# Some Dependency Parsing Work

Mark Anderson

# Overview

## Developing

- Chunk-and-Pass
- Distillation

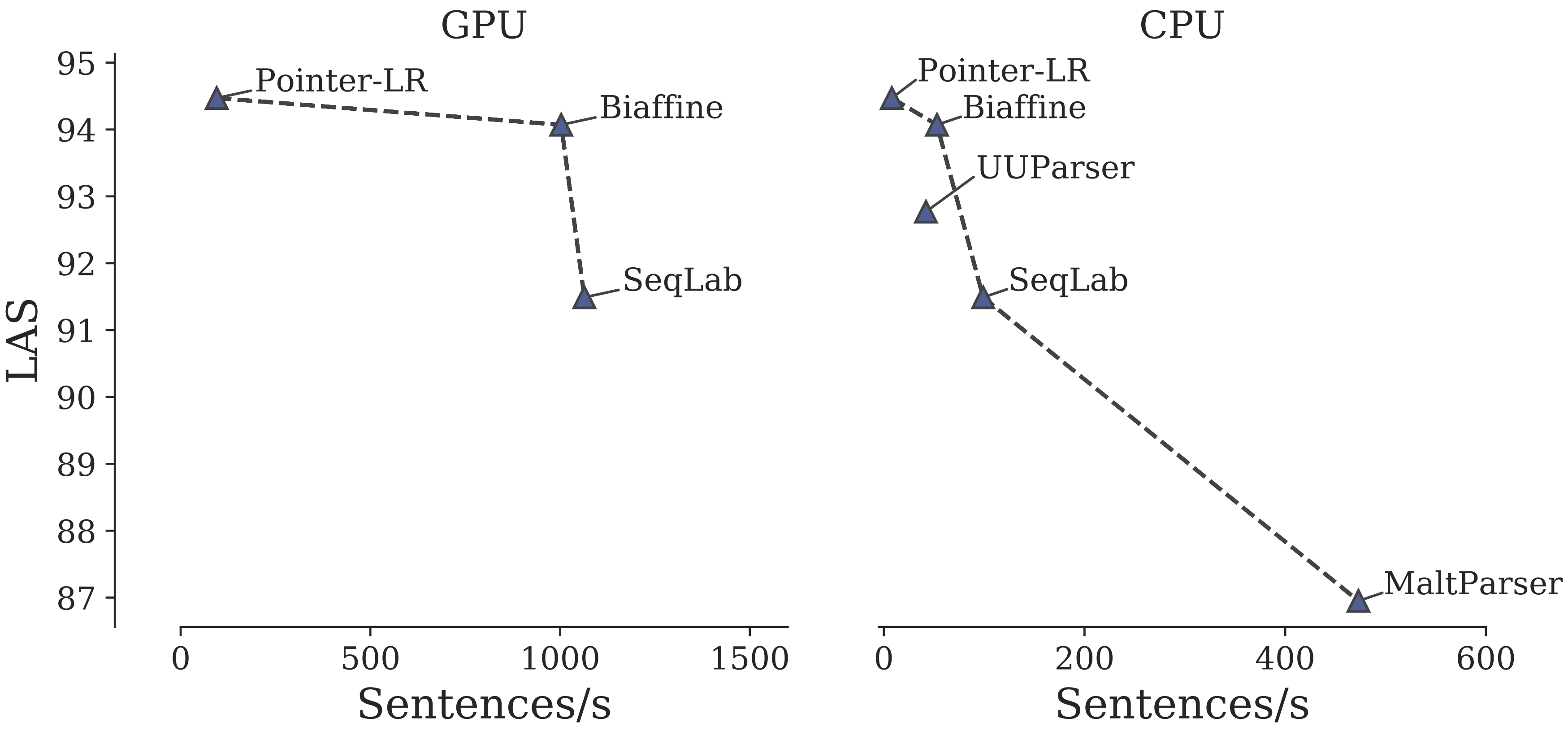
## Evaluating

- Edge displacement
- POS tags

# Part I

## Developing Parsers

# Pareto Front for PTB (WSJ)



# Chunk and Pass

# Chunk and Pass

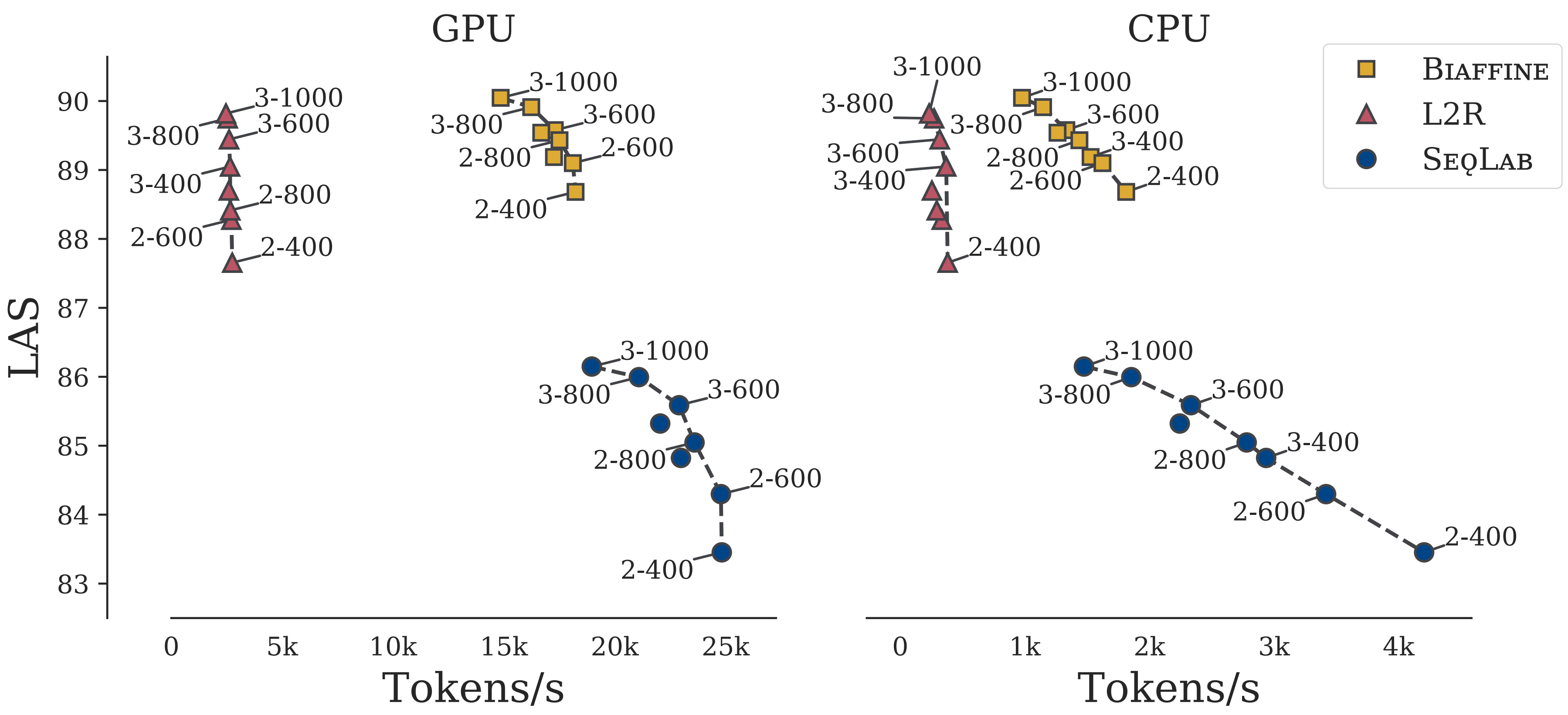
## "Now-or-never" bottleneck[1]

## 3 steps

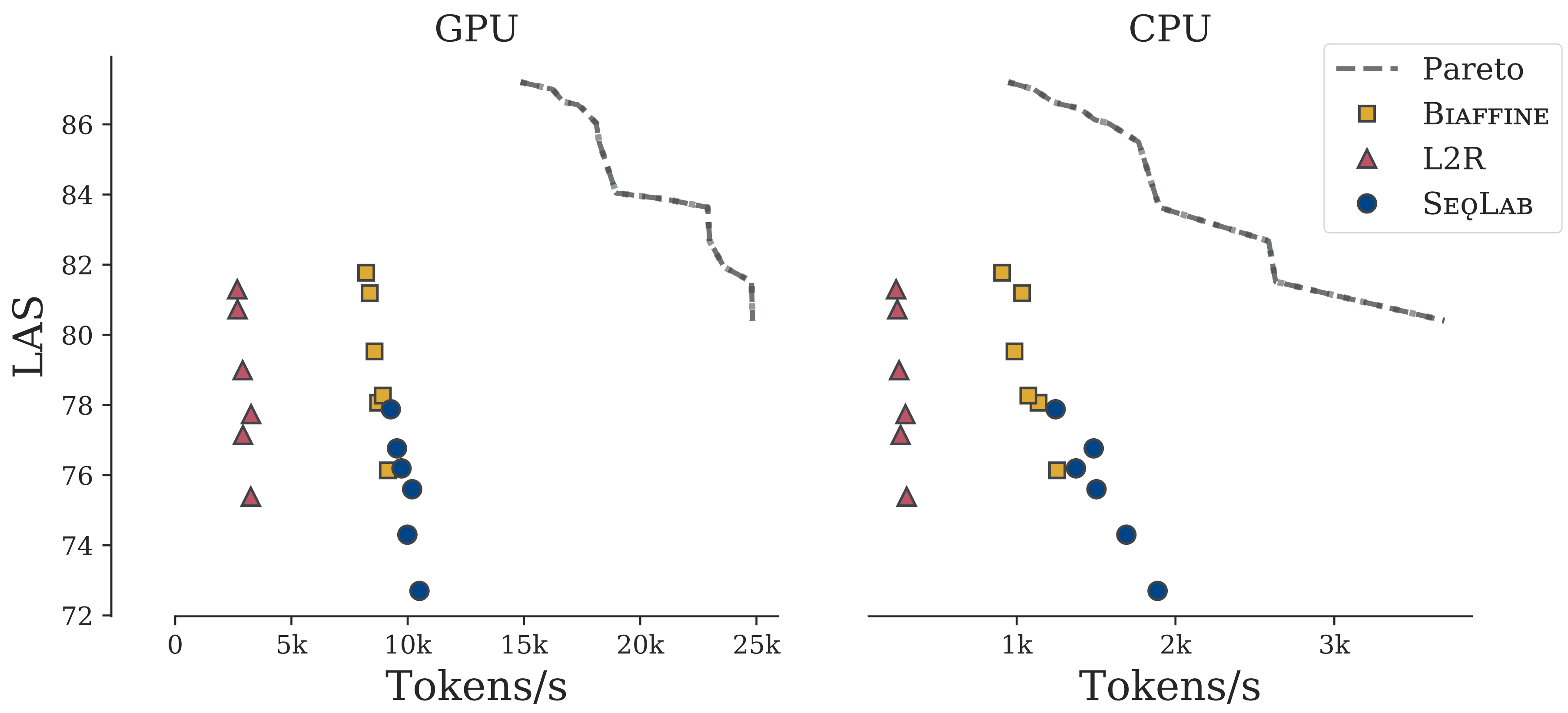
1. Shallow parse (chunk) --> Compressed data and shallow syntax
2. Parse chunks --> Higher-order syntactic relations
3. Collate --> Combined 1 and 2 for full parse

[1] Christiansen, M.H. and Chater N., *The Now-or-Never bottleneck: A fundamental constraint on language*, 2015

# Pareto Front for UD (zh, hi, ko, pl)



# Pareto Front for UD (zh, hi, ko, pl)



## **Chunking** — Each word is labelled, **B**, **I**, or **O**.

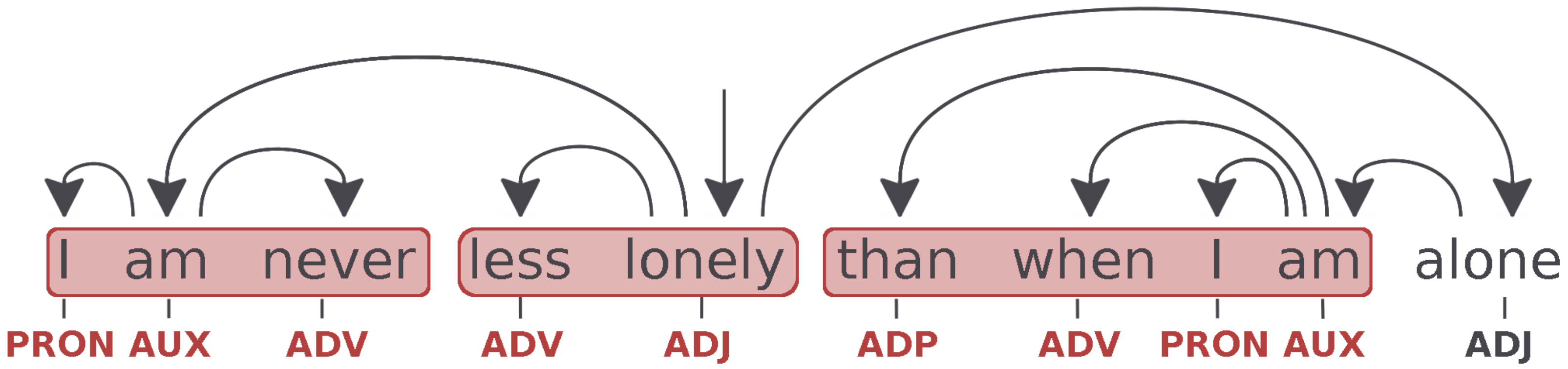
| **B** | **I** | **O** |
| --- | --- | --- |
| A token that begins a chunk. | A token inside of a chunk. | Anything outside of a chunk. |
| Suffixed with chunk phrase type. | Also suffixed with chunk phrase type. | |
| E.g. B-NP for a noun phrase. | E.g. I-VP for a verb phrase. | |

# Extracting chunks

1. Evolutionary technique (slow...)
2. Information theory

# Chunk candidate criteria

1. The components are syntactically linked
2. There is only one level of dependency (one head and its dependents)
3. The components are continuous.
4. No dependents within a chunk has a dependent outwith the chunk.


I am never less lonely than when I am alone
PRON AUX ADV ADV ADJ ADP ADV PRON AUX ADJ

(DET ADJ NOUN)

(PRON AUX ADV)

(PART VERB)

(ADP ADV PRON AUX)

(SCONJ ADV VERB)

(AUX AUX VERB)

(PRON PROPN VERB)

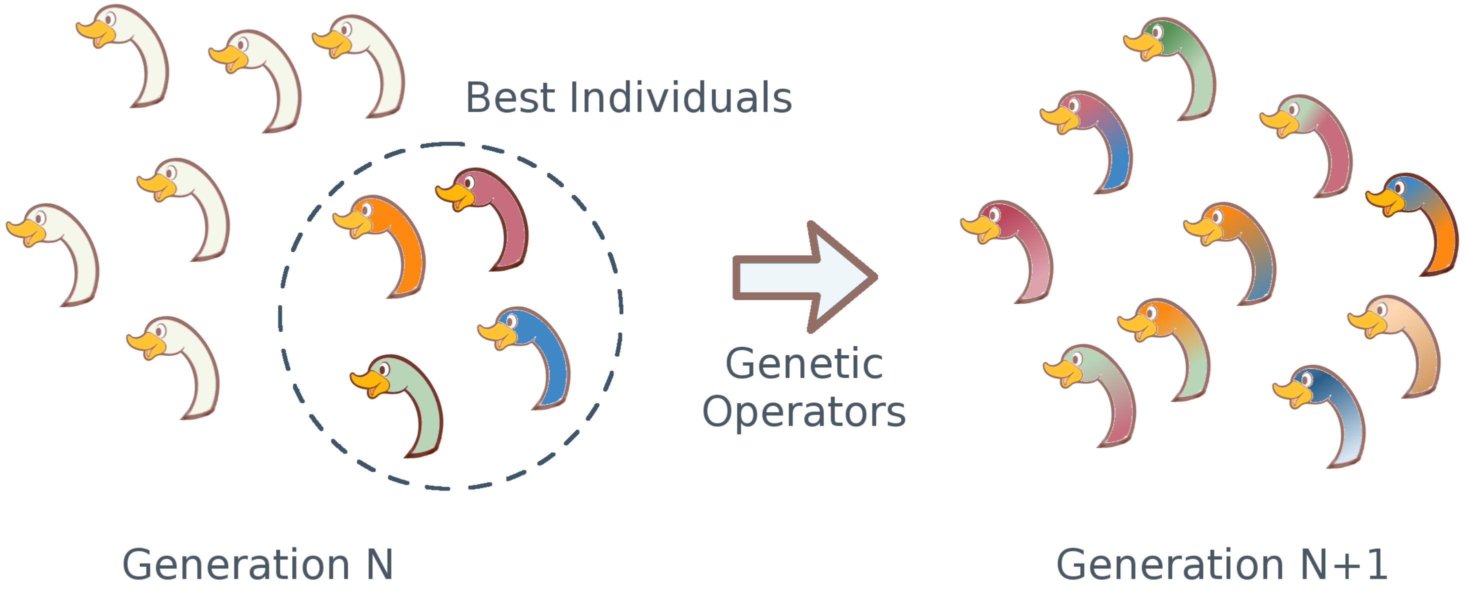
(CCONJ PRON AUX DET ADJ NOUN)

# Extract 2615 unique rules from UD English EWT treebank v2.3

512 occur more than 5 times.

$1.34 \times 10^{154}$ different rule sets.

# Evolutionary Search



# Evolutionary Search

Individual =[0,1,0,0,1 .... 0,1]

**(DET ADJ NOUN)** **(PRON AUX ADV)** **(PART VERB)**

Fitness = Chunking F1-score
+ 0.5 x proportion of
max compression

# Proportion of max compression

$$r = \frac{N_{tokens} + N_{chunks}}{N_{tokens}}$$

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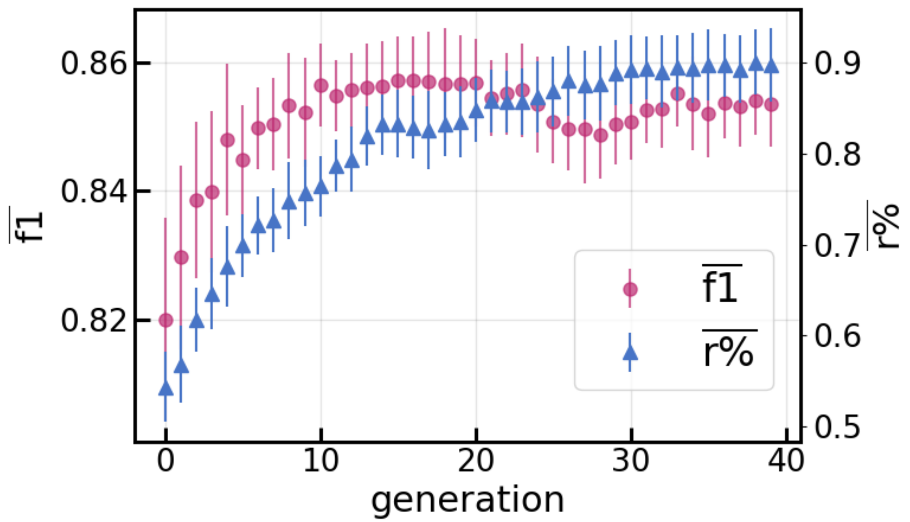
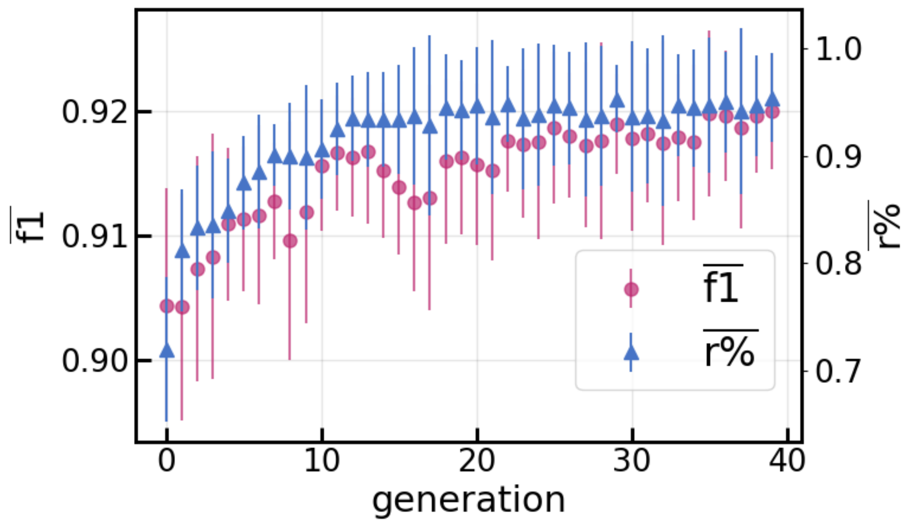
$$r_{prop} = \frac{r_{subset} - 1}{r_{all} - 1}$$

## English-EWT



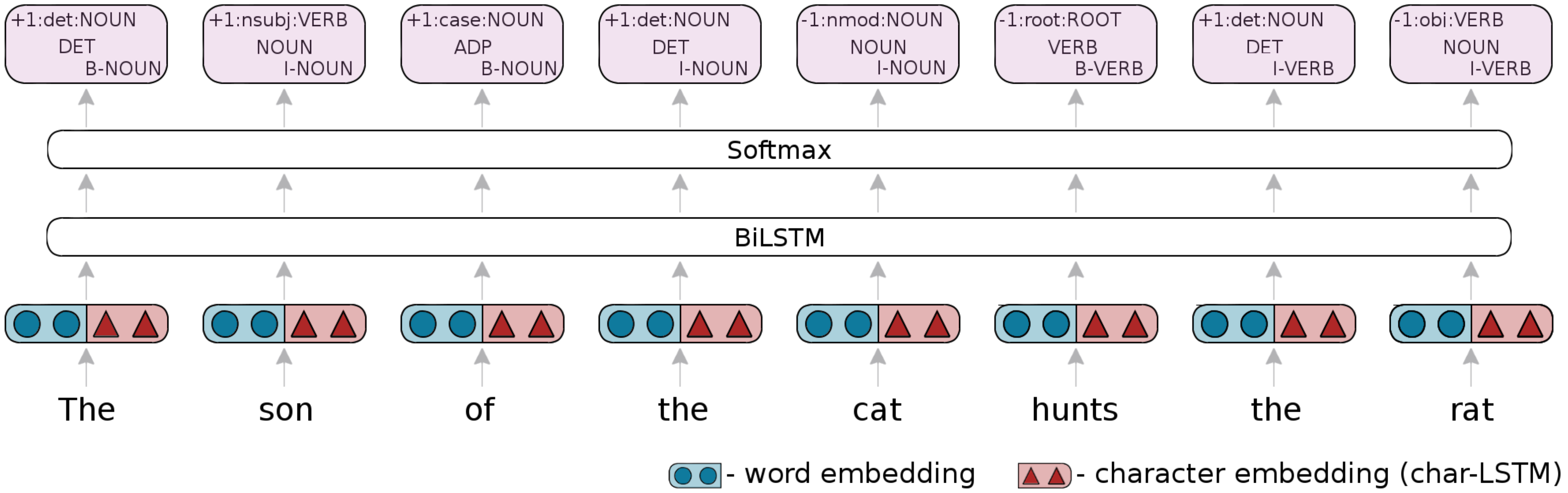

## Japanese-GSD



# SYSTEM DETAILS.

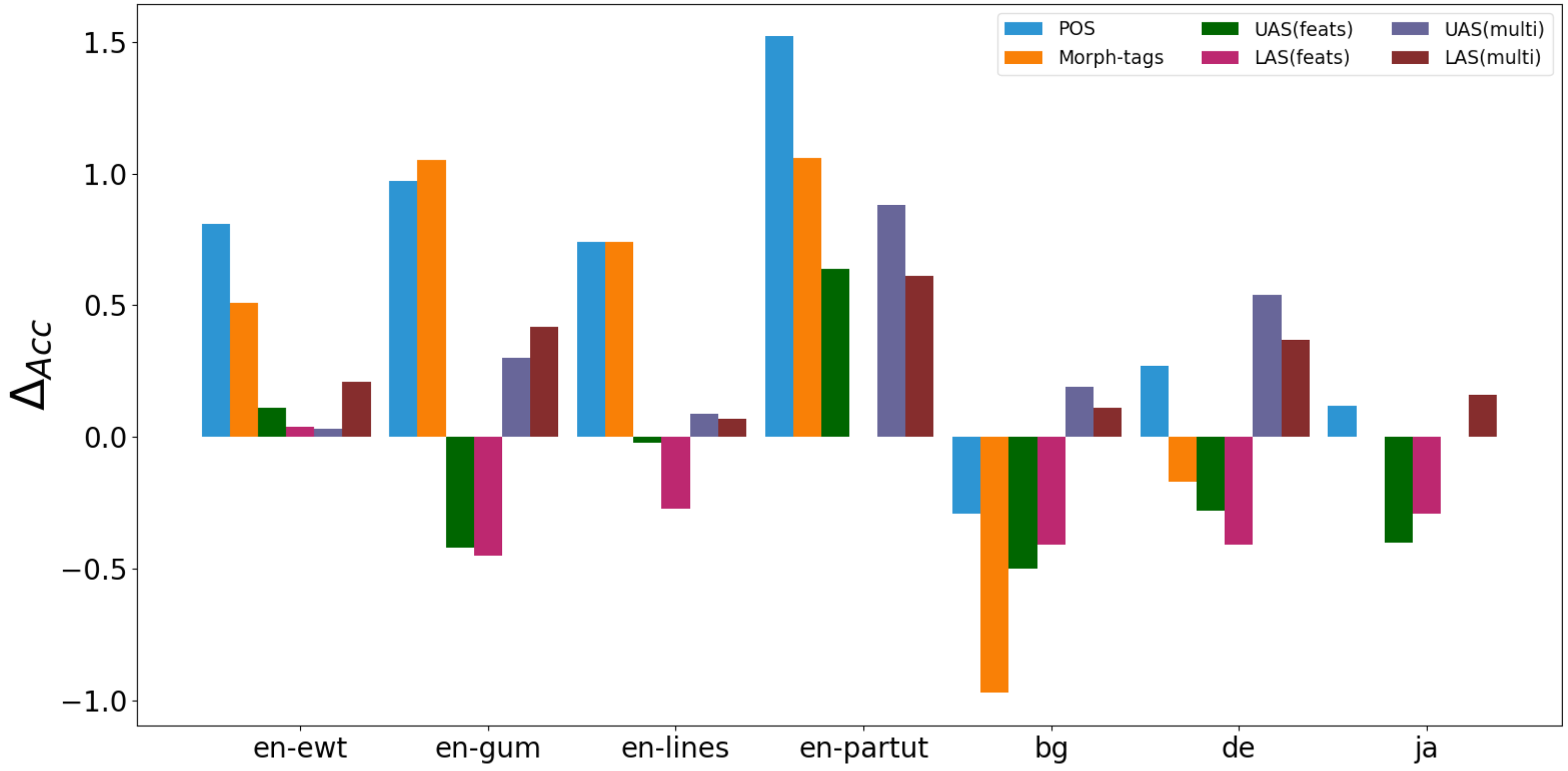
We use a neural sequence labelling toolkit, NCRF++.[1] And a relative POS tag position encoding for sequence labelling parsing.[2]

[1]Yang, J. and Zhang Y., *NCRF++: An Open-source Neural Sequence Labeling Toolkit*, 2018
[2]Spoustová, D.J. and Spousta M. *Dependency Parsing as a Sequence Labeling Task*, 2010



# Broad results

Difference between **with** and **without** chunks.

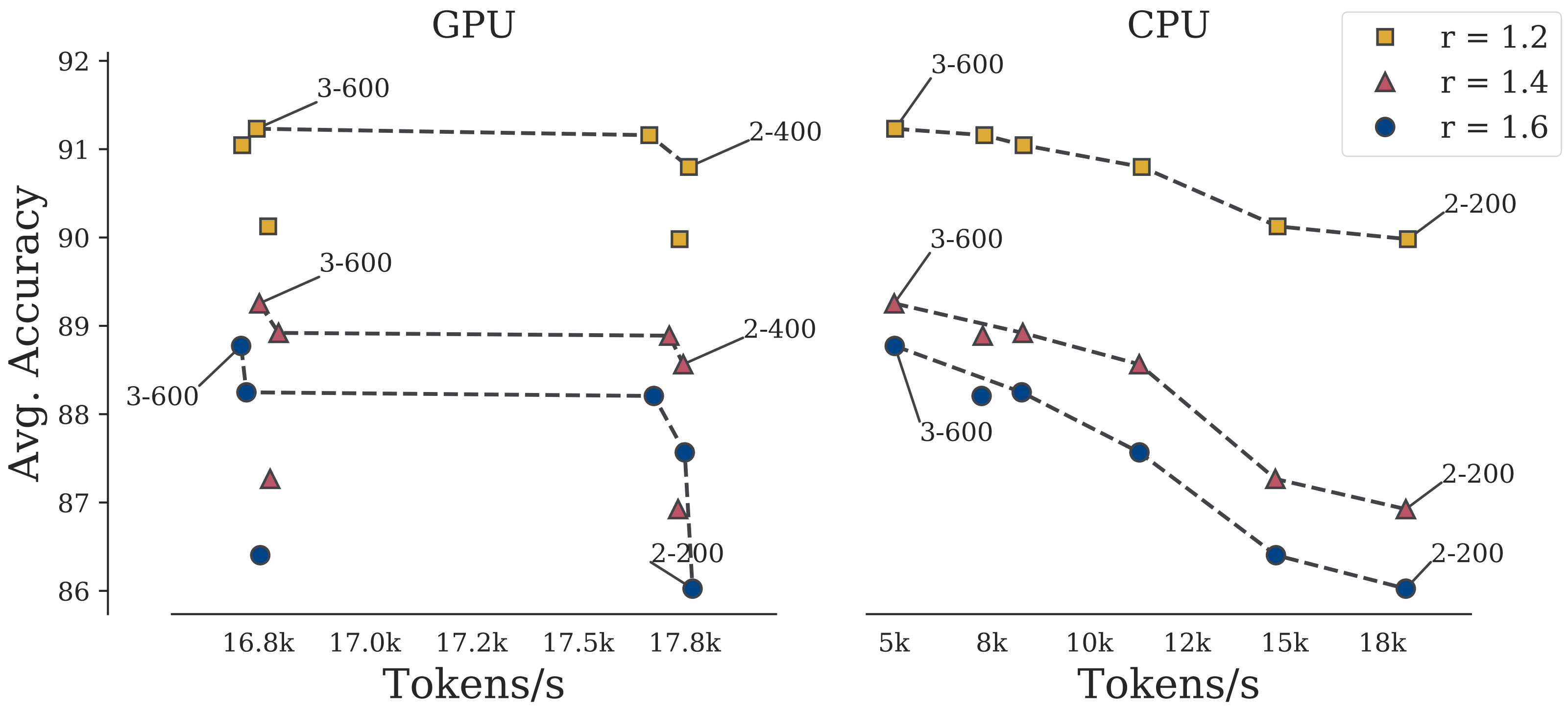


# Chunk and Pass Parsing

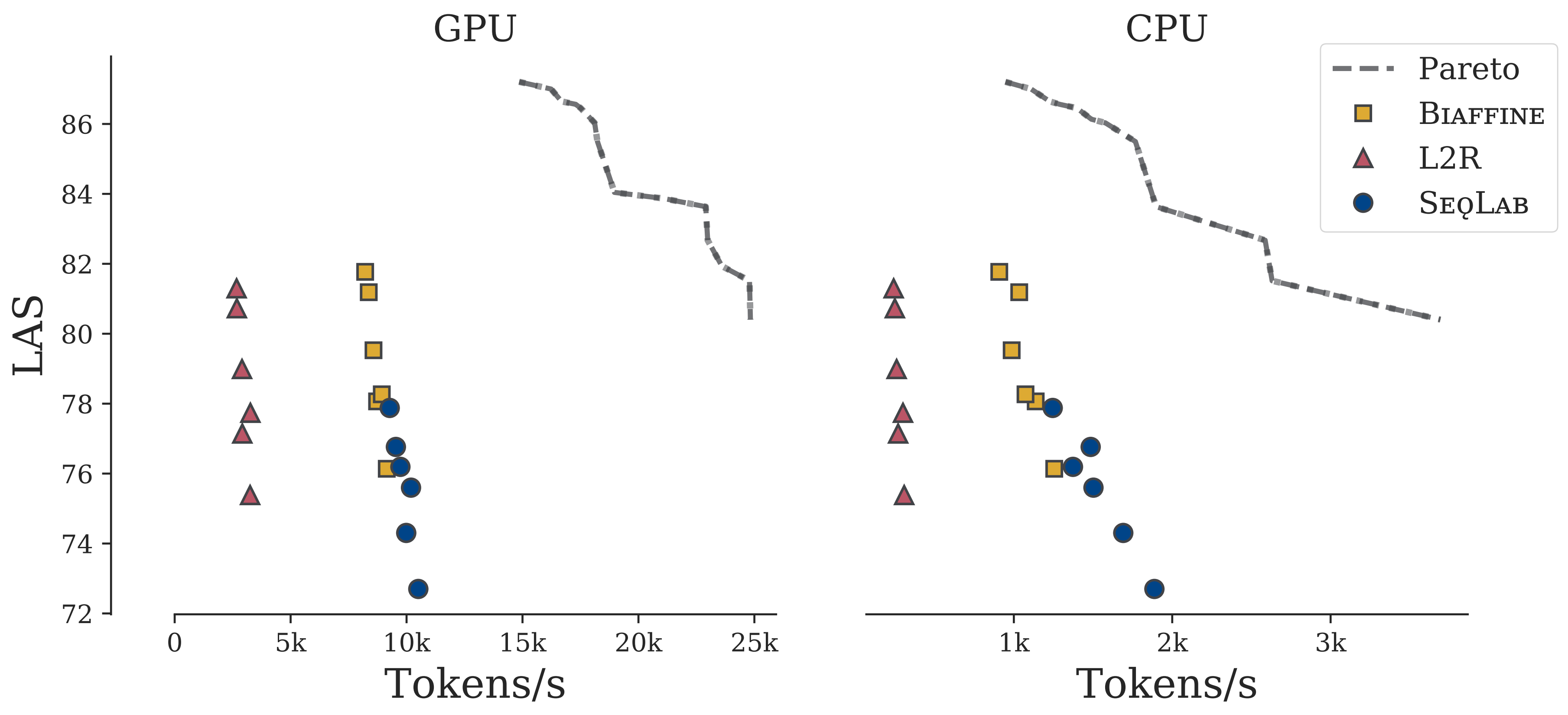
- Normalised PMI (used various thresholds to obtain different amount of compression)
- Compared to/with leading sytems (biaffine, l2r, and sequence labelling).
- All same network type (BiLSTM).

# Chunker performance (BiLSTM w/ fastText and char embeddings)

Varying compression and network size. Reasonable performance.
Extends to labelled edge predictions.
(Chinese, Hindi, Korean, and Polish)

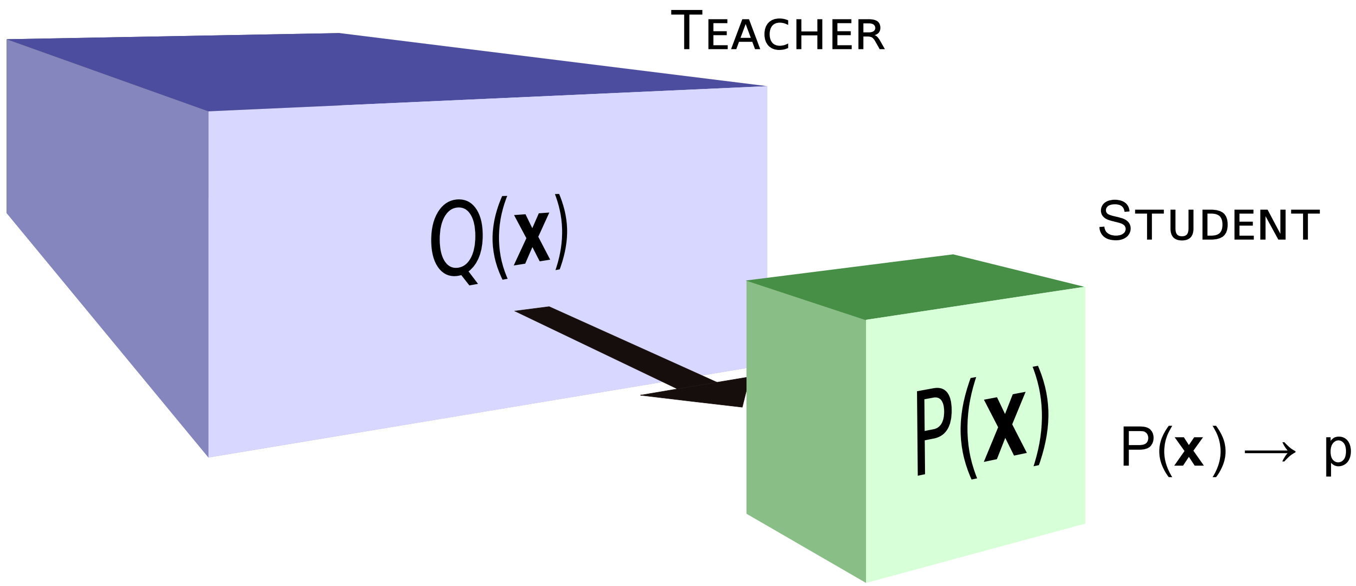


# Pareto Front for UD (zh, hi, ko, pl)



# Distillation

# Teacher-student distillation




$P(\mathbf{x}) \to p(h|\,\mathbf{x})$

$\mathcal{L}_{KL}(Q(\mathbf{x}),P(\mathbf{x})) + \mathcal{L}_{CE}(p(h|\mathbf{x}))$

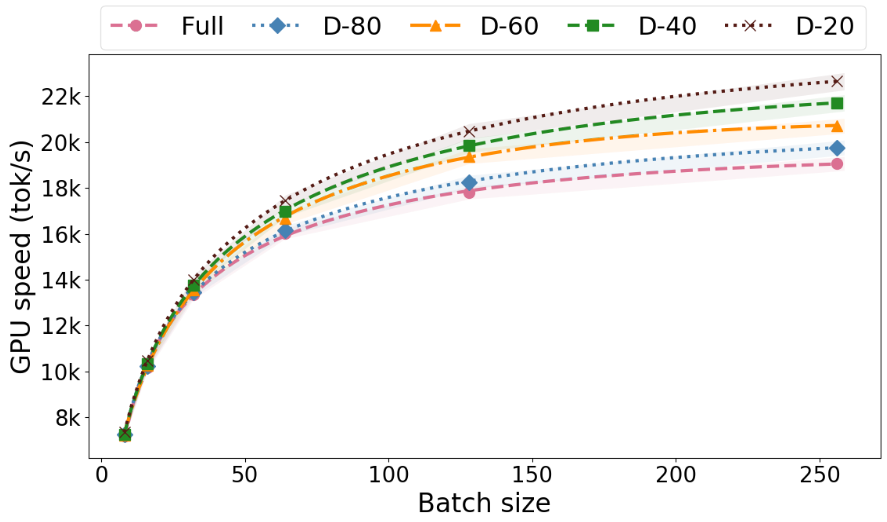
# Experiments

- Used Biaffine (fast and accurate).
- Compared against teacher and small models.
- Used UDv2.4 (Ancient Greek, Chinese, English, Finnish, Hebrew, Russian, Tamil, Uyghur, and Wolof). Treebanks based on subset used in de Lhoneux et al. (2017).[1]
- Compress to 20%, 40%, 60%, and 80% of original model.
- fastText and gold POS tags. (°‸°)

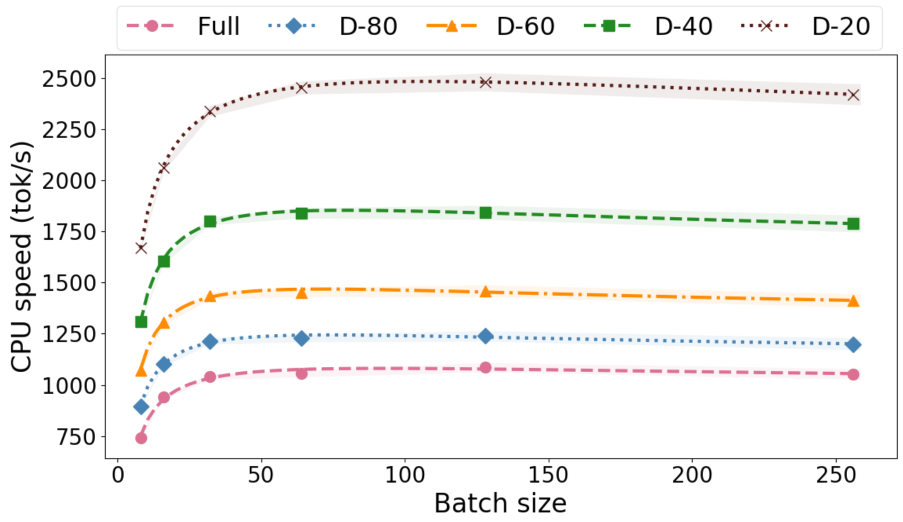
[1] de Lhoneux, M., Stymne, S. and Nivre, J. *Old school vs. new school: Comparing transition-based parsers with and without neural network enhancement*, 2017

# SPEED

## GPU

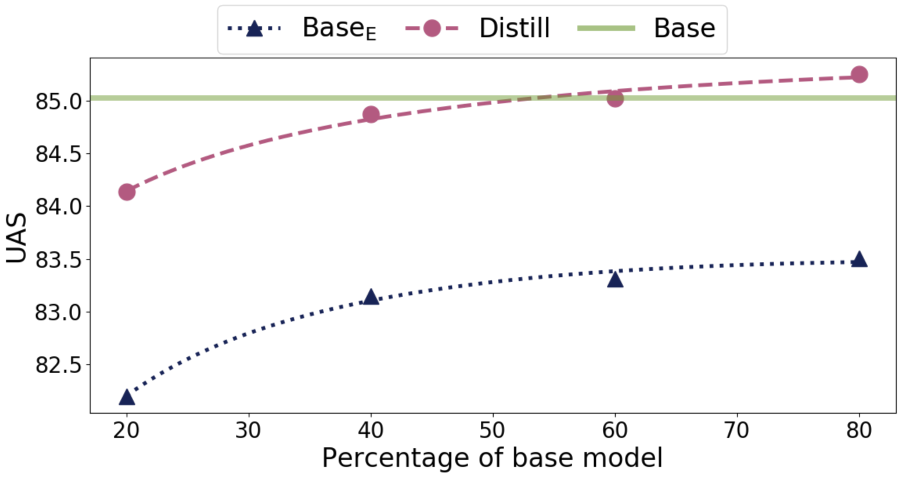



## CPU

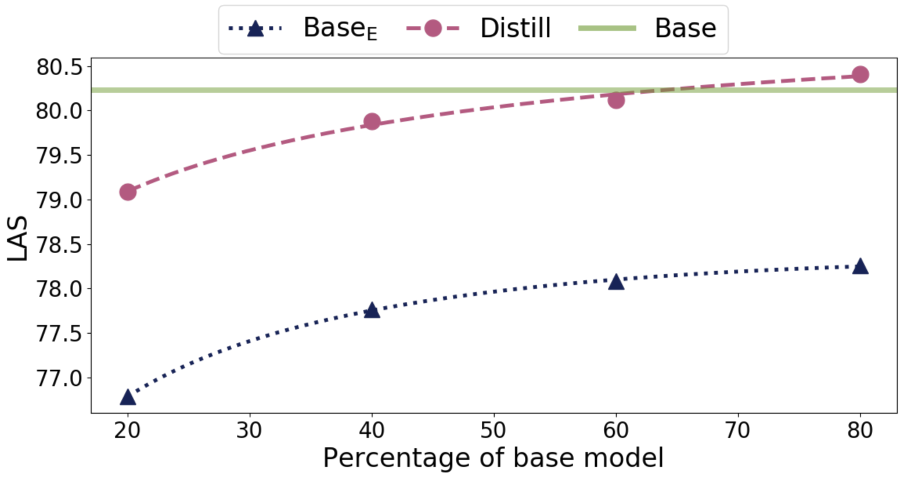


# Accuracy

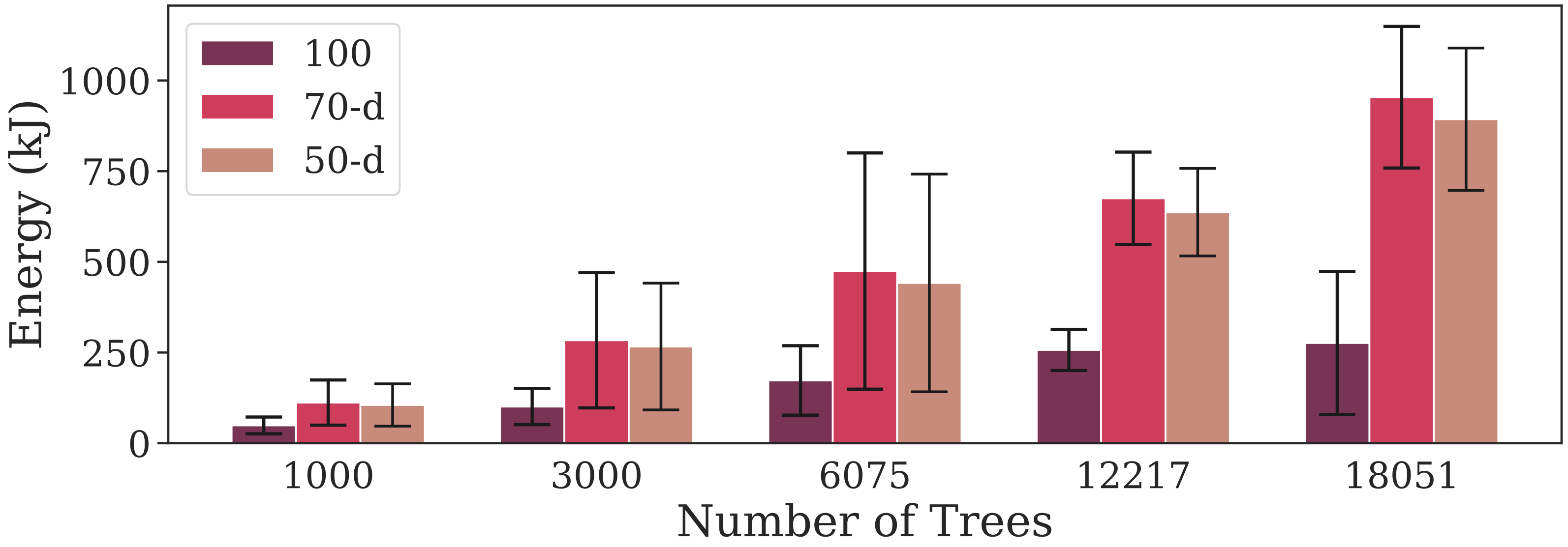
## UAS




## LAS



# Energy cost

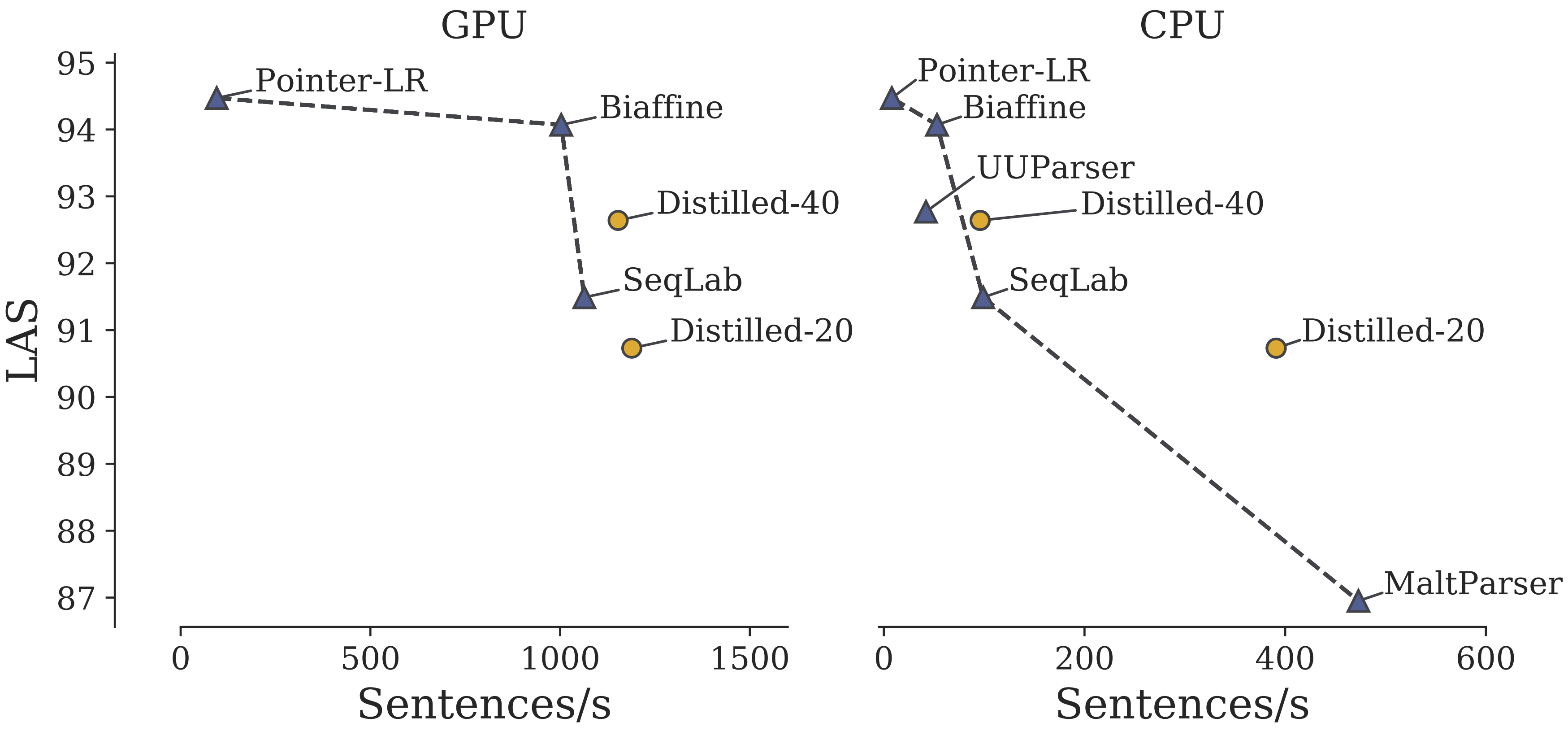


100
70-d
50-d
Energy (kJ)
0
250
500
750
1000
1000
3000
6075
12217
18051
Number of Trees

# Inconsistent

- Subsequent work using only randomly initialised word and character.
- Didn't outperform small baselines.

# Pareto Front for PTB (WSJ)



# Part II

## Evaluating Parsers

# Dependency displacement

# Transition-based algorithms

**Different transition-based algorithms perform differently on different treebanks**

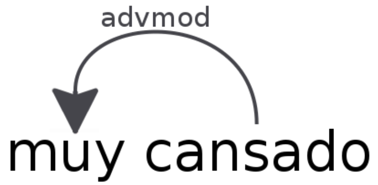
**Perhaps because certain algorithms are inherently biased to creating edges that match given languages/treebanks?**

- Used a non-NN parser, MaltParser.[1]
- Contains multiple algorithms.
- Differences between algorithms observed still seen in NN implementations.[2]
- 76 treebanks from UD v2.2.

[1] Nivre, J. et al., *MaltParser: A language-independent system for data-driven dependency parsing*, 2007.
[2] de Lhoneux, M., Stymne, S. and Nivre, J. *Old school vs. new school: Comparing transition-based parsers with and without neural network enhancement*, 2017

# Transition-based algorithms

| STACK | BUFFER |
|---|---|
| | Estoy muy ca.. |
| SHIFT | b0 to top of STACK |
| Estoy | muy cansado |
| SHIFT | b0 to top of STACK |
| Estoy muy | cansado por... |
| REDUCE(right-advmod) | remove s0 from STACK |
| Estoy | cansado por... |



# Algorithms

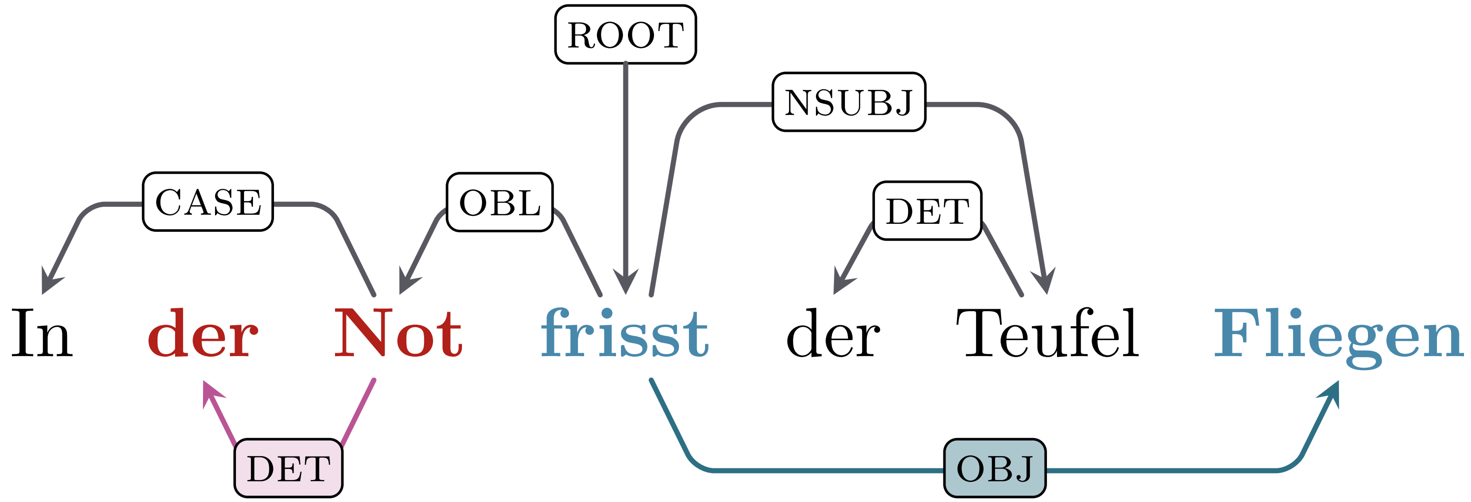
## Projective

- Arc Standard
- Arc Eager
- Covington Projective

## Non-projective

- Arc Swap
- Covington Non-projective

# Dependency displacement

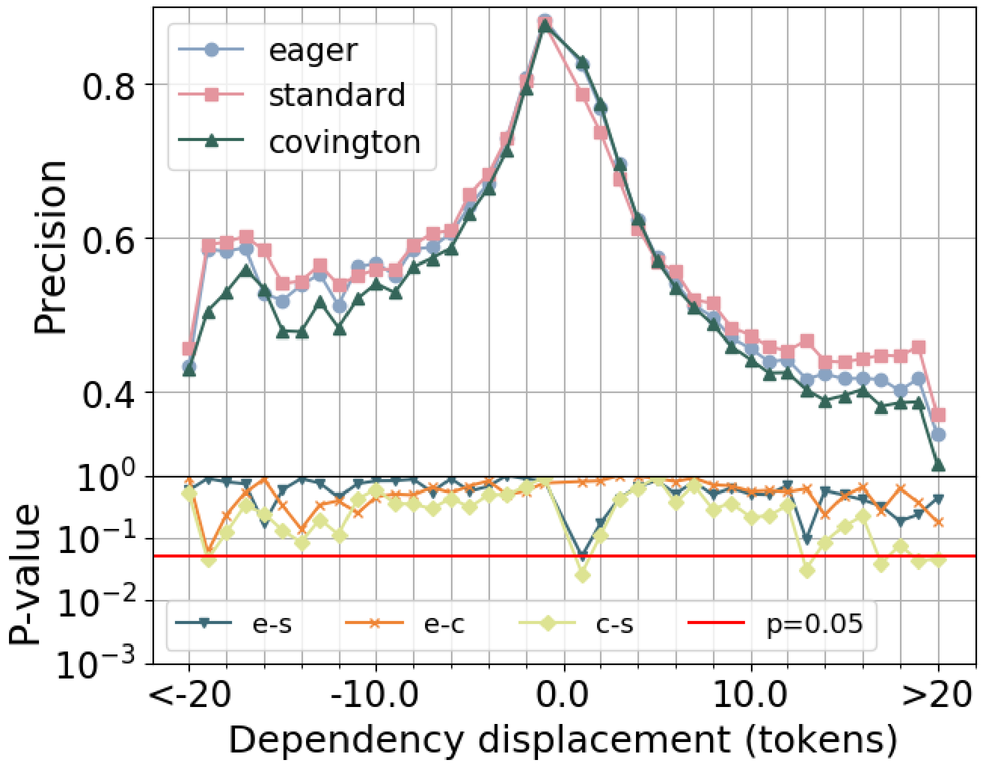



DET edge between der and Nott: -1 (2-3)

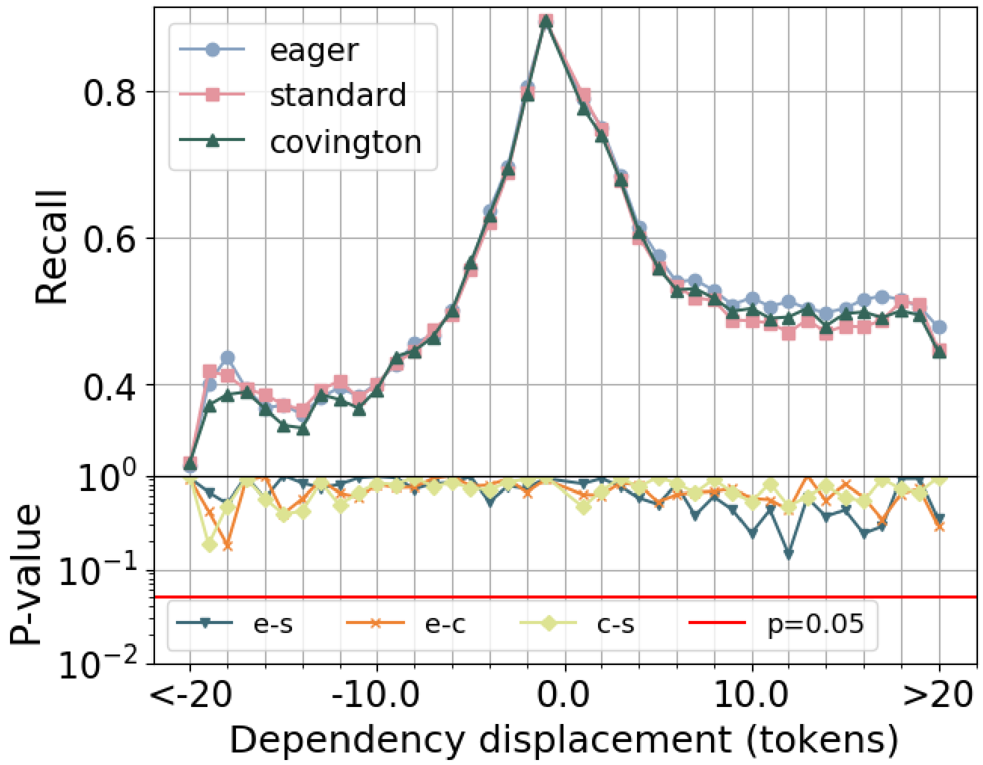
OBJ edge between frisst and Fliegen: 3 (7-4)

# Projective algorithms

## Precision

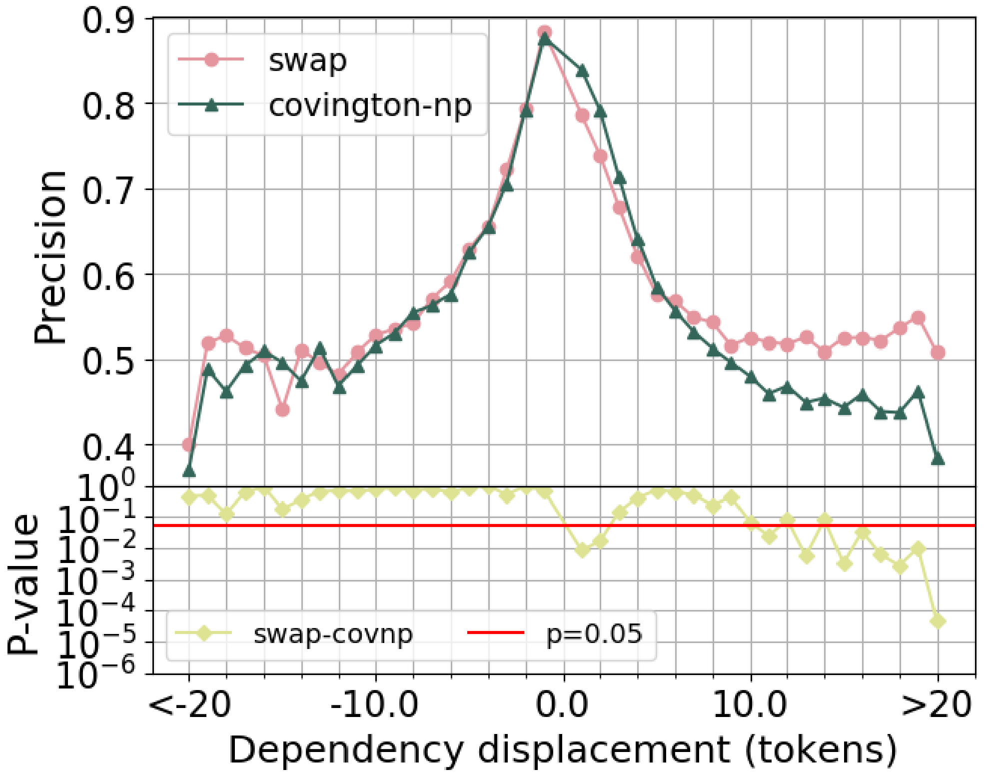



## Recall

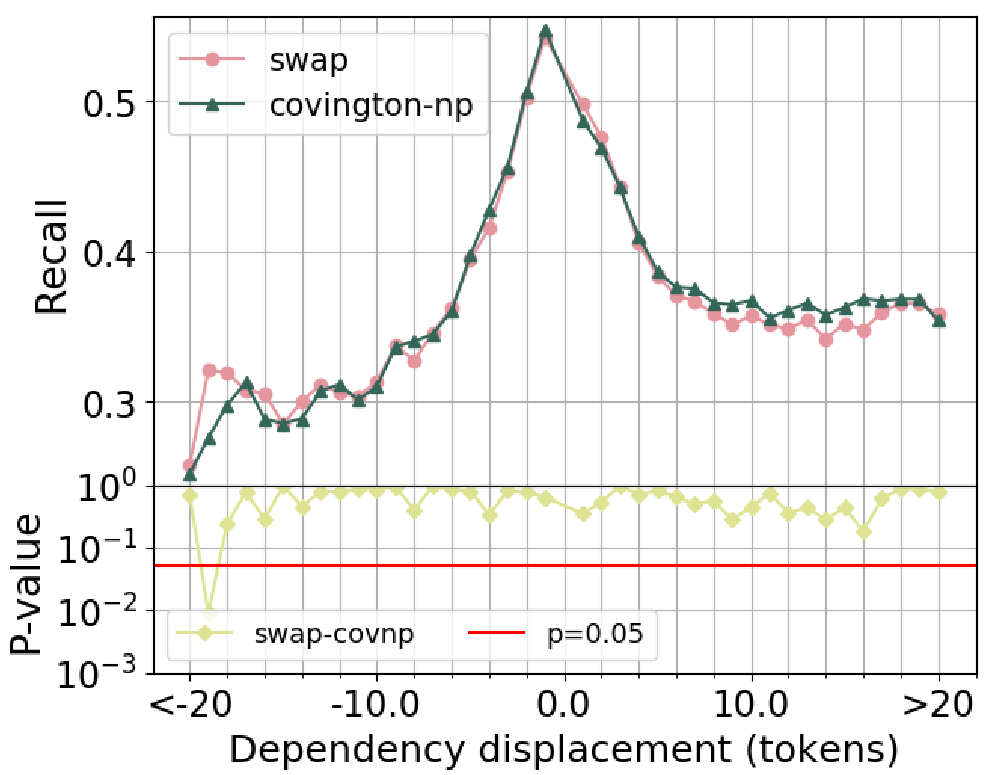


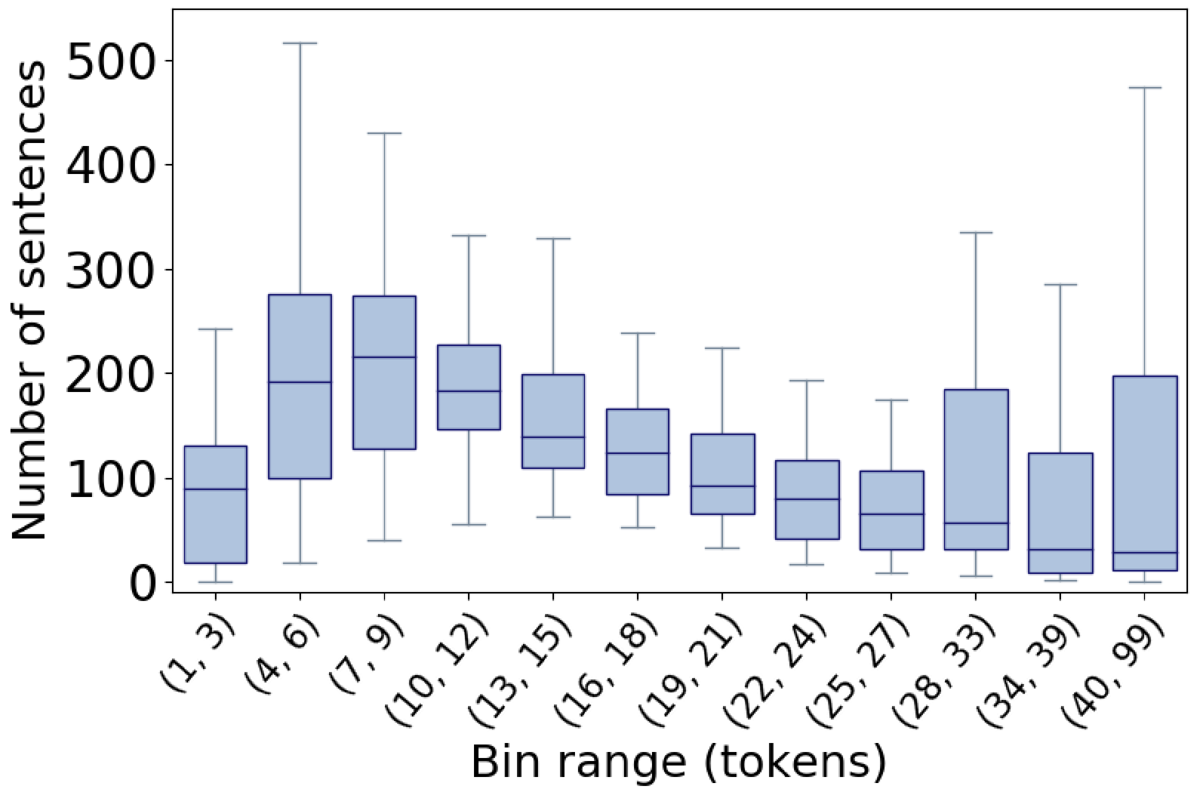
# Non-projective algorithms

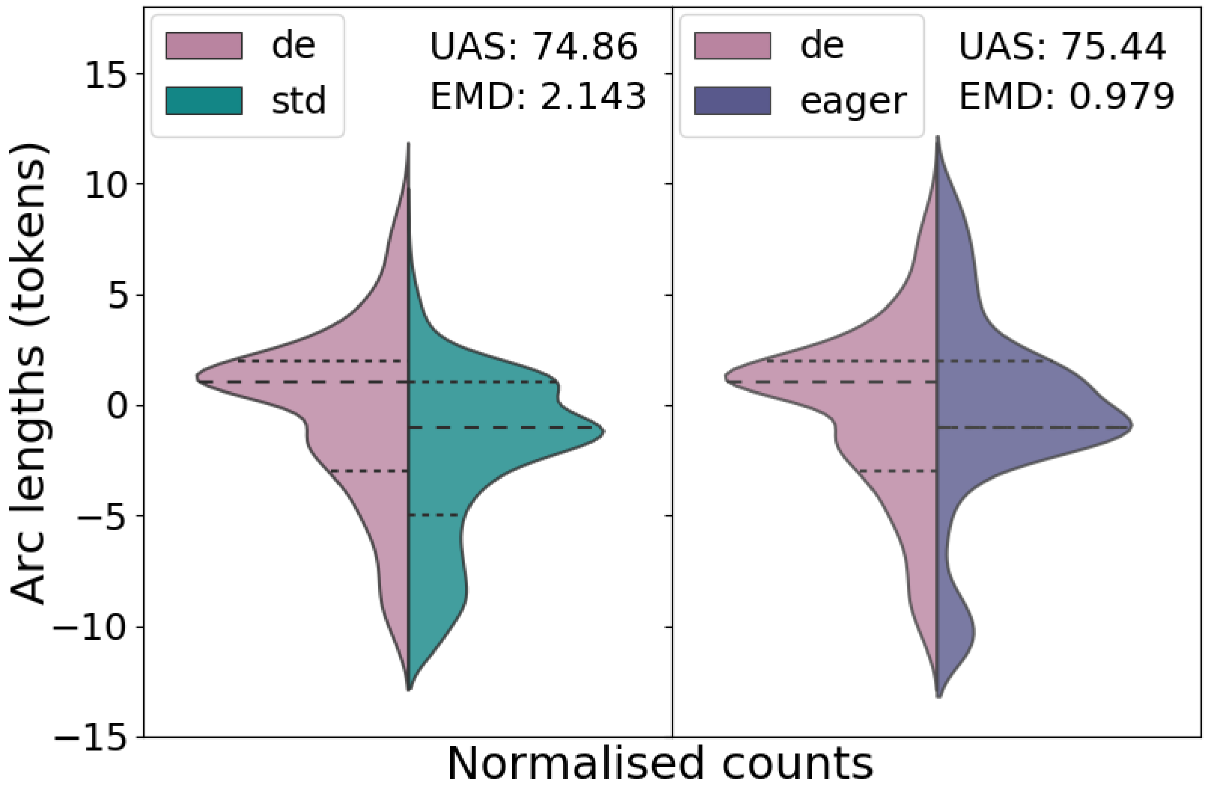
## Precision



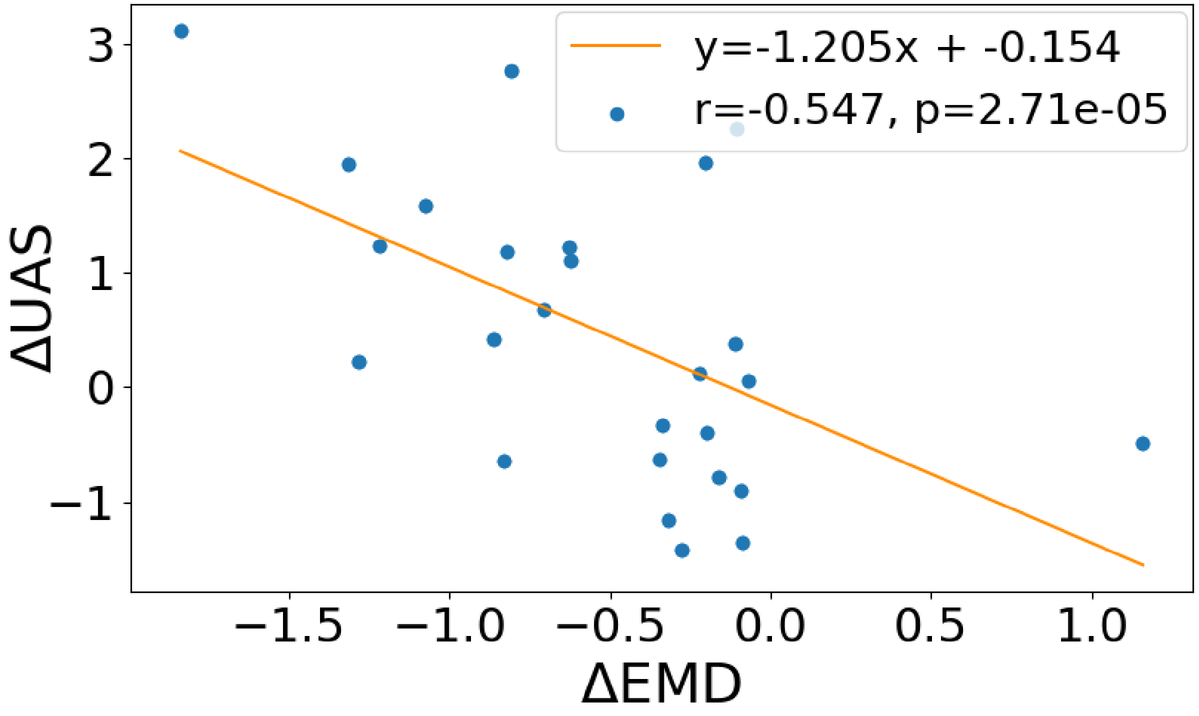

## Recall

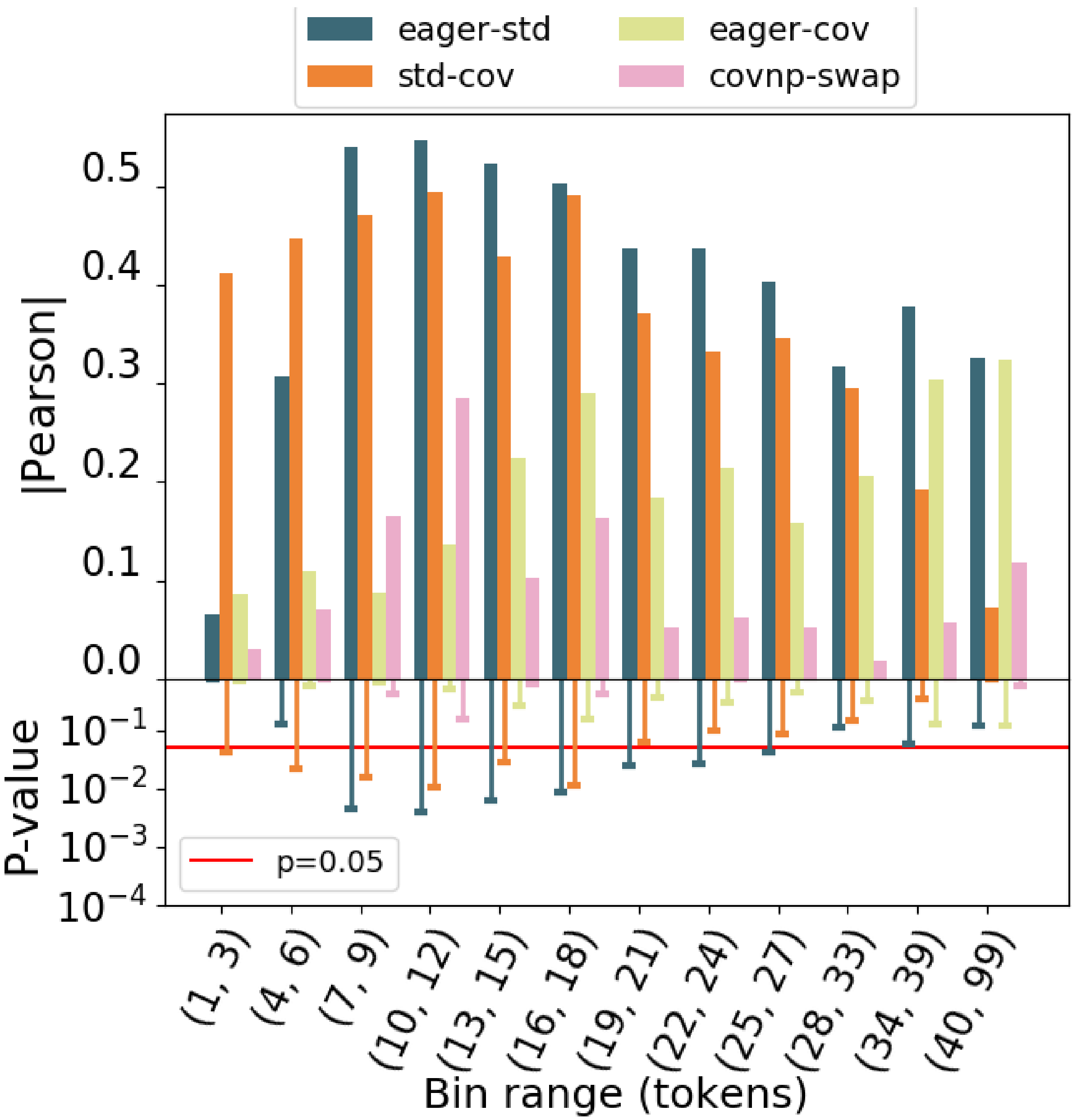



Number of sentences
0
100
200
300
400
500
(1, 3)
(4, 6)
(7, 9)
(10, 12)
(13, 15)
(16, 18)
(19, 21)
(22, 24)
(25, 27)
(28, 33)
(34, 39)
(40, 99)
Bin range (tokens)



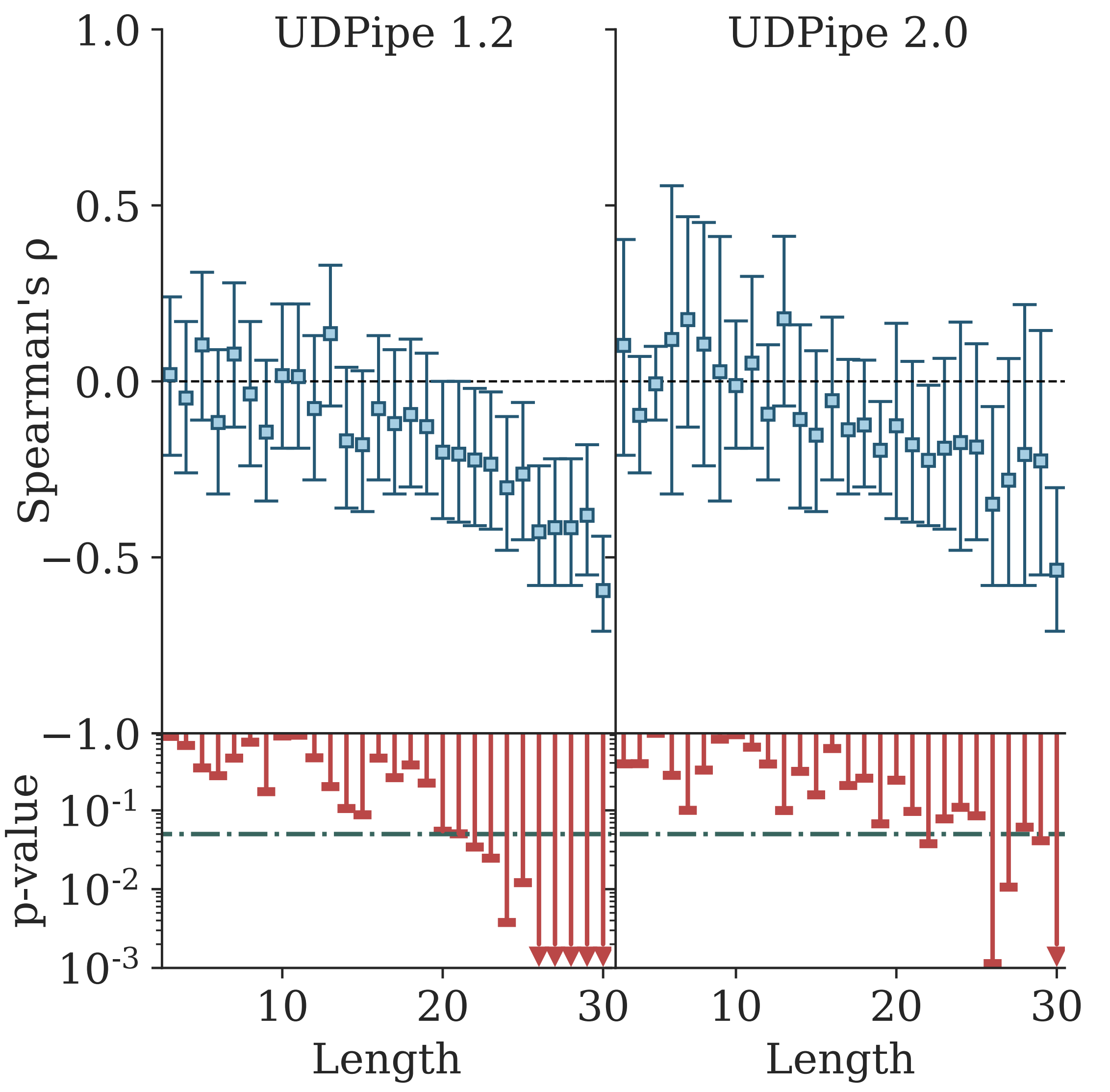
de
std
UAS: 74.86
EMD: 2.143
de
eager
UAS: 75.44
EMD: 0.979
15
10
5
0
−5
−10
−15
Arc lengths (tokens)
Normalised counts


y=-1.205x + -0.154
r=-0.547, p=2.71e-05
ΔUAS
ΔEMD
3
2
1
0
−1
−1.5
−1.0
−0.5
0.0
0.5
1.0

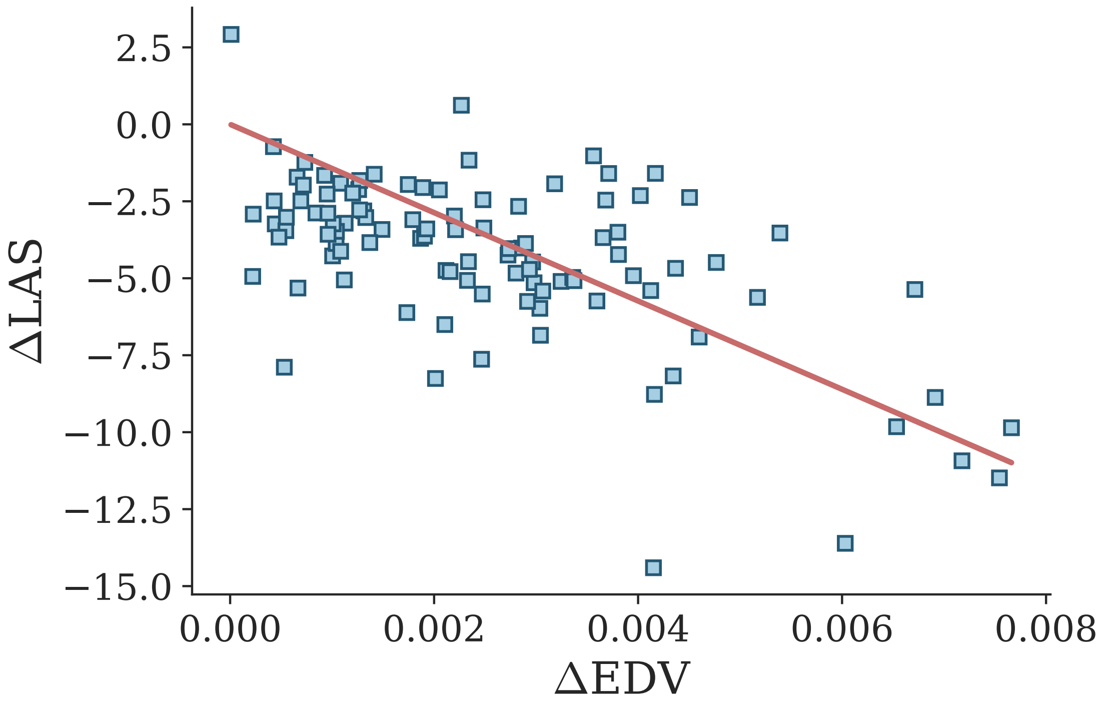


eager-std
std-cov
eager-cov
covnp-swap
|Pearson|
0.0
0.1
0.2
0.3
0.4
0.5
P-value
$10^{-1}$
$10^{-2}$
$10^{-3}$
$10^{-4}$
p=0.05
(1, 3)
(4, 6)
(7, 9)
(10, 12)
(13, 15)
(16, 18)
(19, 21)
(22, 24)
(25, 27)
(28, 33)
(34, 39)
(40, 99)
Bin range (tokens)

# Training vs Test Data



# Adversarial Splits



# Universal POS tags

# Parsers

## UUParser

Transition-based parser out of Uppsala developed from TB BIST Parser.[1,2]

## Biaffine

Graph-based parser developed from GB BIST Parser.[3]

word⊕char⊕upos

External pre-trained word embeddings, mainly fastText.

Same treebanks from distillation work.

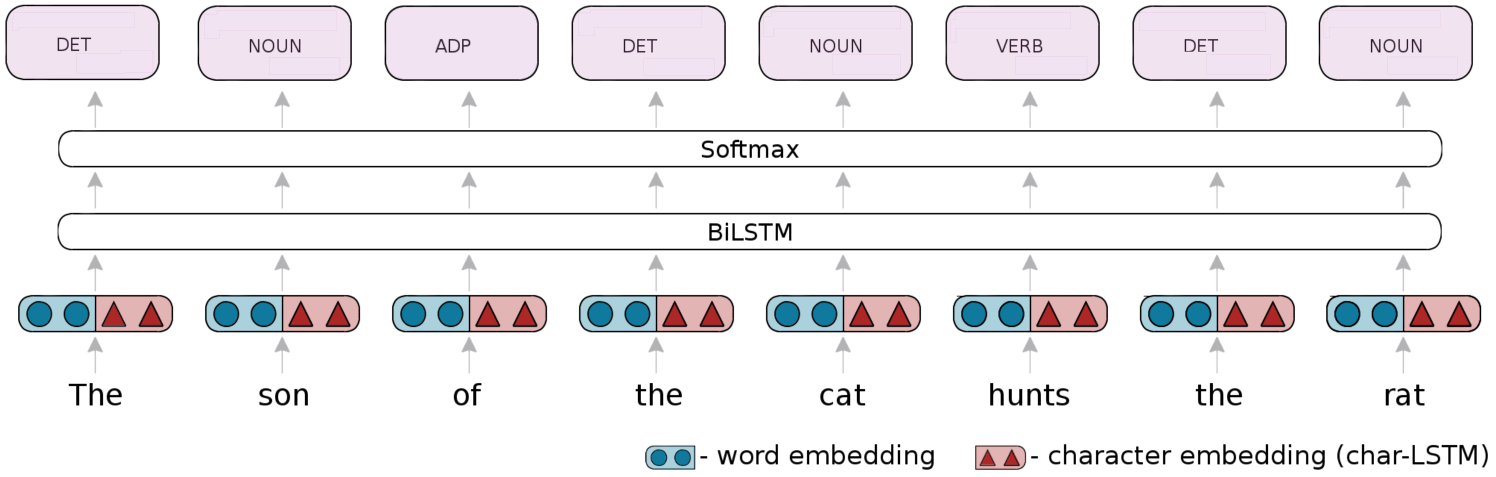
[1]Kiperwasser, E. and Goldberg, Y. *Simple and accurate dependency parsing using bidirectional LSTM feature representations*, 2016
[2]Smith, A., de Lhoneux, M., Stymne, S. and Nivre, J. *An investigation of the interactions between pre-trained word embeddings, character models and POS tags in dependency parsing*, 2018
[3]Dozat, T. and Manning, C.D., *Deep biaffine attention for neural dependency parsing*, 2017

# Controlling UPOS accuracy

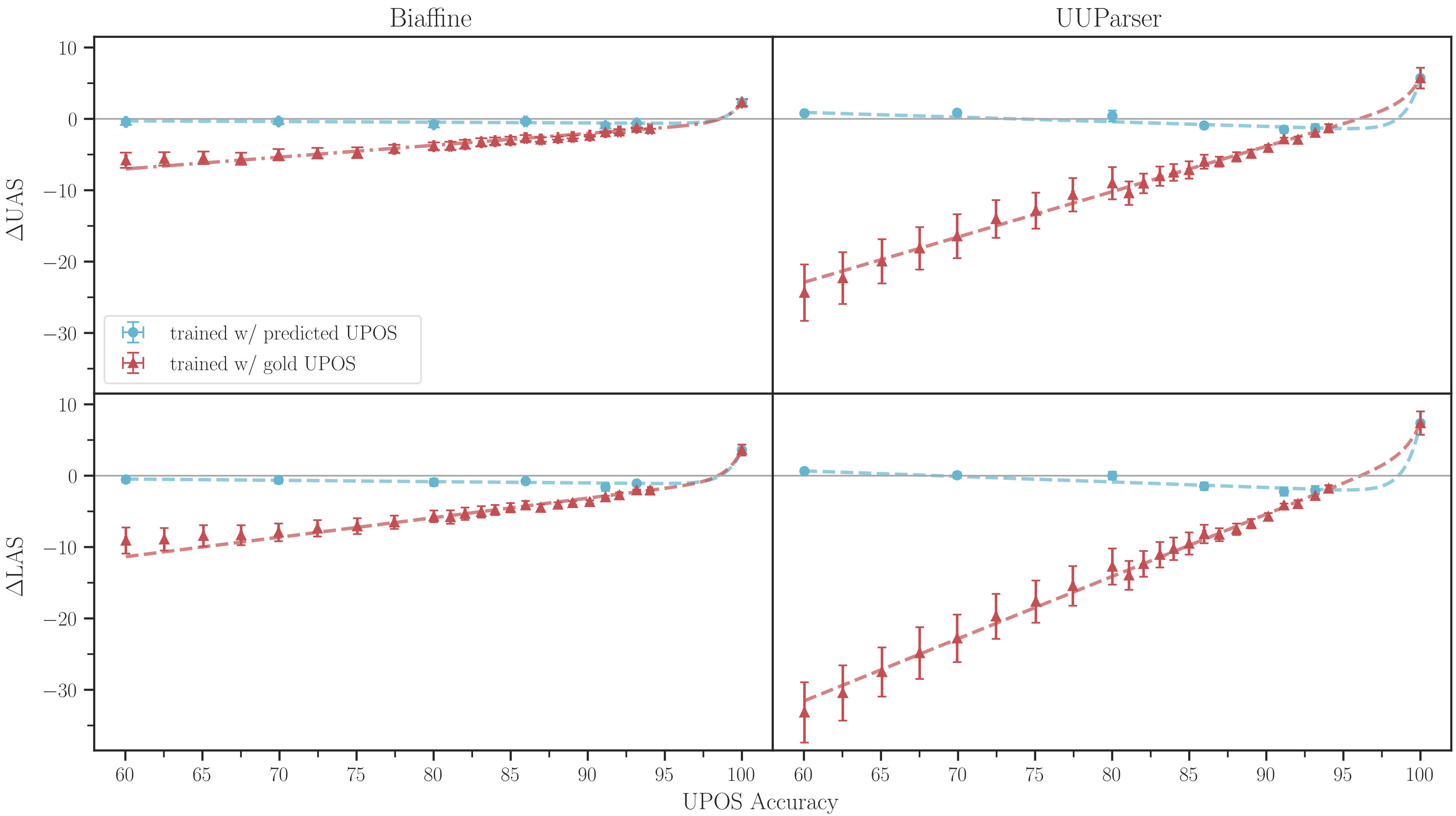
**NCRF++** BiLSTM SL framework

**BINS:**: 2.5±0.3 from 60 to 80 and 1±0.3 from 80 onwards.

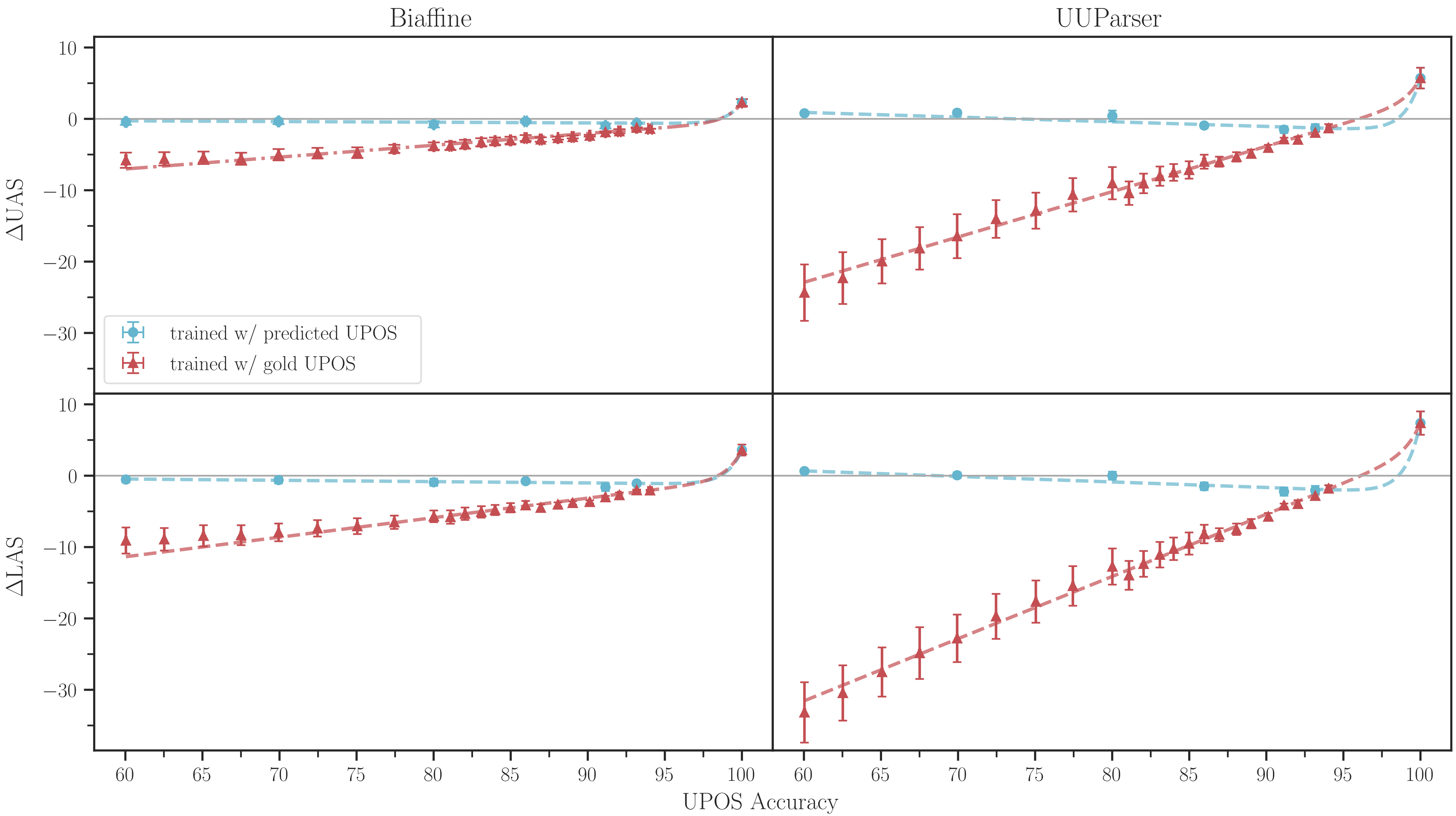
**PARSERS:** For training used gold tags and a subset of accuracy bins (60, 70, 80, 86, 91, and 93).



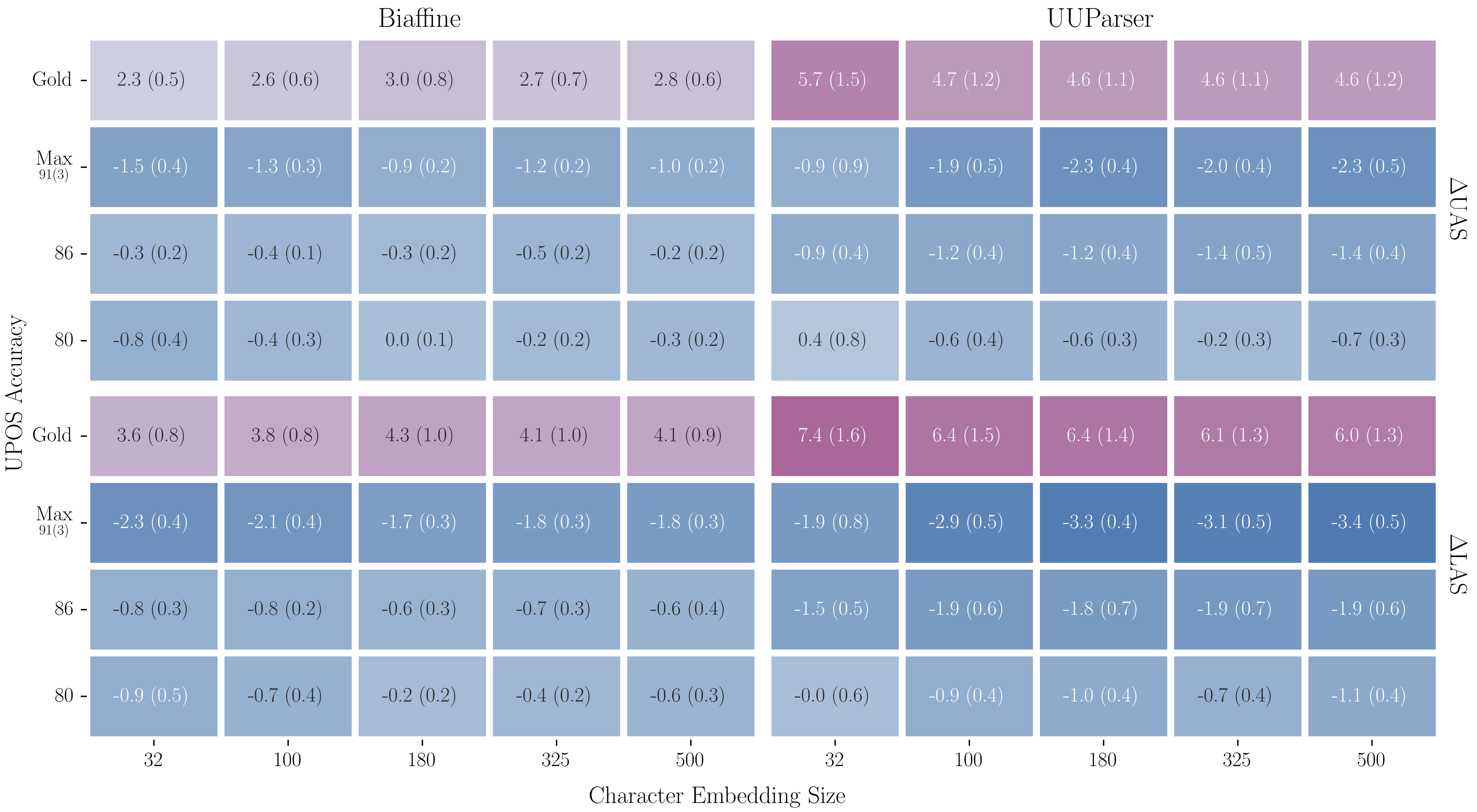
# Experiment 1



# Experiment 1

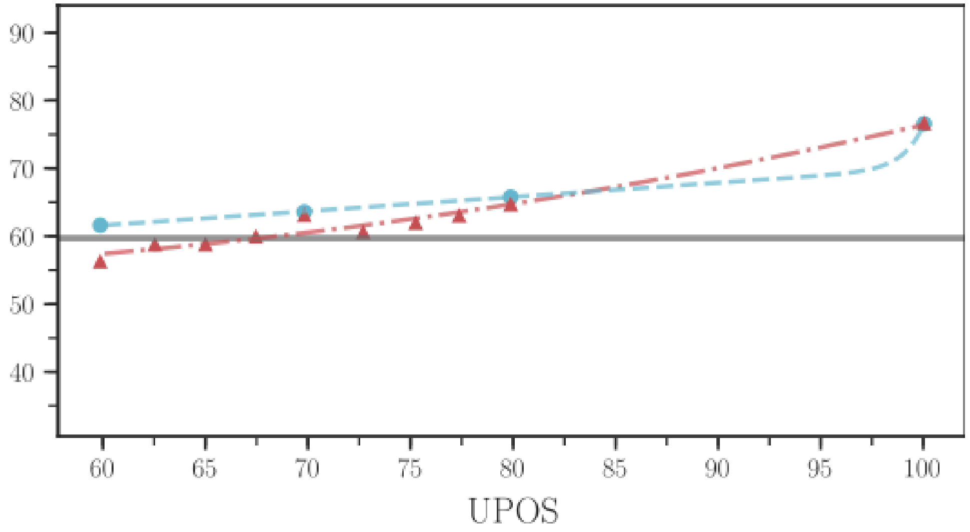


# Experiment 2

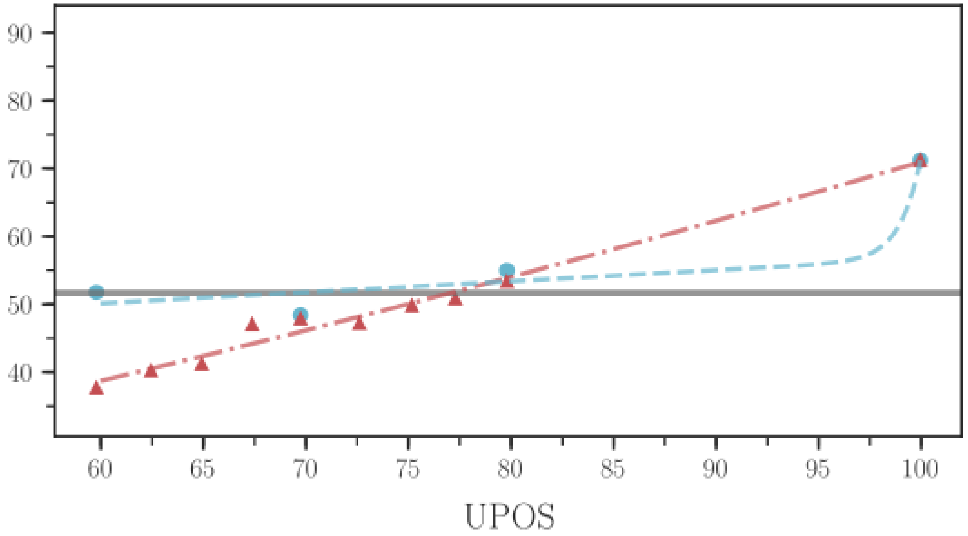


# Tamil results (~400 sentences)

UAS




LAS




Still some improvement with low-accuracy taggers.

# Very low-resource

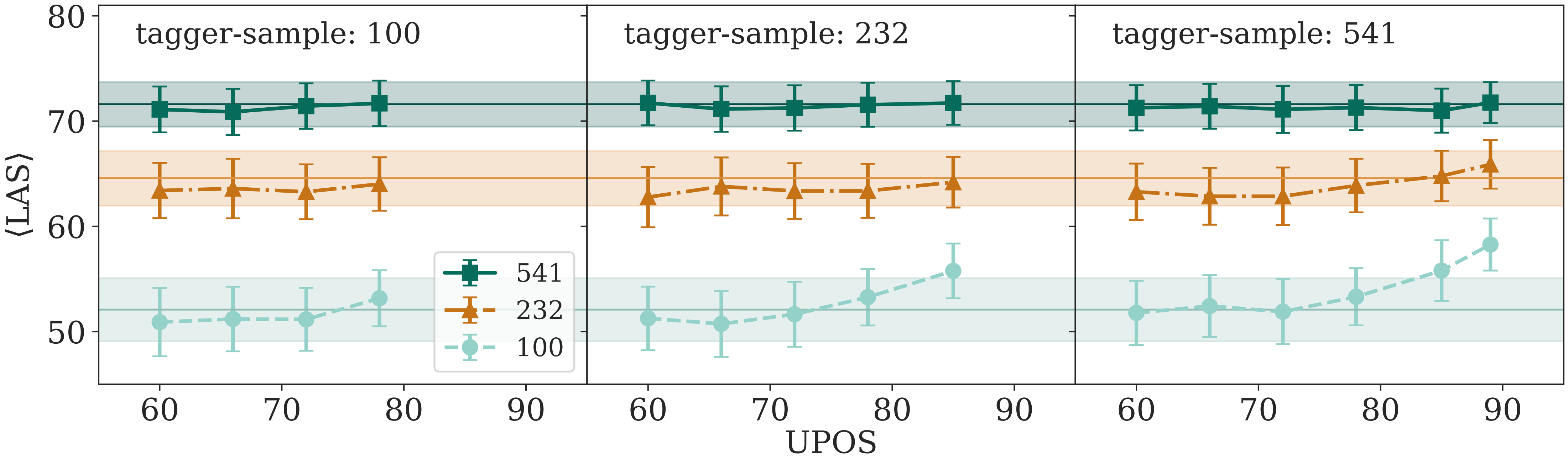
| | UPOS | | LAS | | | |
|---|---|---|---|---|---|---|
| | Single | Multi | None | Pred | Gold | Multi |
| **bxr** | 48.72 | 48.34 | 10.45 | 12.36 | 20.31 | 14.41 |
| **kk** | 53.37 | 52.14 | 22.48 | 21.63 | 36.66 | 23.50 |
| **kmr** | 50.56 | 53.73 | 19.16 | 18.31 | 35.54 | 21.58 |
| **olo** | 37.84 | 37.37 | 9.74 | 10.89 | 17.54 | 7.59 |
| **hsb** | 53.44 | 47.28 | 18.36 | 20.03 | 41.88 | 14.66 |
| **avg** | 48.79 | 47.77 | 16.04 | 16.64 | 30.39 | 16.25 |

# Fairly low-resourced

| | UPOS | | LAS | | | |
|---|---|---|---|---|---|---|
| | Single | Multi | None | Pred | Gold | Multi |
| **be** | 92.82 | 87.29 | 61.82 | 64.91 | 68.87 | 62.28 |
| **gl** | 93.54 | 88.56 | 70.60 | 72.73 | 79.06 | 70.54 |
| **lt** | 79.25 | 71.51 | 37.17 | 35.94 | 48.30 | 38.96 |
| **mr** | 80.58 | 76.46 | 57.04 | 58.74 | 64.32 | 56.31 |
| **orv** | 87.77 | 81.60 | 49.53 | 51.34 | 60.24 | 50.33 |
| **ta** | 86.88 | 79.23 | 63.85 | 62.75 | 74.31 | 63.15 |
| **cy** | 91.77 | 86.41 | 72.10 | 72.93 | 80.71 | 73.00 |
| **avg** | 85.89 | 77.77 | 55.24 | 56.52 | 64.13 | 55.10 |

# Artificial Low-resource

Indonesian GSD, Irish IDT, Japanese GSD, and Wolof WTB.

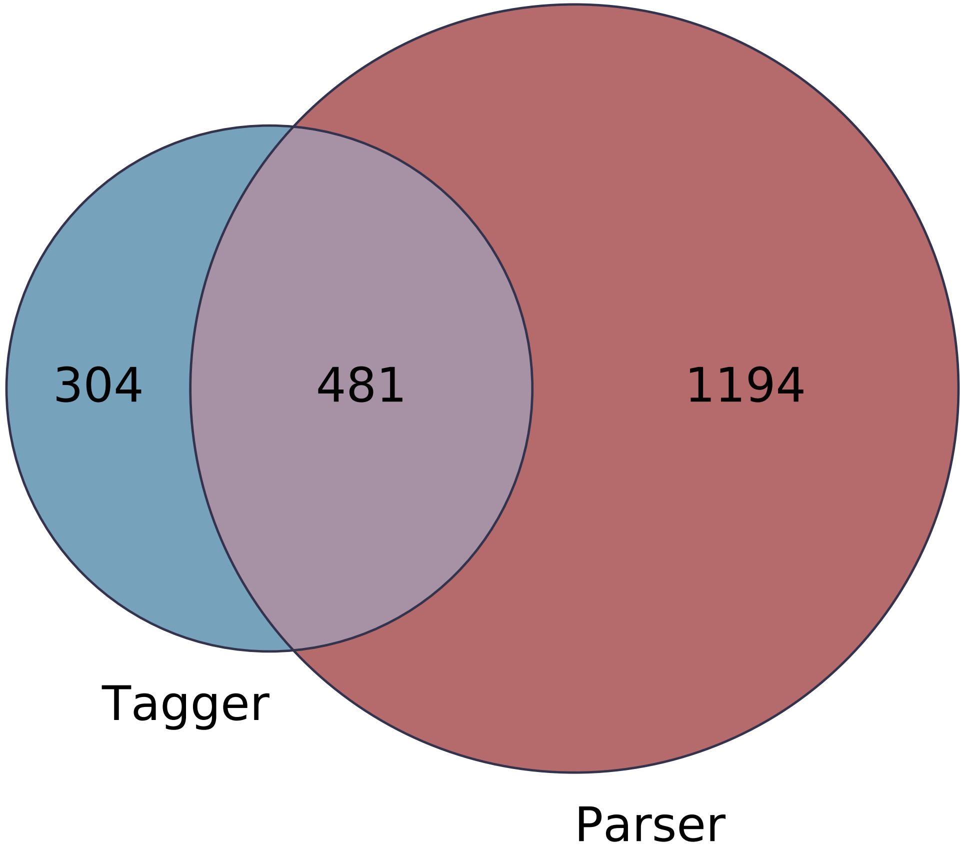


# Probing Experiment

Arabic, Basque, Finnish, Indonesian, Irish, Japanese, Korean, Tamil, Turkish, Vietnamese, and Wolof

- Trained parser (Biaffine)
- Finetuned parser to predict POS tags
- Trained taggers with same sytem

# Probing Experiment




Union of errors (average over treebanks).

## Masking Experiment

| | None | Pred. | $M\neg E_T$ | $M\neg E_P$ | $M\forall E_T$ | Gold |
|---|---|---|---|---|---|---|
| **ar** | 83.29 | 82.87 | 84.17 | 84.06 | 84.45 | 84.73 |
| **eu** | 81.12 | 81.14 | 82.33 | 82.62 | 83.13 | 84.45 |
| **fi** | 85.96 | 86.04 | 86.88 | 87.09 | 87.61 | 88.80 |
| **id** | 79.04 | 78.95 | 82.20 | 82.69 | 81.08 | 82.95 |
| **ga** | 76.13 | 76.57 | 76.62 | 76.65 | 77.46 | 77.90 |
| **ja** | 93.15 | 92.72 | 94.41 | 94.38 | 94.39 | 95.30 |
| **ko** | 85.40 | 85.86 | 87.53 | 87.82 | 87.44 | 88.52 |
| **ta** | 65.61 | 64.50 | 70.24 | 66.67 | 66.01 | 71.95 |
| **tr** | 66.67 | 67.68 | 67.62 | 67.66 | 67.84 | 68.86 |
| **vi** | 58.43 | 60.09 | 65.42 | 66.75 | 65.18 | 70.87 |
| **wo** | 77.87 | 78.49 | 82.03 | 81.39 | 81.11 | 85.41 |
| **avg** | 77.52 | 77.72 | 79.95 | 79.80 | 79.61 | 81.79 |

- None — no tags.
- Pred. — predicted tags.
- $M\neg E_T$ — gold tags except tagger errors.
- $M\neg E_P$ — gold tags except parser errors.
- $M\forall E_T$ — gold tags only tagger errors.
- Gold — all gold tags.

# End

# Collaborators (work presented)

Carlos Gómez Rodríguez

Mathieu Dehouck

David Vilares

# Conclusion

## Developing

- Chunk-and-Pass
- Distillation

## Evaluating

- Edge displacement
- POS tags