</td>
<td>43.7</td>
</tr>
<tr>
<td>es</td>
<td>38.1</td>
<td>49.4</td>
<td>57.3</td>
<td>53.3</td>
<td>79.7</td>
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</tr>
<tr>
<td>it</td>
<td>44.8</td>
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<tr>
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</table>
Malt Parser, stack-lazy algorithm (nonprojective)
- Same algorithm for all, no optimization
- Same selection of training features for all treebanks

Trained on the first 1000 sentences only
- Tested on the whole test set
- Default score: UAS (unlabeled attachment)
- Only harmonized data used (HamleDT 3.0 = UD v1 style)
- Single source language for every target
Delexicalized Dependency Parsing with Harmonized Data
Who Helps Whom?

- Czech (62.44) $\Leftarrow$ Croatian (63.27), Slovenian (62.87)
- Slovak (59.47) $\Leftarrow$ Croatian (60.28), Slovenian (59.32)
- Polish (77.92) $\Leftarrow$ Croatian (66.42), Slovenian (64.31)
- Russian (66.86) $\Leftarrow$ Croatian (57.35), Slovak (55.01)
- Croatian (75.52) $\Leftarrow$ Slovenian (58.96), Polish (55.42)
- Slovenian (76.17) $\Leftarrow$ Croatian (62.92), Finnish (59.79)
- Bulgarian (78.44) $\Leftarrow$ Croatian (74.39), Slovenian (71.52)
Who Helps Whom?

- Catalan (75.28) ⇔ Italian (71.07), French (68.30)
- Italian (76.66) ⇔ French (70.37), Catalan (68.66)
- French (69.93) ⇔ Spanish (64.28), Italian (63.33)
- Spanish (67.76) ⇔ French (67.61), Catalan (64.54)
- Portuguese (69.89) ⇔ Italian (69.48), French (66.12)
- Romanian (79.74) ⇔ Croatian (67.01), Latin (66.75)
Who Helps Whom?

- Swedish (75.73) ⇐ Danish (66.17), English (65.41)
- Danish (75.19) ⇐ Swedish (59.23), Croatian (56.89)
- English (72.68) ⇐ German (57.95), French (56.70)
- German (67.04) ⇐ Croatian (58.68), Swedish (57.48)
- Dutch (60.76) ⇐ Hungarian (41.90), Finnish (37.89)
How Big Swedish Treebank Yields Similar Results as Delex from Danish?

![Graph showing the relationship between training sentences and UAS score. The graph shows a trend where the UAS score increases with the number of training sentences. There is a highlighted point at 66.17 UAS with approximately 75 sentences.]
Multiple Source Treebanks

- So far: select one source at a time
  - How to select the best possible source?

- Alternative 1: train on all sources concatenated
  - Possibly with "weights" — take only part of a treebank, or take multiple copies of a treebank, or omit some treebanks

- Alternative 2: train on each source separately, then vote
  - Separate voting about every node's incoming edge
  - Weights — how much do we trust each source?

The result should be a tree!

Chu-Liu-Edmonds MST algorithm, as in graph-based parsing
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Observation: We cannot compare trees!
  - In real-world applications, target trees will not be available
Syntactic Similarity of Languages

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- Problem 1: What if no relative is available? (Buryat...)
Example: CoNLL 2018 Parsing Shared Task

- Low-resource languages:
  - IE: Breton, Faroese, Naija, Upper Sorbian, Armenian, Kurmanji
  - Other: Kazakh, Buryat, Thai
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High(er)-resource languages (selected groups only):
  - 1 Celtic (Irish)
  - 8 Germanic
  - 10 Slavic
  - 1 Iranian
  - 2 Turkic
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19/22
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    - German uses morphology, freer but peculiar word order
    - Icelandic has even more morphology
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- WALS features (recall the first week)
- Language recognition tool
  - But it relies on orthography!
  - cs: Generál přeskupil síly ve Varšavě.
  - pl: Generał przegrupował siły w Warszawie.
  - ru: Генерал перегруппировал войска в Варшаве.
  - en: The general regrouped forces in Warsaw.
## Measuring Treebank Similarity: POS Tag N-grams

<table>
<thead>
<tr>
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<th>en</th>
<th>de</th>
<th>it</th>
<th>cs</th>
</tr>
</thead>
<tbody>
<tr>
<td>DET ADJ NOUN</td>
<td>1.51</td>
<td><strong>1.99</strong></td>
<td>0.96</td>
<td>0.40</td>
</tr>
<tr>
<td>DET NOUN ADJ</td>
<td>0.05</td>
<td>0.26</td>
<td><strong>1.77</strong></td>
<td>0.10</td>
</tr>
<tr>
<td>#sent ADJ NOUN</td>
<td>0.13</td>
<td>0.09</td>
<td>0.02</td>
<td><strong>0.52</strong></td>
</tr>
<tr>
<td>NOUN PUNCT #sent</td>
<td>2.44</td>
<td>1.18</td>
<td>1.41</td>
<td><strong>2.73</strong></td>
</tr>
<tr>
<td>VERB PUNCT #sent</td>
<td>0.48</td>
<td><strong>1.48</strong></td>
<td>0.23</td>
<td>0.58</td>
</tr>
</tbody>
</table>
Kullback-Leibler Divergence

- \( UPOS \) ... universal set of 17 coarse-grained tags (from UD)
- \( UPOS' = UPOS \cup \{ \#sent \} \) ... added sentence boundaries
- \((t_{i-2}, t_{i-1}, t_i)\) where \(t_{i-2}, t_{i-1}, t_i \in UPOS'\) ... trigram of tags at positions \(i - 2 \ldots i\) of the corpus
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- \( P_{\text{Corpus}}(x, y, z) = \frac{\text{count}_{\text{Corpus}}(x, y, z)}{\sum_{a,b,c \in \textit{UPOS}'} \text{count}_{\text{Corpus}}(a, b, c)} = \frac{\text{count}_{\text{Corpus}}(x, y, z)}{|\text{Corpus}|} \)
  - \(x, y, z \in \textit{UPOS}'\)
  - Smoothing: need non-zero probability of every possible trigram

\[ D_{KL}(P_A || P_B) = \sum x;y;z P_A(x; y; z) \log \frac{P_A(x; y; z)}{P_B(x; y; z)} \]

- \( KL_{\text{cpos}}(\text{tgt}; \text{src}) \) = \( D_{KL}(P_{\text{tgt}} || P_{\text{src}}) \) ... Asymmetric: amount of info lost when using the source distribution to approximate the true target distribution


In Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing, Short Papers
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  - $x, y, z \in UPOS'$
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- $KL_{cpos^3}(tgt, src) = D_{KL}(P_{tgt} \| P_{src})$
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- $UPOS' = UPOS \cup \{\#sent\}$ ... added sentence boundaries
- $(t_{i-2}, t_{i-1}, t_i)$ where $t_{i-2}, t_{i-1}, t_i \in UPOS'$ ... trigram of tags at positions $i - 2$ ... $i$ of the corpus
- $P_{Corpus}(x, y, z) = \frac{\text{count}_{Corpus}(x,y,z)}{\sum_{a,b,c \in UPOS'} \text{count}_{Corpus}(a,b,c)} = \frac{\text{count}_{Corpus}(x,y,z)}{|Corpus|}$
  - $x, y, z \in UPOS'$
  - Smoothing: need non-zero probability of every possible trigram
- $D_{KL}(P_A||P_B) = \sum_{x,y,z} P_A(x, y, z) \cdot \log \frac{P_A(x,y,z)}{P_B(x,y,z)}$
- $KL_{cpos^3}(tgt, src) = D_{KL}(P_{tgt}||P_{src})$
  - Asymmetric: amount of info lost when using the source distribution to approximate the true target distribution
    - In Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing, Short Papers
How to Make the Languages More Similar?


- Transition-based parsers rely on word order
  - en: the following question (features: s0=ADJ, b0=NOUN)
  - fr: la question suivante (features: s0=NOUN, b0=ADJ)
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- Preprocess training data
  - Reorder words
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- How do we know?
  - Heuristics based on WALS
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- How do we know?
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  - UPOS language model
    - Generate all permutations in window of 3 words
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  - en: the following question (features: s0=ADJ, b0=NOUN)
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- Preprocess training data
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- How do we know?
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    - Generate all permutations in window of 3 words
    - Discard non-projective subtrees; if nothing left, retain source sequence
How to Make the Languages More Similar?


- Transition-based parsers rely on word order
  - en: the following question (features: s0=ADJ, b0=NOUN)
  - fr: la question suivante (features: s0=NOUN, b0=ADJ)

- Preprocess training data
  - Reorder words
  - Remove words

- How do we know?
  - Heuristics based on WALS
  - UPOS language model
    - Generate all permutations in window of 3 words
    - Discard non-projective subtrees; if nothing left, retain source sequence
    - Score them by target-language model
    - Take the best permutation