Old School vs. New School: Comparing Transition-Based Parsers with and without Neural Network Enhancement

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Overview

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  - are growing in number and size at a fast pace
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Our proposal

Work on a small but representative sample of UD treebanks

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Straka et al. (2015) trained Parsito, a neural network parser for UD
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This Work

Carry out a comparison of the 2 on a small sample

Treebank Sampling

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- availability of morphological features
- quality of the treebank (according to UD validation tests)

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language	coarse	fine	main argument for inclusion
Czech	indo-eur	balto-slavic	largest UD treebank
Chinese	sino-tibetan	sinitic	isolating language
Finnish	uralo-altaic	finno-ungric	many different domains
English	indo-eur	germanic	largest + full manual check
AncientGreekPR	indo-eur	hellenic	amount of non-projectivity
Kazakh	uralo-altaic	turkic	smallest; full manual check
Tamil	dravidian	tamil	small; language family
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UDPipe used for tagging POS and morphological features

SyntaxNet (Andor et al., 2016) :

- *reported results*

Comparing Parsing Accuracy

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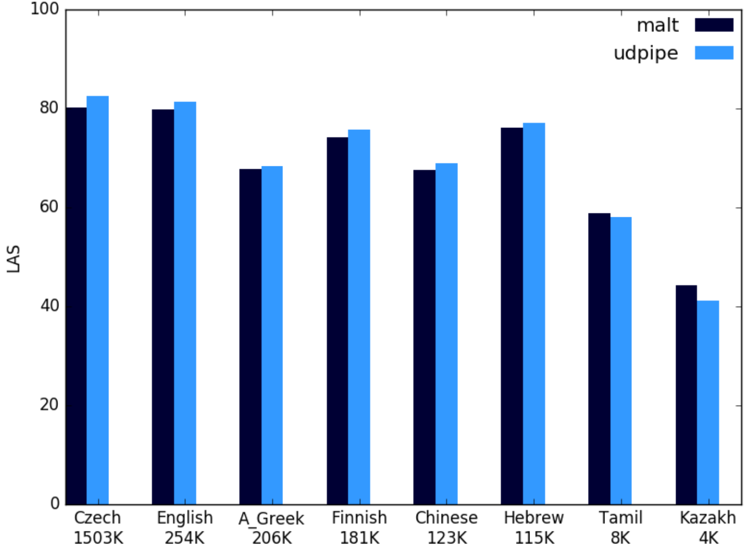

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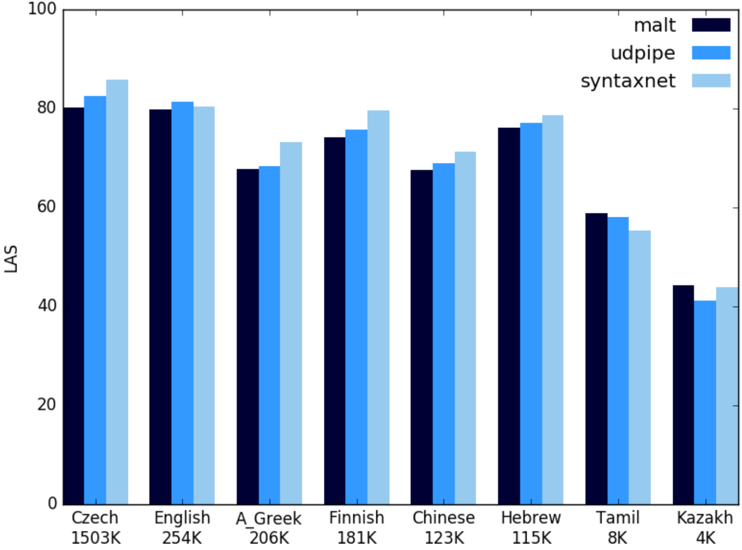

Impact of Training Size on Neural Network Parsing

Learning curve experiment:

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MaltParser: arc-standard swap with lazy oracle and extended feature model
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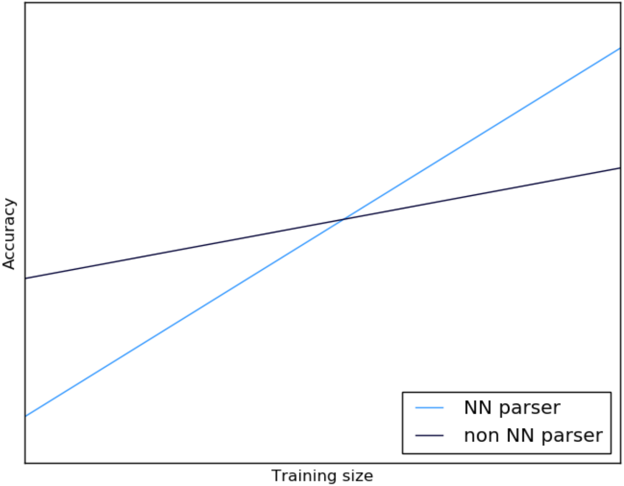
UDPipe: arc-standard swap with lazy oracle and default hyperparameters

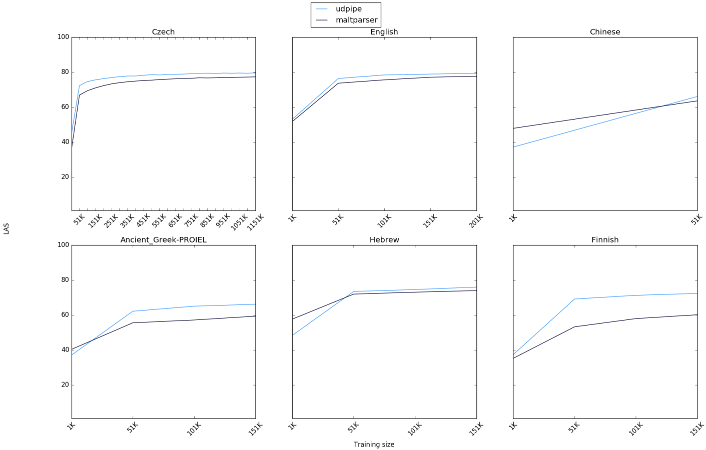
Splits: 1K to max with 50K splits
zoom on small data sizes: 1K to 15K

Impact of Training Size on Neural Network Parsing

Expectation



Reality


udpipe
maltparser
Czech
English
Chinese
Ancient_Greek-PROIEL
Hebrew
Finnish
LAS
Training size
100
80
60
40
20
51K
151K
251K
351K
451K
551K
651K
751K
851K
951K
1051K
1151K
1K
101K
201K

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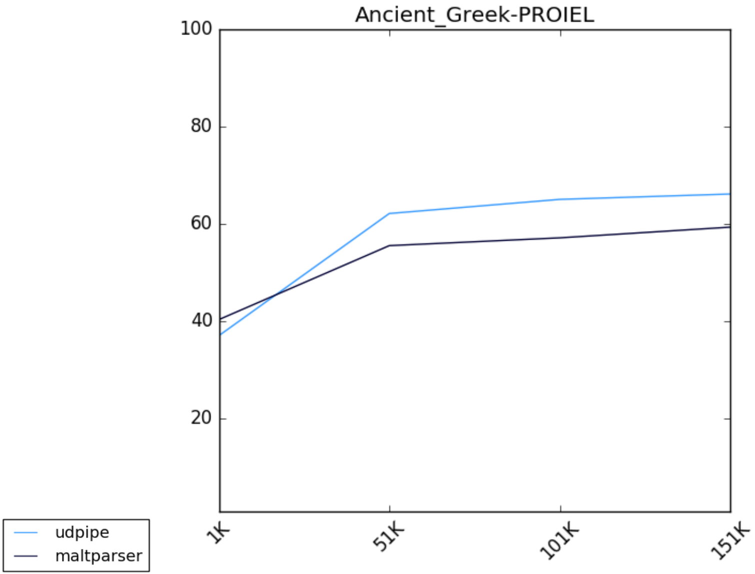

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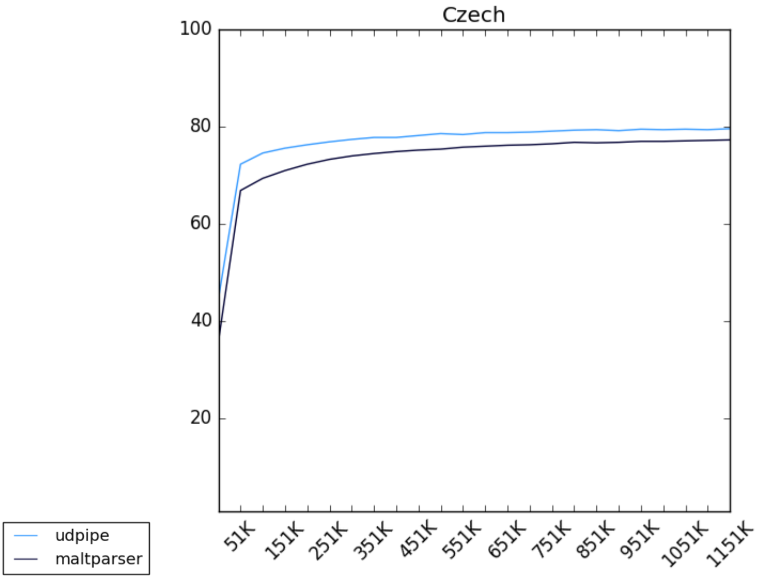

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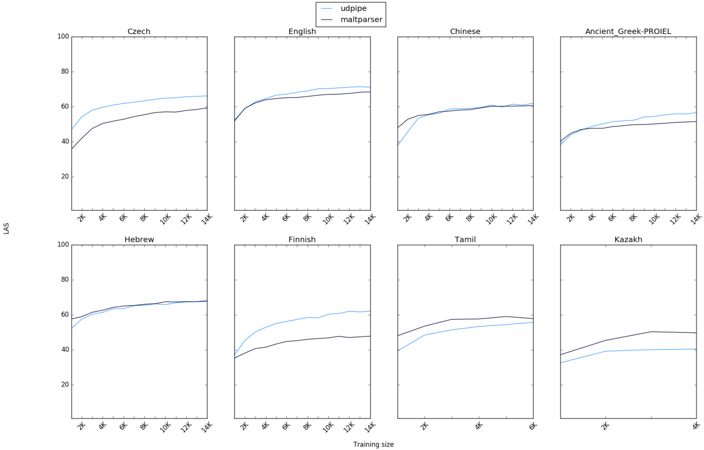

Error Analysis

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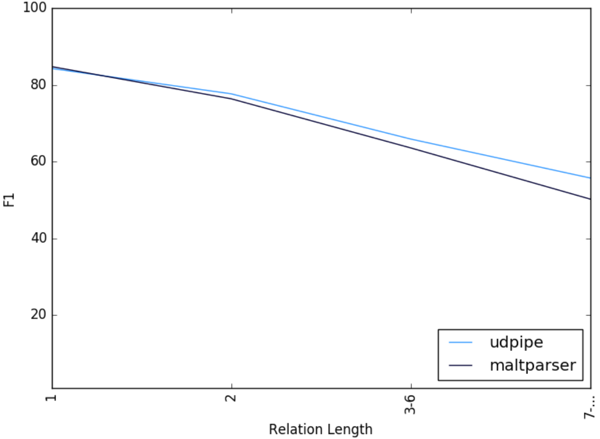
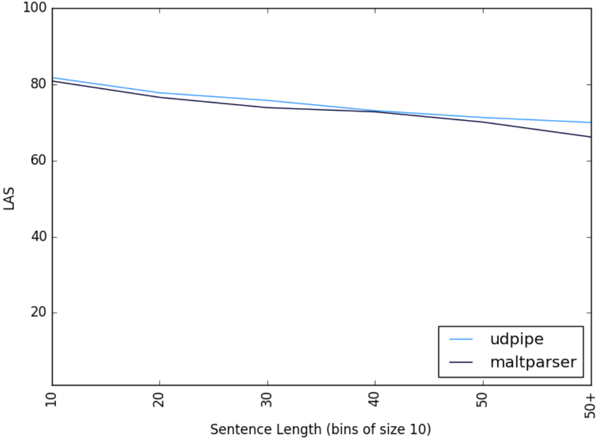
- Concatenating 9K of all development sets + all development set for Kazakh and Tamil

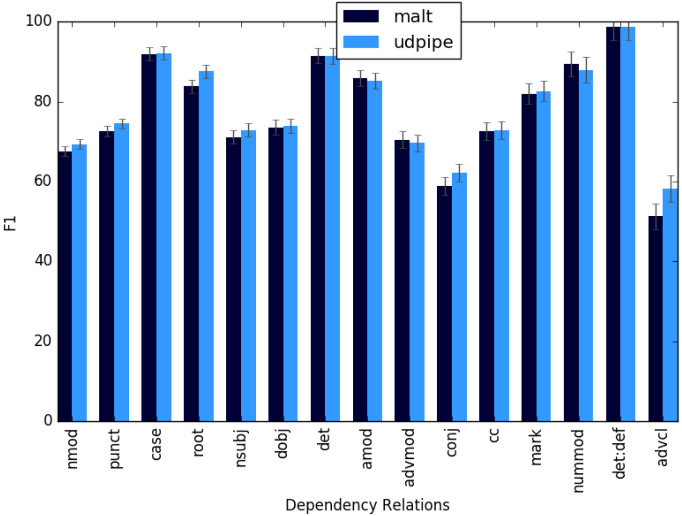
Error Analysis: Relation Length



Error Analysis: Sentence Length



Error Analysis: Dependency Relations



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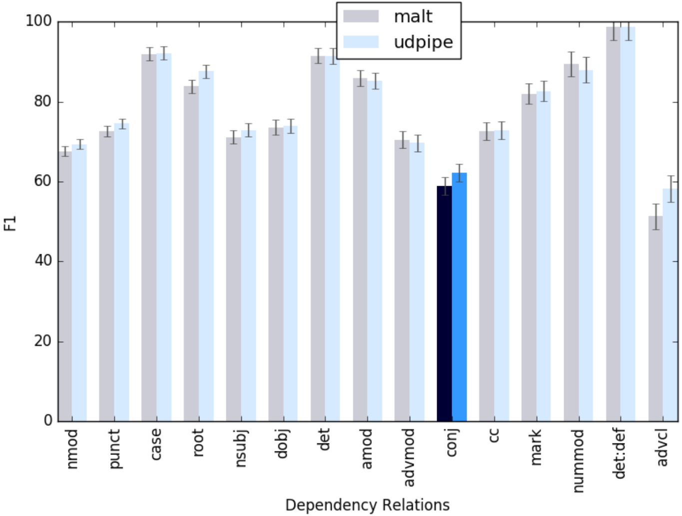

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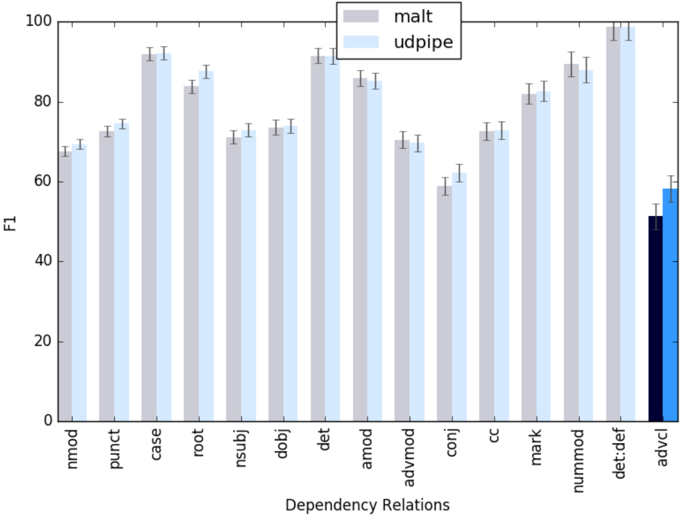

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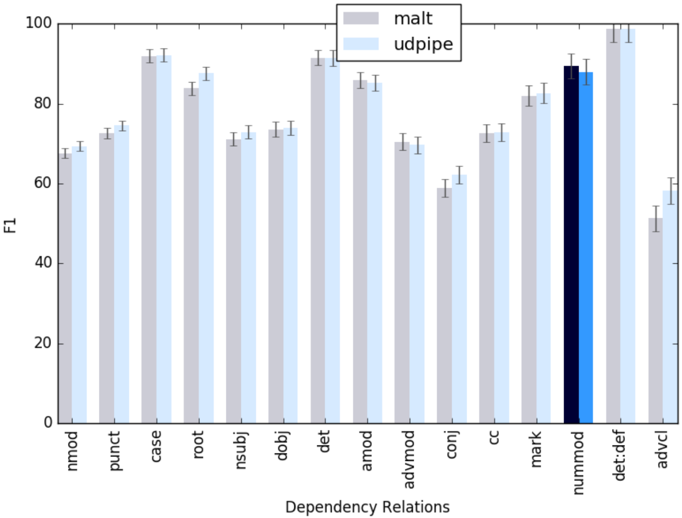
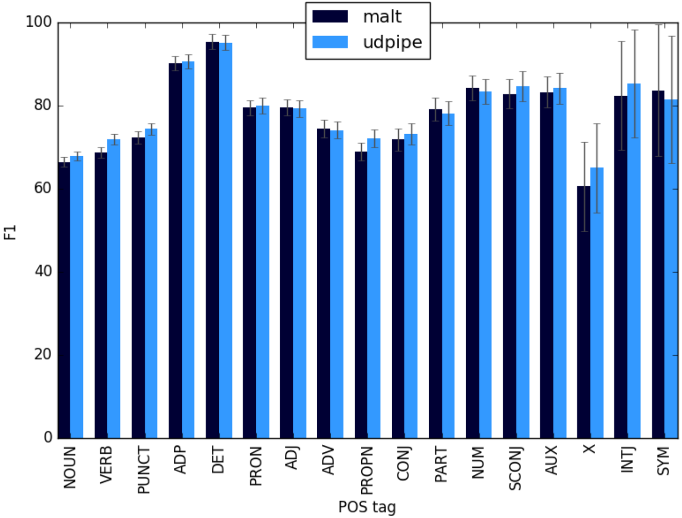


Error Analysis: POS tags



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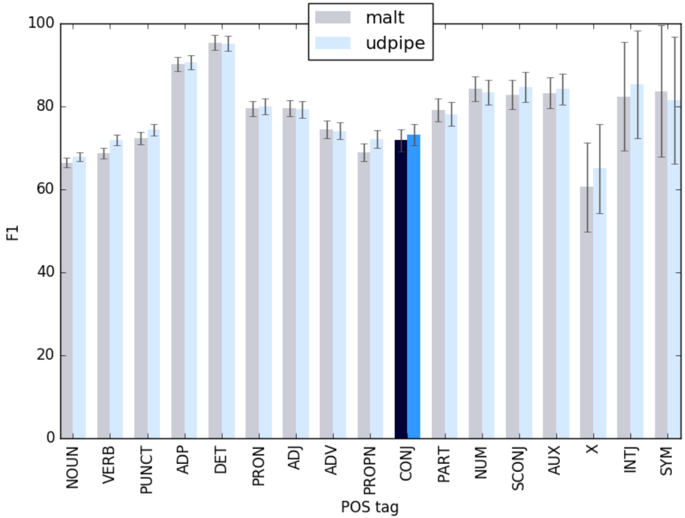

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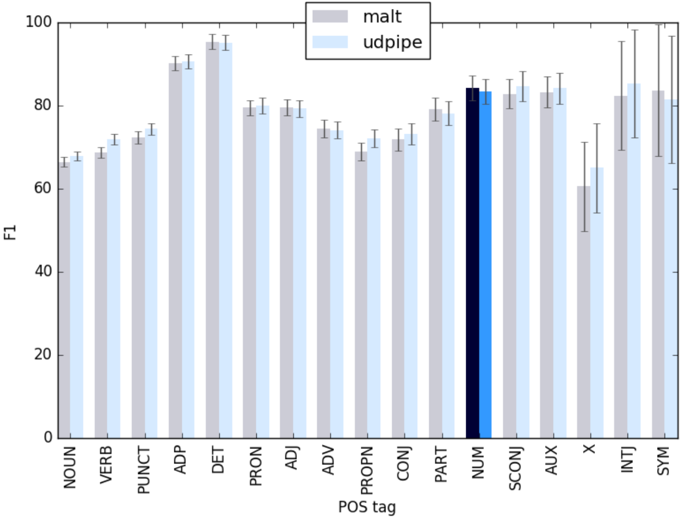

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Future Work

- Effect of beam search
- More fine-grained error analysis

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