ARTIFICIALLY EVOLVED CHUNKS FOR MORPHOSYNTACTIC ANALYSIS

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WHY CHUNK?

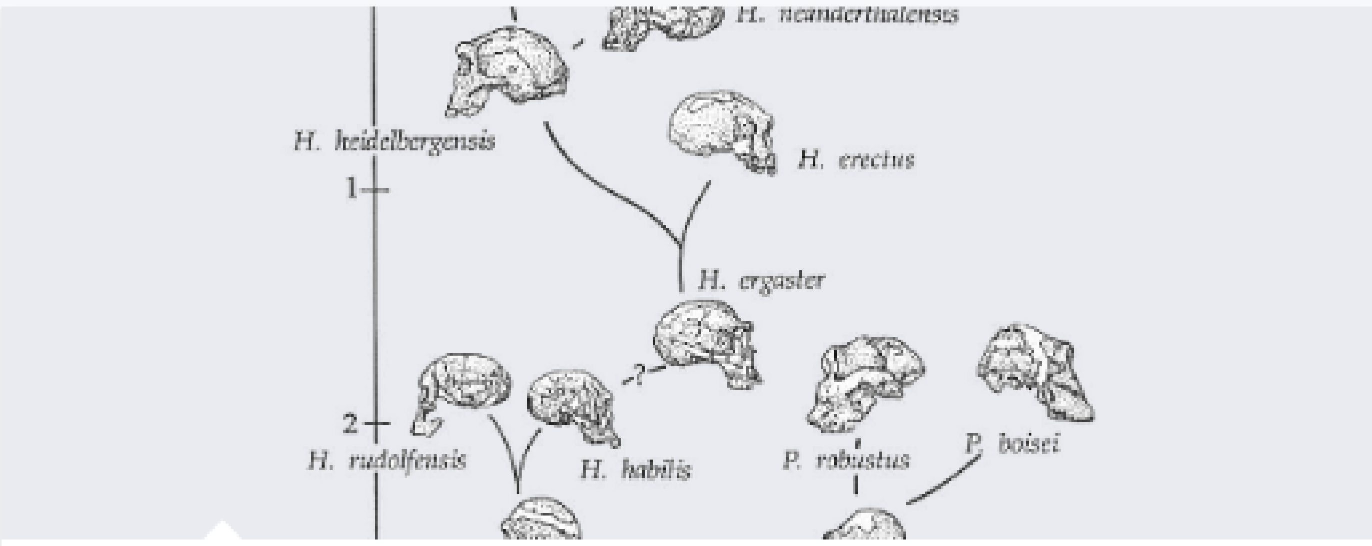
Chunking can help **constituency parsing** (Ciravegna and Lavelli, 1999; Tsuruoka and Tsujii, 2005).

It can also be beneficial for **dependency parsing** (Attardi and Dell'Orletta, 2008; Tammewaret et al., 2015).

And for **UD parsing** and **POS tagging** for English treebanks (Lacroix, 2018).

Psycholinguistic grounds for considering chunking (Christiansen and Chater, 2016).

CHUNKS



EVOLUTIONARY SEARCH

EXPERIMENTS

Chunk candidate criteria:

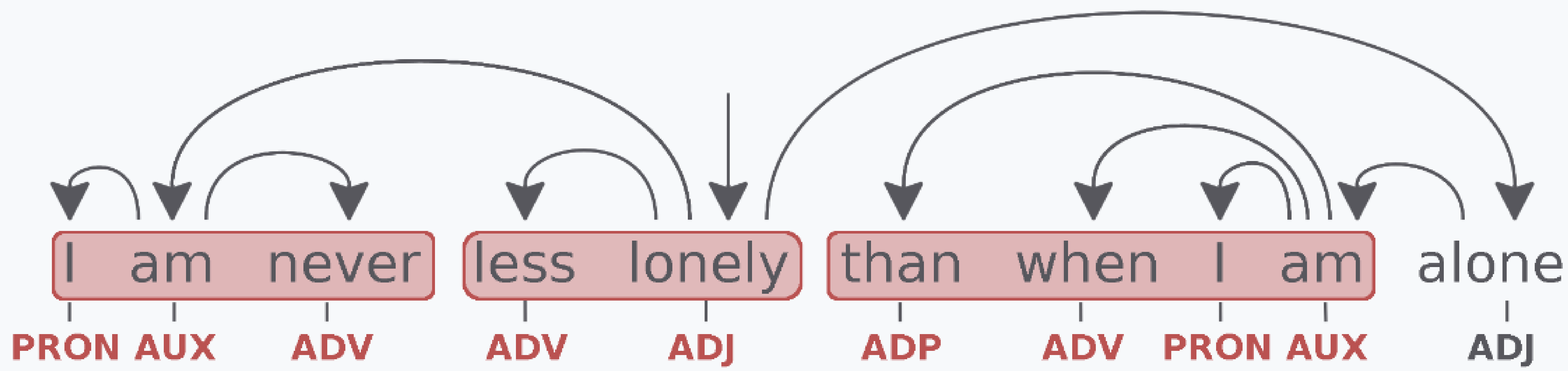
```
1. The components are syntactically linked

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.
```

Extracting rules.



Extracting rules.

(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)

CHUNKING

A sequence labelling task.

Each word is labelled, **B**, **I**, or **O**.

B

A token that begins a chunk.

Suffixed with chunk phrase type.

E.g. B-NP for a noun phrase.

I

A token inside of a chunk.

Also suffixed with chunk phrase type.

E.g. I-VP for a verb phrase.

O

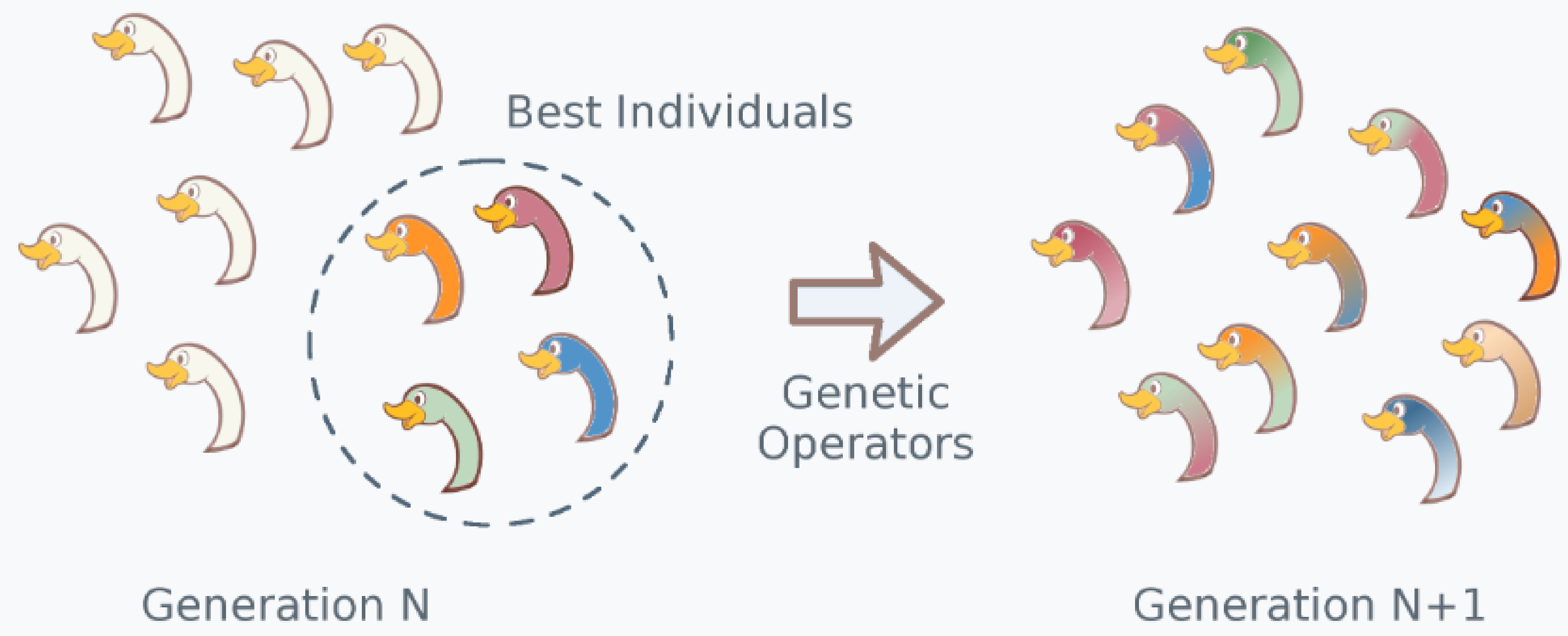
Anything outside of a chunk.

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

512 occur more than 5 times.

1.34×10^{154} different rule sets.

EVOLUTIONARY SEARCH



Binary Representation of Rule-sets

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

Compression, r:

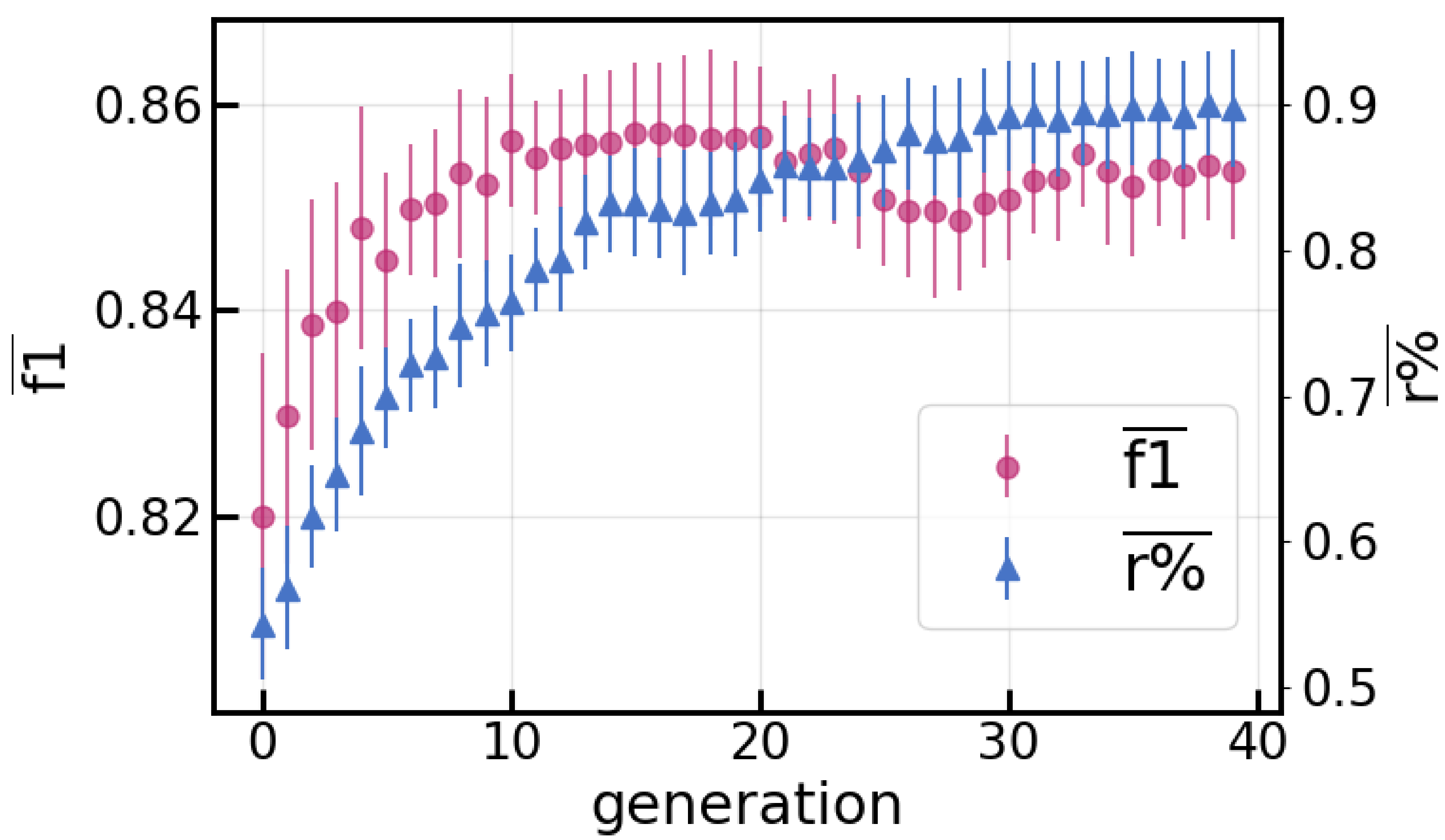
$$r = {}^{\#tokens}/_{(\#chunks\ +\ \#tokens_{out})}$$

$$r\% = {}^{(r_{subset}\ -1)}/_{(r_{all-1})}$$

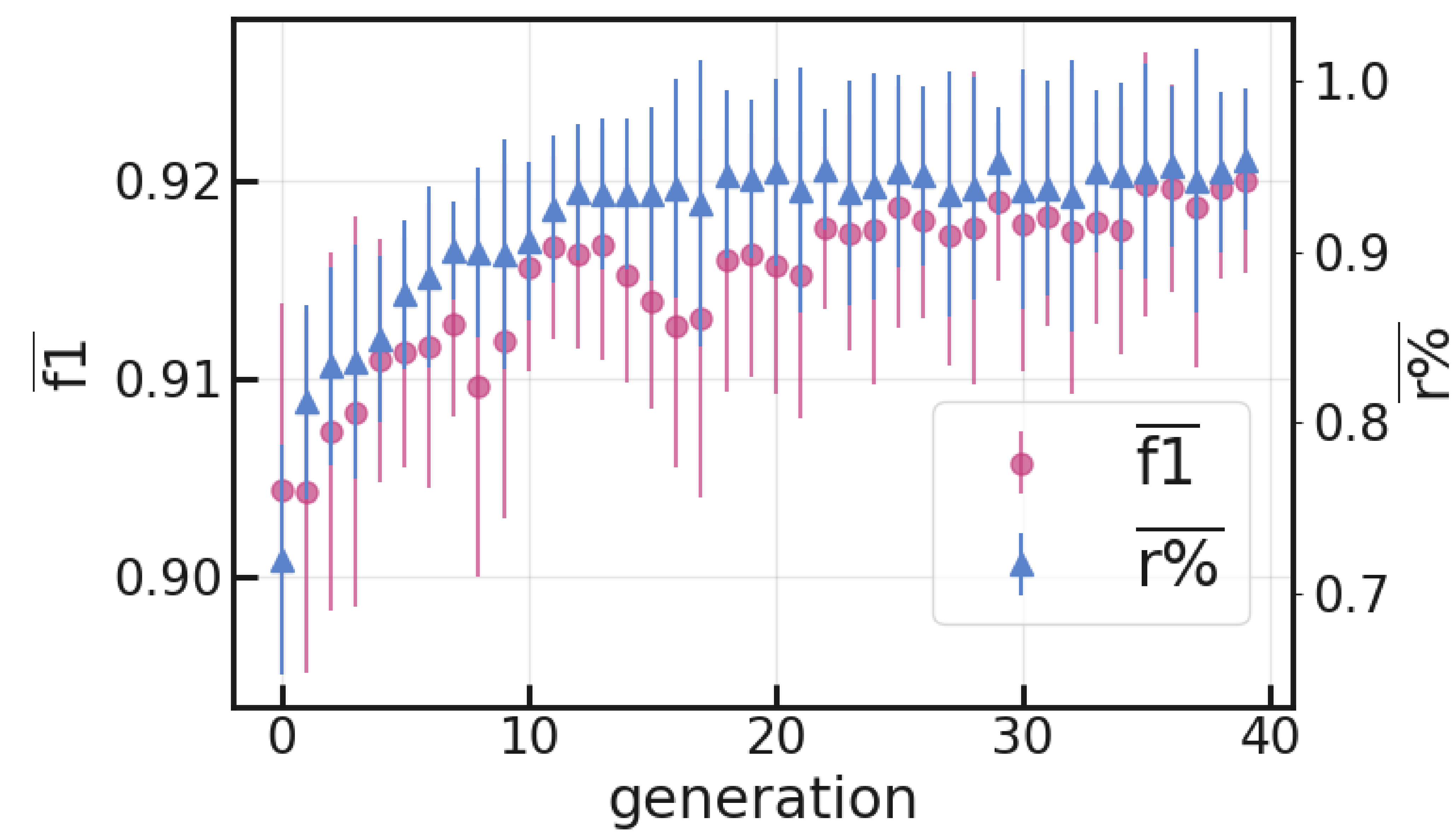
Algorithm 1 Evolutionary algorithm

```
for gen ← max_gen do
    for ind in population do
        ind.fit ← GetFitness(ind)
    end for
    offspring ← select(population)
    offspring ← clone(offspring)
    for pair in offspring_2i, offsrping_2i+1 do
        if random < P_crossover then
            pair ← Crossover(pair)
        end if
    end for
    for ind in offspring do
        if random < P_mutate then
            ind ← Mutate(ind)
        end if
    end for
    population ← offspring
end for
function GetFitness(ind)
    rules ← Convert(ind)
    train, dev ← ChunkTreebanks(rules)
    TrainChunker(train)
    F1 ← EvalulateChunker(dev)
    Rp ← GetMaxRProportion(dev)
    return F1 + 0.5·Rp
end function
```

English-EWT

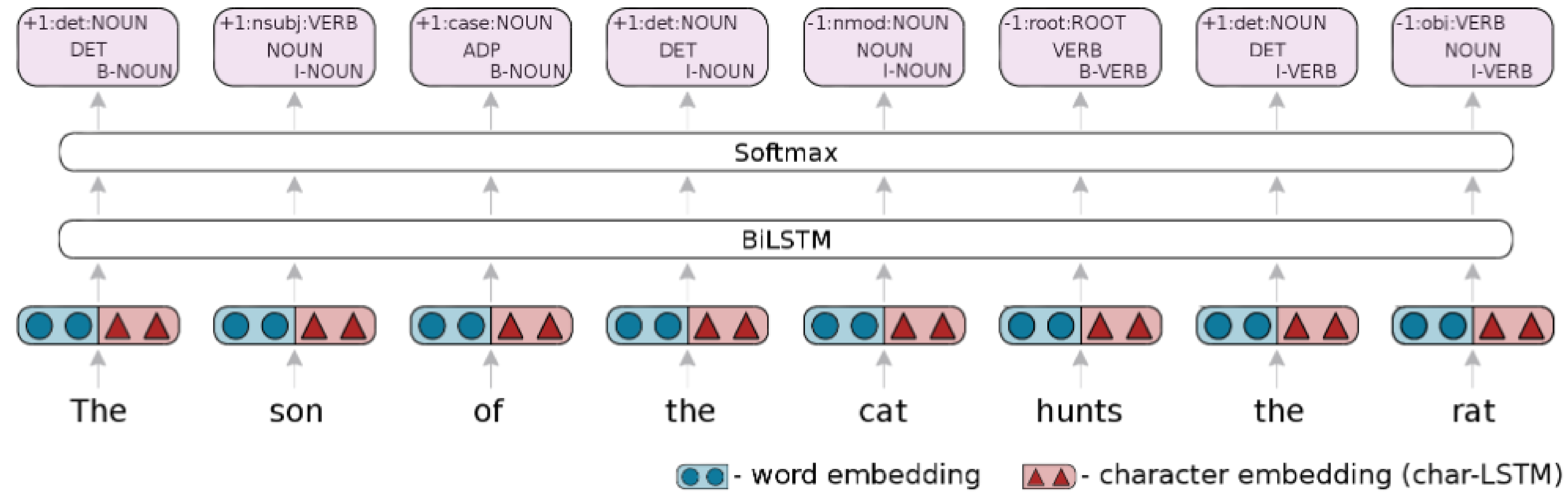


Japanese-GSD



Network Details

We use the neural sequence toolkit NCRF++ developed by Yang and Zhang, 2018.



EXPERIMENT 1

DETAILS OF EXPERIMENT 1

1. **Multi-task Tagging**
   Use a combination of POS tagging, morphological-feature tagging, and chunking.

2. **Baselines**
   Compare against UDPipe 2.0 models and against the NCRF++ framework as single-task for each tagging task.

Results of Experiment 1

English Treebanks

	EWT		GUM		LINES		PARTUT	
	POS	**FEATS**	**POS**	**FEATS**	**POS**	**FEATS**	**POS**	**FEATS**
udpipe	94.44	95.37	93.88	94.21	94.73	94.83	94.10	94.01
single	95.08	96.09	94.61	94.92	95.64	95.57	94.69	94.54
pos+feats	95.23	96.21	94.60	95.26	95.59	95.71	94.63	94.16
pos+feats+chunks$_{75}$	**95.89**	**96.72**	**95.58**	**96.31**	**96.38**	**96.45**	96.04	95.60
pos+feats+chunks$_{95}$	95.86	96.52	95.52	96.21	96.35	96.33	**96.21**	**95.60**

Results of Experiment 1

Bulgarian (BG), German (DE), and Japanese (JA)

	BG		DE		JA	
	POS	FEATS	POS	FEATS	POS	FEATS
udpipe	**97.78**	**95.55**	92.03	70.18	96.39	-
single	97.41	95.06	93.07	87.14	96.97	-
pos+feats	97.69	94.84	92.90	**87.28**	-	-
pos+feats+chunks$_{75}$	97.49	94.58	**93.34**	87.03	96.98	-
pos+feats+chunks$_{95}$	97.44	94.45	92.90	87.11	**97.09**	-

Results of Experiment 1

Chunking

	BASELINE (SINGLE)		MULTI (WITH POS + FEATS)	
	75%	95%	75%	95%
en-ewt	89.99	91.59	91.84	92.98
en-gum	85.76	88.11	88.08	89.98
en-lines	86.01	88.38	88.45	90.67
en-partut	88.36	90.78	91.79	93.30
bg	92.27	92.60	93.79	94.45
de	88.74	88.97	89.35	89.62
ja	93.35	92.73	94.39	94.02

EXPERIMENT 2

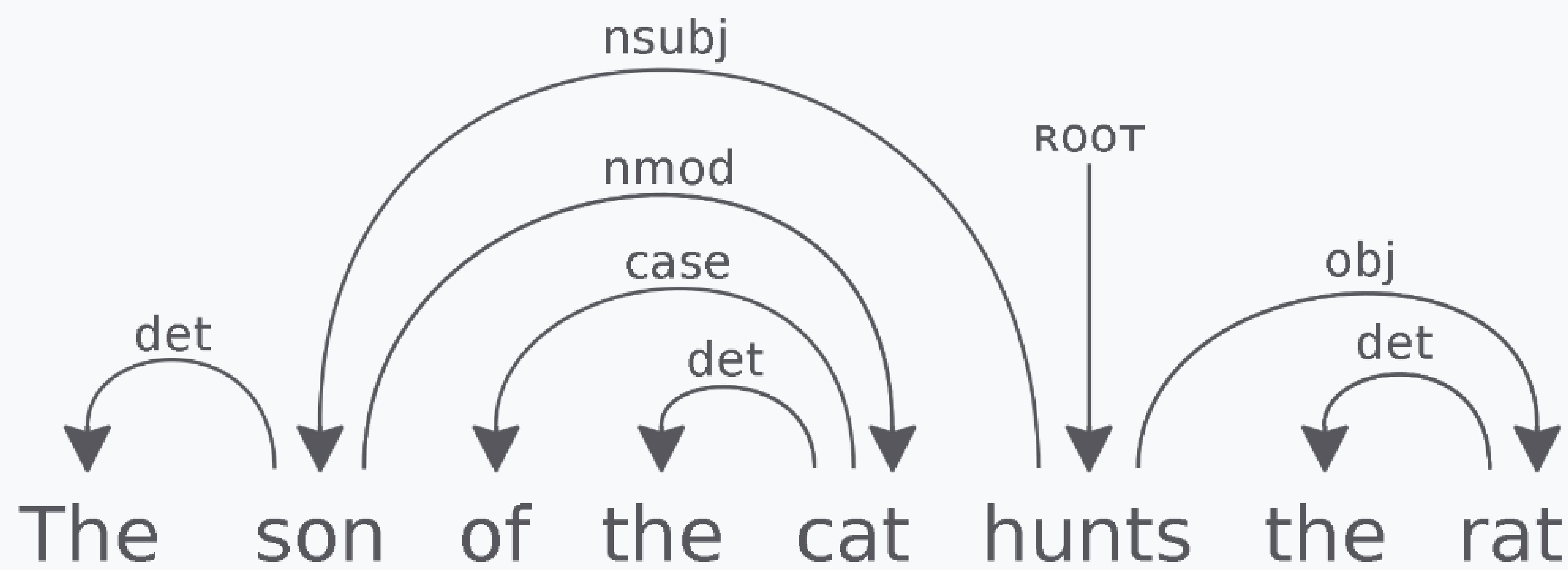
DETAILS OF EXPERIMENT 2

1. **Feature Ablation for Sequence-labelleling Parsing**
   Use a combination of POS tags, morphological-feature tags, and chunks as predicted from the best performing pos-feats-chunk model from experiment 1 as input features.

2. **Baselines**
   First uses no features but uses UDPipe predicted POS tags to decode sequence-labelling parsing encoding. Compare against UDPipe 2.0 models and against the NCRF++ framework as single-task for each tagging task.

   Second baseline uses UDPipe predicted POS tags as input.

Dependency Parsing as Sequence Labelling



The → +1:det:NOUN
son → +1:nsubj:VERB
of → +1:case:NOUN
...
So it goes.

Results of Experiment 2

English Treebanks

	EWT		GUM		LINES		PARTUT	
	UAS	LAS	UAS	LAS	UAS	LAS	UAS	LAS
no feature^{udpipe}	80.97	77.87	76.70	72.71	76.43	71.87	81.63	78.67
pos^{udpipe}	84.88	81.79	81.09	76.87	79.06	74.08	84.01	80.63
pos	86.15	83.29	**83.03**	**79.31**	80.76	76.12	85.83	82.69
pos+feats	86.32	83.37	82.83	79.13	**81.15**	**76.48**	86.71	83.60
pos-chunks$_{75}$	85.84	82.87	82.49	78.83	80.86	76.04	87.03	83.86
pos-chunks$_{95}$	85.80	82.86	81.95	78.19	80.32	75.55	86.65	83.86
pos-feats-chunks$_{75}$	**86.43**	**83.41**	82.61	78.86	81.13	76.21	87.09	83.86
pos-feats-chunks$_{95}$	85.99	83.04	82.15	78.50	80.82	76.09	**87.35**	**84.04**

Results of Experiment 2

Bulgarian (BG), German (DE), and Japanese (JA)

	BG		DE		JA	
	UAS	LAS	UAS	LAS	UAS	LAS
no features^{udpipe}	86.49	82.43	63.20	58.86	89.96	88.43
pos^{udpipe}	89.48	85.30	79.39	74.04	92.49	90.42
pos	89.47	85.11	81.77	76.69	**93.68**	**91.70**
pos-feats	**89.74**	**85.48**	**82.05**	**77.12**	-	-
pos+chunks$_{75}$	89.23	84.67	81.49	76.54	93.28	91.41
pos+chunks$_{95}$	89.06	84.77	81.55	76.40	92.95	91.20
pos+feats+chunks$_{75}$	89.11	84.83	81.77	76.71	-	-
pos+feats+chunks$_{95}$	89.24	85.07	81.41	76.38	-	-

EXPERIMENT 3

DETAILS OF EXPERIMENT 3

1. **Multi-task Framework for Sequence-labelling Parsing**
   Use a combination of POS tags, morphological-feature tags, and chunks as auxillary task for sequence-labelling persing.

   Weighted as 1x parsing, 0.5x POS tagging (as needed for decoding), 0.25x morphological-feature tagging, and 0.25x chunking.

2. **Baselines**
   First is dependency parsing as a single task while using UDPipe predicted POS tags to decode.

   POS tagging alone and POS tagging with morphological-feature tagging.

Results of Experiment 3

English Treebanks

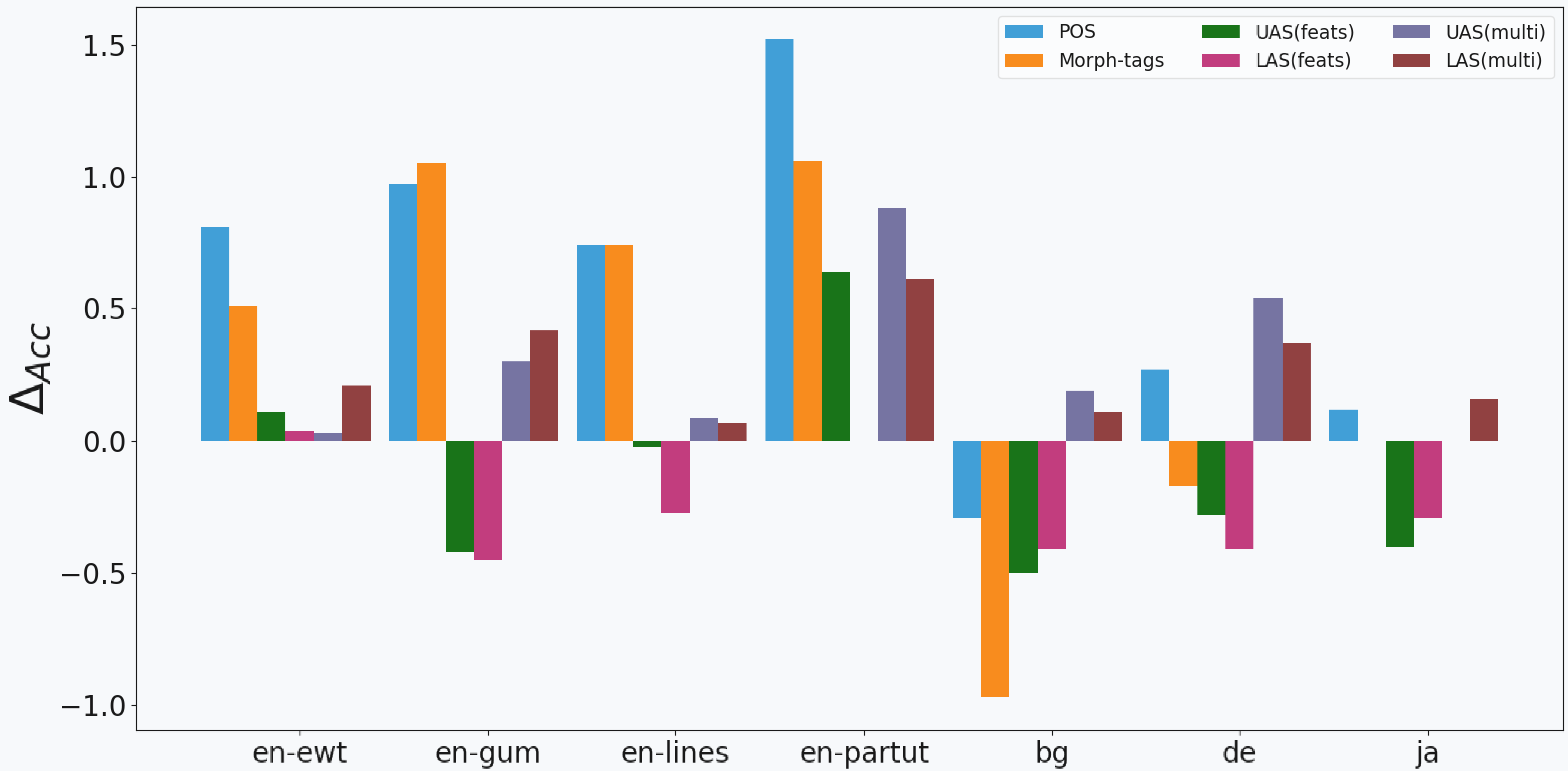
	EWT		GUM		LINES		PARTUT	
	UAS	**LAS**	**UAS**	**LAS**	**UAS**	**LAS**	**UAS**	**LAS**
$\text{single}^{\text{udpipe}}$	80.97	77.87	76.70	72.71	76.43	71.87	81.63	78.67
pos	84.52	81.30	78.94	74.96	78.75	74.13	83.66	80.25
pos+feats	84.21	81.14	79.51	75.42	78.56	73.87	84.10	81.31
pos-chunks_{75}	**84.55**	**81.51**	79.54	75.48	78.17	73.55	83.86	81.13
pos-chunks_{95}	84.42	81.34	79.60	75.54	78.72	**74.20**	83.57	80.16
$\text{pos-feats-chunks}_{75}$	84.25	81.24	**79.81**	**75.84**	78.75	73.95	84.01	80.90
$\text{pos-feats-chunks}_{95}$	84.24	81.18	79.48	75.36	**78.84**	74.15	**84.98**	**81.92**

Results of Experiment 3

Bulgarian (BG), German (DE), and Japanese (JA)

	BG		DE		JA	
	UAS	LAS	UAS	LAS	UAS	LAS
single^{udpipe}	86.49	82.43	63.20	58.86	89.96	88.43
pos	88.00	83.89	80.75	75.59	**93.25**	91.45
pos-feats	88.07	83.89		75.50	-	-
pos+chunks$_{75}$	87.90	83.66	**81.29**	**75.96**	**93.25**	**91.61**
pos+chunks$_{95}$	88.07	83.93	80.98	75.71	93.04	91.28
pos+feats+chunks$_{75}$	**88.26**	**84.00**	80.77	75.52	-	-
pos+feats+chunks$_{95}$	88.09	83.67	80.69	75.63	-	-

Accuracy Differences



Concluding Remarks.

Automatically extracted chunks can be leveraged.

Results show they are especially useful when used in a multi-task framework for POS tagging, morphological-feature tagging, and sequence-labelling parsing.

Evolutionary search can be further fine-tuned.

Run parallel to lower running time.

Use adaptive parameters.

Shallow syntactic information can be useful

Raises questions about the interplay between different levels of syntactic abstraction.

And whether the efficacy of chunks are dependent on linguistic features of a given language.

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Work completed under the supervision of **Carlos Goméz-Rodríguez** and in collaboration with **David Vilares**.

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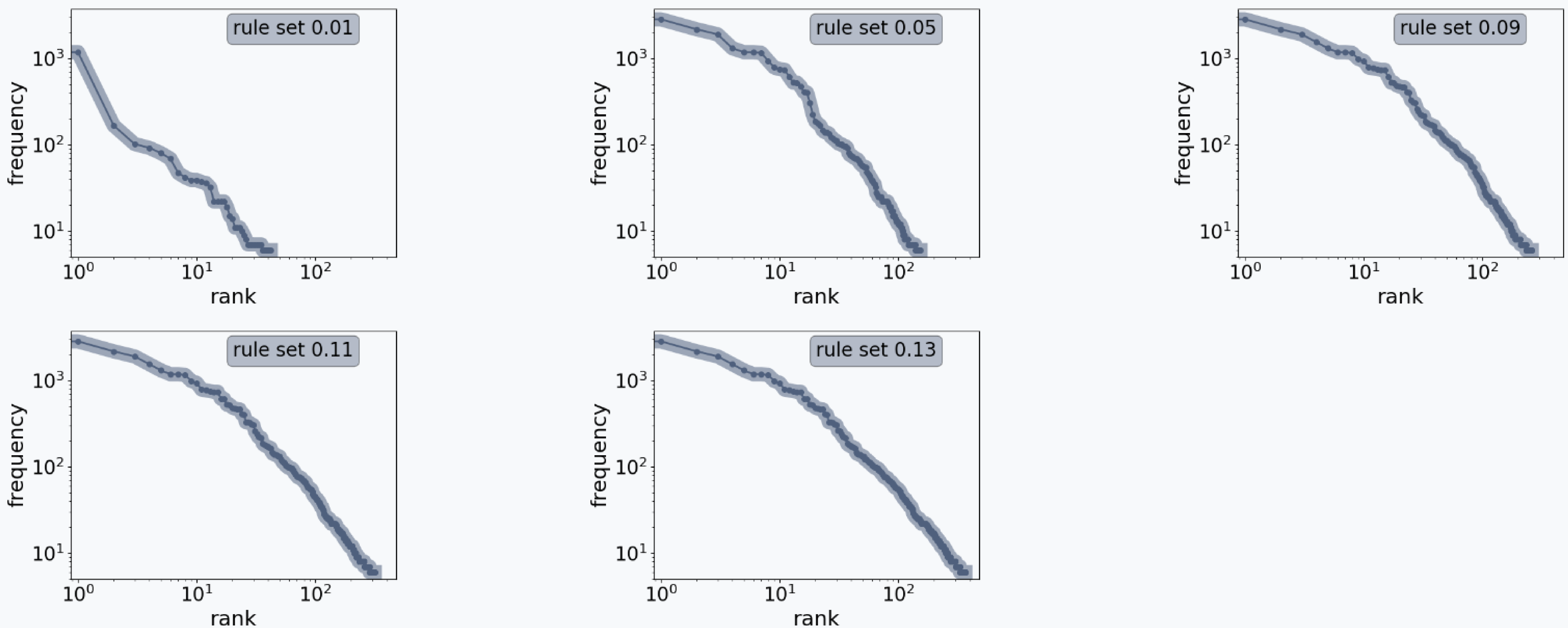
Thanks

Extra Slides

Frequencies of rules



Distribution of rule lengths