Delexicalized Parsing

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Delexicalized Parsing

- 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.*

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  - `((NNS (IN NN))    ((MD (VB CC VB)) (IN (DT NN))))`
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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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- DET governs ADJ
  ADJ governs NOUN

Swedish

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Treebank Normalization

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- DET governs ADJ
  ADJ governs NOUN
- NUM governs NOUN
- GEN governs NOM
  Ruslands vej
  Russia's way

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- NOUN governs both DET and ADJ
- NOUN governs NUM
- NOM governs GEN
  års inkomster
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Treebank Normalization

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- DET governs ADJ
  ADJ governs NOUN
- NUM governs NOUN
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  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
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  års inkomster
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- COORD: member on previous member, commas and conjs on next member

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- 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
- 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)
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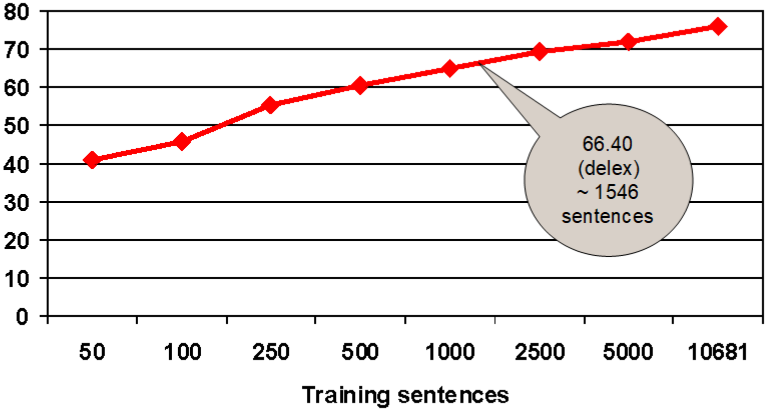
How Big Swedish Treebank Yields Similar Results?



Unlabeled F_1-score

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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)

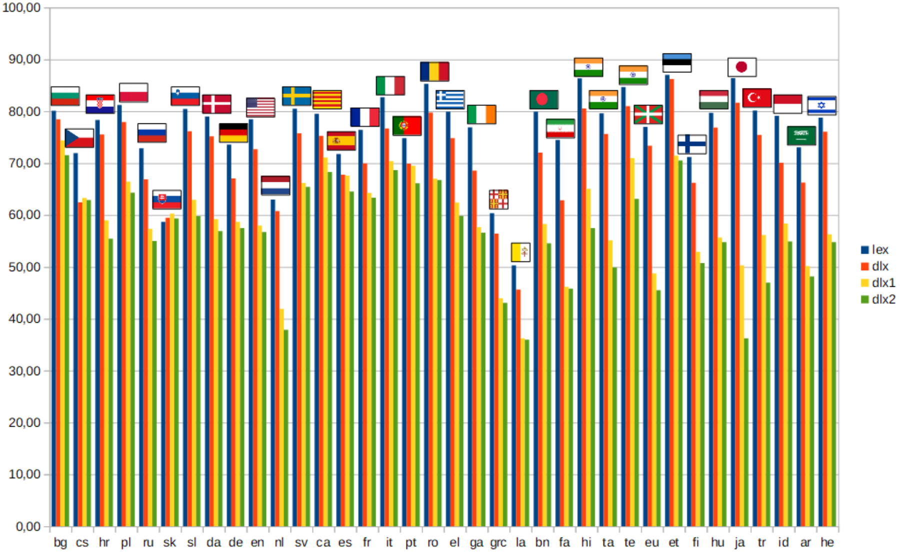
Target Test Language	Source Training Language: da	de	el	en	es	it	nl	pt	sv
da	**79.2**	45.2	44.0	45.9	45.0	<u>48.6</u>	46.1	48.1	47.8
de	34.3	**83.9**	53.2	47.2	45.8	53.4	<u>55.8</u>	55.5	46.2
el	33.3	52.5	**77.5**	<u>63.9</u>	41.6	59.3	57.3	58.6	47.5
en	34.4	37.9	<u>45.7</u>	**82.5**	28.5	38.6	43.7	42.3	43.7
es	38.1	49.4	57.3	53.3	**79.7**	<u>68.4</u>	51.2	66.7	41.4
it	44.8	56.7	66.8	57.7	64.7	**79.3**	57.6	<u>69.1</u>	50.9
nl	38.7	43.7	<u>62.1</u>	60.8	40.9	50.4	**73.6**	58.5	44.2
pt	42.5	52.0	66.6	69.2	68.5	<u>74.7</u>	67.1	**84.6**	52.1
sv	44.5	57.0	57.8	58.3	46.3	53.4	54.5	<u>66.8</u>	**84.8**

Single-Source, Harmonized (DZ, summer 2015)

- 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) ⇐ Croatian (63.27), Slovenian (62.87)
- Slovak (59.47) ⇐ Croatian (60.28), Slovenian (59.32)
- Polish (77.92) ⇐ Croatian (66.42), Slovenian (64.31)
- Russian (66.86) ⇐ Croatian (57.35), Slovak (55.01)
- Croatian (75.52) ⇐ Slovenian (58.96), Polish (55.42)
- Slovenian (76.17) ⇐ Croatian (62.92), Finnish (59.79)
- Bulgarian (78.44) ⇐ Croatian (74.39), Slovenian (71.52)

Who Helps Whom?

- Catalan (75.28) $\Leftarrow$ Italian (71.07), French (68.30)
- Italian (76.66) $\Leftarrow$ French (70.37), Catalan (68.66)
- French (69.93) $\Leftarrow$ Spanish (64.28), Italian (63.33)
- Spanish (67.76) $\Leftarrow$ French (67.61), Catalan (64.54)
- Portuguese (69.89) $\Leftarrow$ Italian (69.48), French (66.12)
- Romanian (79.74) $\Leftarrow$ Croatian (67.01), Latin (66.75)

Who Helps Whom?

- Swedish (75.73) $\Leftarrow$ Danish (66.17), English (65.41)
- Danish (75.19) $\Leftarrow$ Swedish (59.23), Croatian (56.89)
- English (72.68) $\Leftarrow$ German (57.95), French (56.70)
- German (67.04) $\Leftarrow$ Croatian (58.68), Swedish (57.48)
- Dutch (60.76) $\Leftarrow$ Hungarian (41.90), Finnish (37.89)

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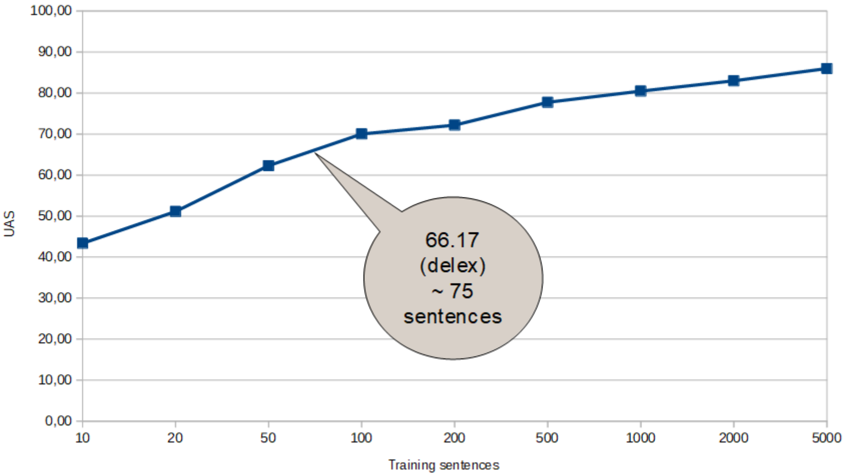

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- High(er)-resource languages (selected groups only):
  - 1 Celtic (Irish)
  - 8 Germanic
  - 10 Slavic
  - 1 Iranian
  - 2 Turkic

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    - 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

	en	de	it	cs
DET ADJ NOUN	1.51	**1.99**	0.96	0.40
DET NOUN ADJ	0.05	0.26	**1.77**	0.10
#sent ADJ NOUN	0.13	0.09	0.02	**0.52**
NOUN PUNCT #sent	2.44	1.18	1.41	**2.73**
VERB PUNCT #sent	0.48	**1.48**	0.23	0.58

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 $i-2$ … i of the corpus

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  - Asymmetric: amount of info lost when using the source distribution to approximate the true target distribution
  - Rudolf Rosa, Zdeněk Žabokrtský (2015). KL_{cpos^3} – a Language Similarity Measure for Delexicalized Parser Transfer.
    - 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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  - Reorder words
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    - Take the best permutation