Parsing Typologically Diverse Languages

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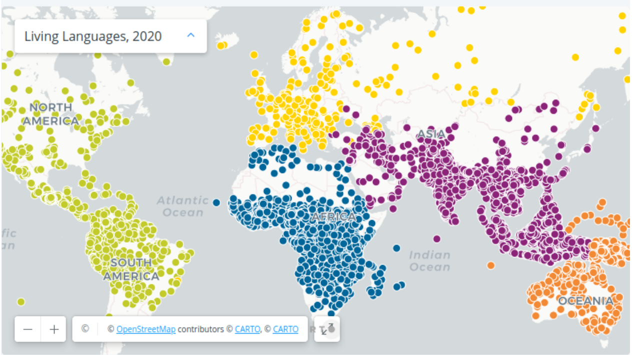
27-28 October 2020

International Workshop on Treebanks and Linguistic Theories

Outline for section 1

The bad news: world's languages



https://www.ethnologue.com/guides/how-many-languages

The good news

🔥 Cross-lingual learning is on the rise 🔥

Figure from Plank (2019)

The bad news

XNLI

The bad news

XQUAD

The good news: UD

UD v1.0

Figure adapted from Nivre et al. (2020)

The good news: UD

UD v2.0

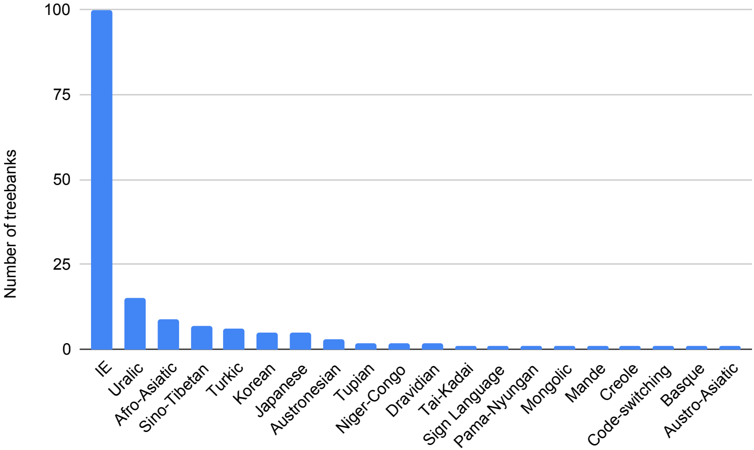
Figure adapted from Nivre et al. (2020)

The good news: UD

UD v2.5

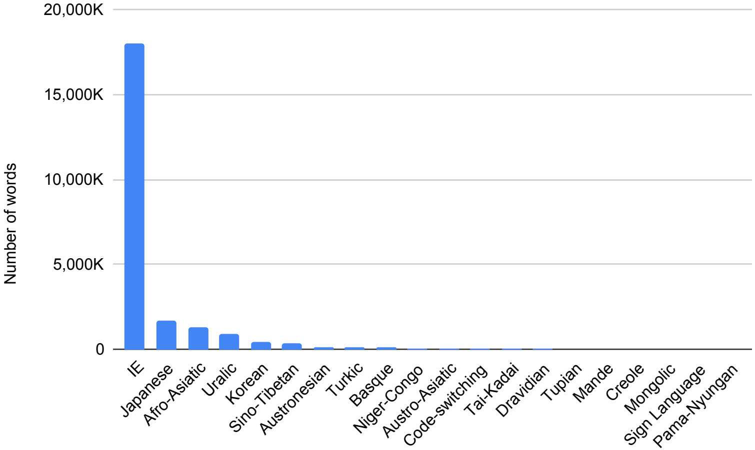
Figure adapted from Nivre et al. (2020)

The bad news



Number of treebanks
100
75
50
25
0
IE
Uralic
Afro-Asiatic
Sino-Tibetan
Turkic
Korean
Japanese
Austronesian
Tupian
Niger-Congo
Dravidian
Tai-Kadai
Sign Language
Pama-Nyungan
Mongolic
Mande
Creole
Code-switching
Basque
Austro-Asiatic

The bad news



Number of words
20,000K
15,000K
10,000K
5,000K
0
IE
Japanese
Afro-Asiatic
Uralic
Korean
Sino-Tibetan
Austronesian
Turkic
Basque
Niger-Congo
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Universal Dependencies: opportunities

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- Do our parsing systems generalize to typologically diverse languages?

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- How well do parsers work in the truly low-resource scenario?

Universal Dependencies: opportunities

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Important questions for multilingual NLP
Parsing as a test case

Outline for section 2

Parser evaluation

CoNLL 2018 results

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- best average LAS: 75.8

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- max LAS best: Polish LFG: 94.8

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How should we evaluate?

Parser evaluation

CoNLL 2018 results

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How should we evaluate?

- average per treebank, language, or language family?

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CoNLL 2018 results

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- max LAS best: Polish LFG: 94.8
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How should we evaluate?

- average per treebank, language, or language family?
- evaluate a representative sample?

Parser evaluation

CoNLL 2018 results

- best average LAS: 75.8
- max LAS best: Polish LFG: 94.8
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How should we evaluate?

- average per treebank, language, or language family?
- evaluate a representative sample?
- report worst case?

The case for not averaging per treebank

Anastasopoulos (2019)

Treebank	UDify	UDPipe
UD_Czech-CAC	**92.4**	90.7
UD_Czech-CLTT	**89.9**	84.3
UD_Czech-FicTree	**92.8**	89.8
UD_Czech-PDT	**92.9**	91.3
UD_Czech-PUD	**88.0**	85.0
UD_North_Sami-Giella	67.1	**74.5**
UD_Polish-LFG	**94.6**	94.2
UD_Polish-SZ	89.2	**91.2**
Average LAS	**88.4**	87.6

The case for not averaging per treebank

Anastasopoulos (2019)

Language	UDify	UDPipe
Czech (avg)	**91.2**	88.2
North Sami	67.1	**74.5**
Polish (avg)	91.9	**92.7**
Average LAS	83.4	**85.1**

The case for not averaging per treebank

Anastasopoulos (2019)

Language Family	**UDify**	**UDPipe**
Slavic	**91.6**	90.5
Uralic	67.1	**74.5**
Average LAS	79.3	**82.5**

Representative sample

Representative sample (de Lhoneux et al., 2017b)

1. Typological variety
    1. Only different genera and as many families as possible
    2. Diversity in morphological complexity
    3. One treebank with high non-projective arcs ratio
2. Variety in treebank sizes and domains
3. High annotation quality

Representative sample

Representative sample (de Lhoneux et al., 2017b)

Treebank Sample.

language	family	genus
Czech	IE	Slavic
Chinese	Sino-tibetan	Sinitic
Finnish	Uralic	Finnic
English	IE	Germanic
Ancient Greek	IE	Hellenic
Kazakh	Turkic	N.western
Tamil	Dravidian	Southern
Hebrew	Afro-Asiatic	Semitic

Representative sample

- Bulgarian, Catalan, Czech, Dutch, English, French, German, Italian, Norwegian, Romanian, Russian and Spanish

Representative sample

- Bulgarian, Catalan, Czech, Dutch, English, French, German, Italian, Norwegian, Romanian, Russian and Spanish
- 12 IE; 5 Romance, 4 Germanic, 3 Slavic

Representative sample

- Bulgarian, Catalan, Czech, Dutch, English, French, German, Italian, Norwegian, Romanian, Russian and Spanish
- 12 IE; 5 Romance, 4 Germanic, 3 Slavic
- This ! is ! not ! a ! representative ! sample !

How accurate are current parsers?

Post CoNLL 2018

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- (m)BERT: +3-4 LAS (Kulmizev et al., 2019; Kondratyuk and Straka, 2019)

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- Finnish: 93 LAS (Virtanen et al., 2019)

How accurate are current parsers?

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- (m)BERT: +3-4 LAS (Kulmizev et al., 2019; Kondratyuk and Straka, 2019)
- Finnish: 93 LAS (Virtanen et al., 2019)
- Thai PUD: 26 LAS (Kondratyuk and Straka, 2019)

Outline for section 3

Low-resource parsing: brief history

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- Annotation projection

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- Treebank translation

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- Delexicalized parsing

Low-resource parsing: brief history

- Annotation projection
- Treebank translation
- Delexicalized parsing
- Typological information

Low-resource parsing: brief history

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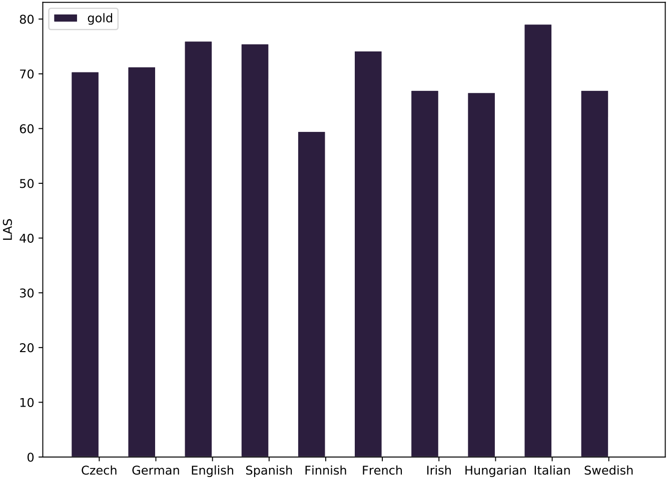
And relies on

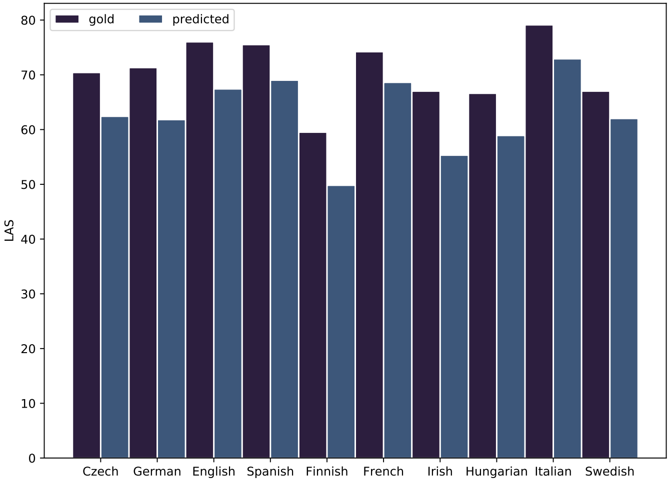
- parallel data
- (gold) POS tags

Low-resource parsing: brief history



Tiedemann (2015)

Low-resource parsing: brief history



Tiedemann (2015)

Low-resource parsing: brief history

POS-taggers for truly low-resource languages are not nearly as accurate! (Kann et al., 2020)

Low-resource parsing: recent developments

Polyglot training:

Low-resource parsing: recent developments

Polyglot training:

- Treebank concatenation

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Polyglot training:

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- Treebank/Language embedding

Low-resource parsing: recent developments

Polyglot training:

- Treebank concatenation
- Treebank/Language embedding
- Typology vector (e.g. WALS)

Polyglot parsing with treebank embeddings

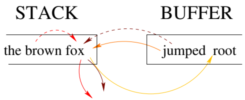
Configuration:

STACK	BUFFER
the brown fox	jumped root

Kiperwasser and Goldberg (2016); de Lhoneux et al. (2017a)

Polyglot parsing with treebank embeddings

Configuration:



Transitions:

LEFT−ARC

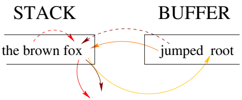
RIGHT−ARC

SHIFT

SWAP

Kiperwasser and Goldberg (2016); de Lhoneux et al. (2017a)

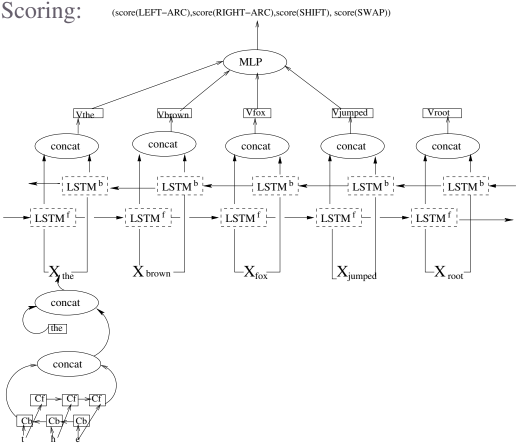
Configuration:



Transitions:

- LEFT–ARC
- RIGHT–ARC
- SHIFT
- SWAP

Scoring:

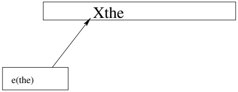


Kiperwasser and Goldberg (2016); de Lhoneux et al. (2017a)

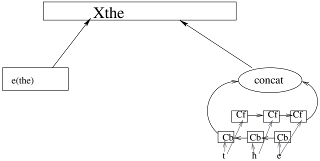
Polyglot parsing with treebank embeddings

Xthe

Polyglot parsing with treebank embeddings



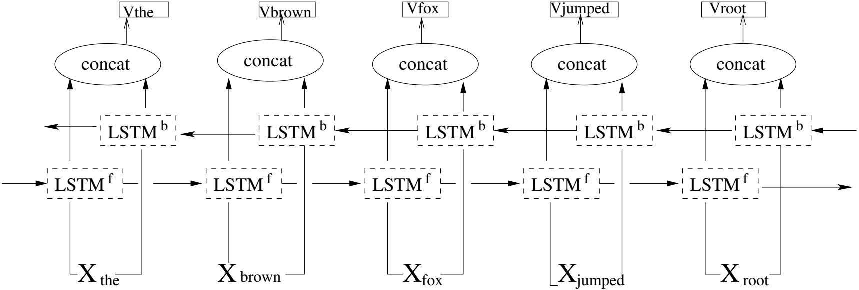
Polyglot parsing with treebank embeddings



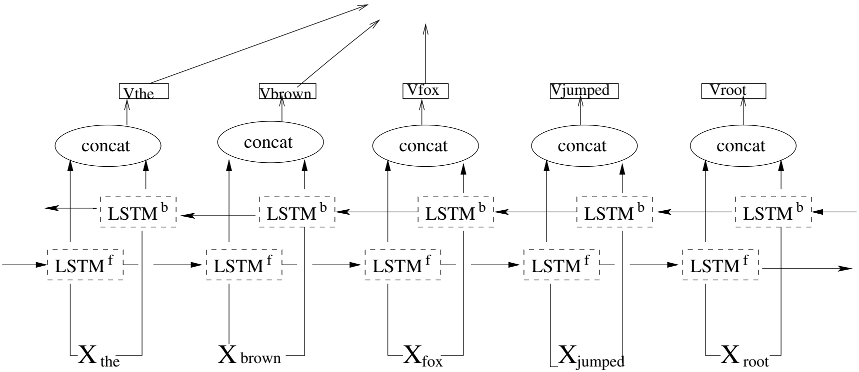
Polyglot parsing with treebank embeddings

X_{the} X_{brown} X_{fox} X_{jumped} X_{root}

Polyglot parsing with treebank embeddings



Polyglot parsing with treebank embeddings



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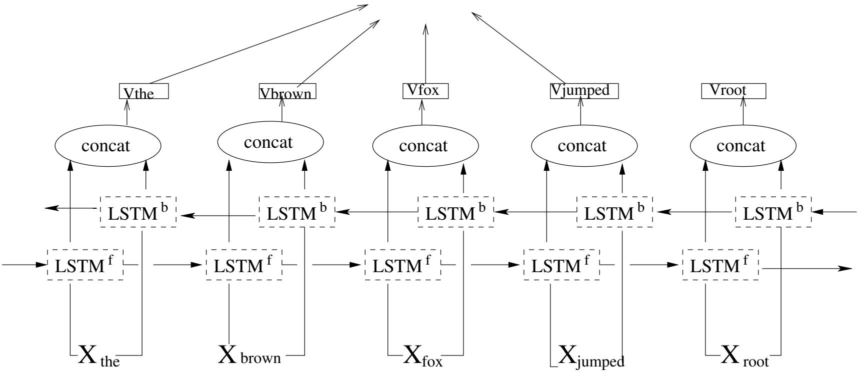
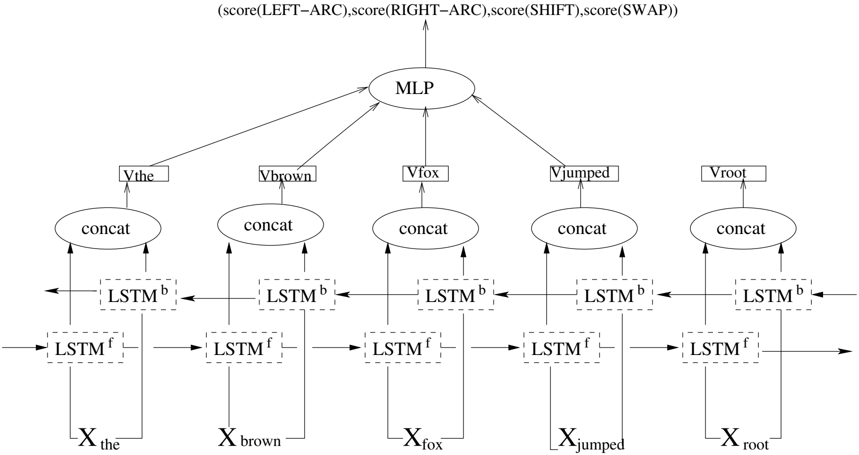


Polyglot parsing with treebank embeddings



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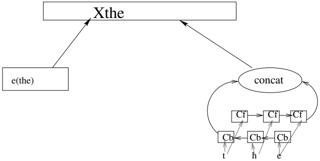

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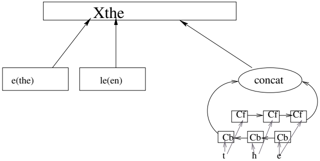

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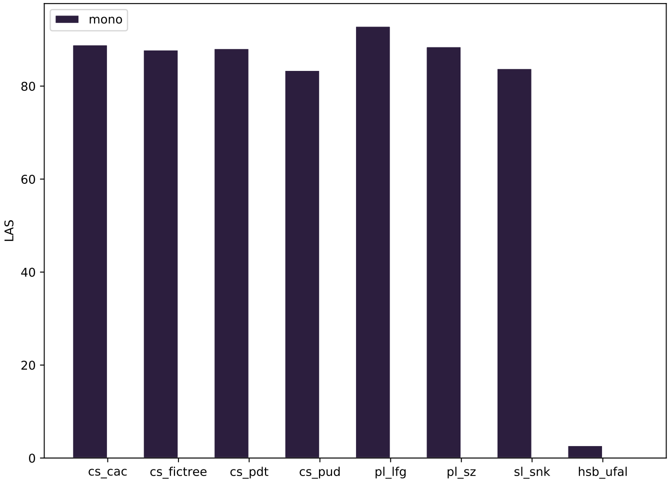
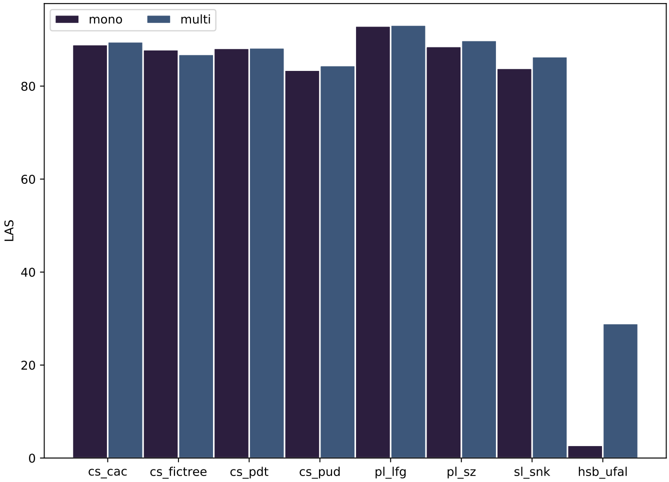


Smith et al. (2018)

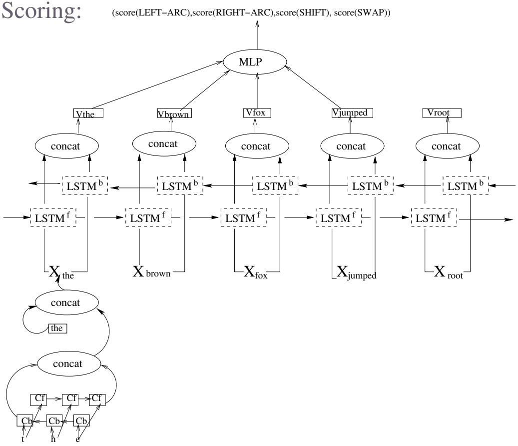
Polyglot parsing with treebank embeddings



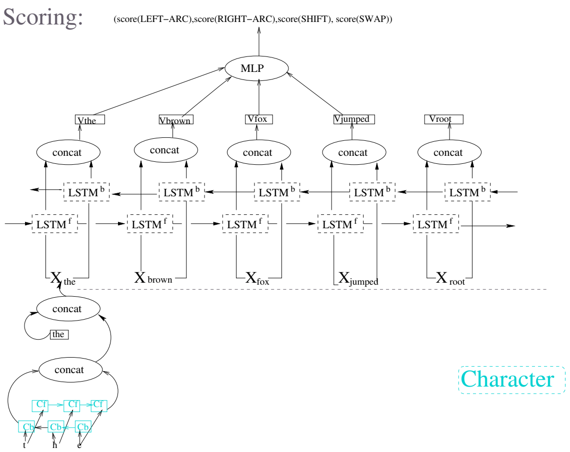
Smith et al. (2018)

Parameter sharing

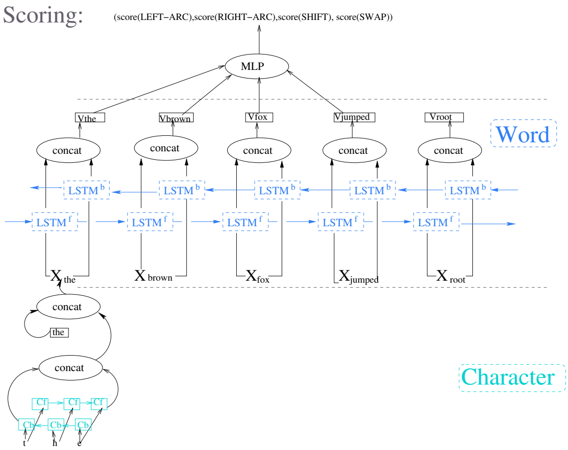
Scoring:



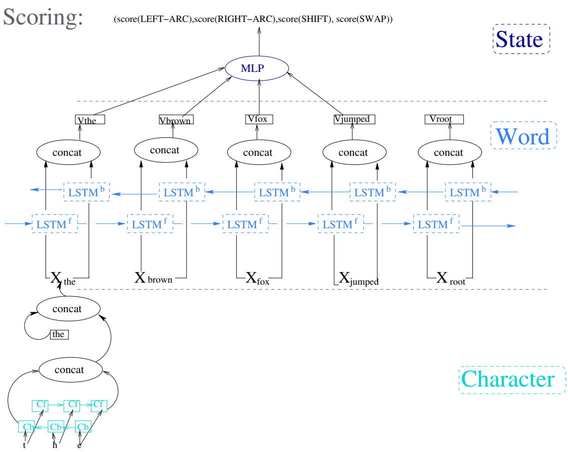
Parameter sharing



Parameter sharing



Parameter sharing



Parameter sharing

- 3 types of sharing: hard, soft, not

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- 3 sets of parameters: MLP, word, char

Parameter sharing

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- 3 sets of parameters: MLP, word, char
- $3^3 = 27$ combinations

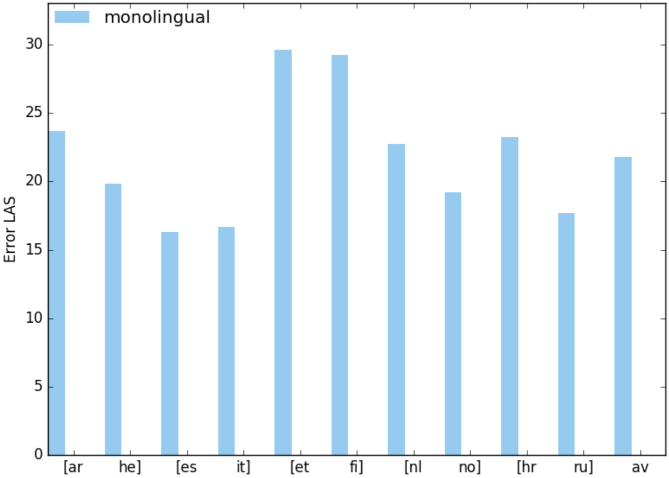
Parameter sharing

Lang	#sen	#tok	Group	Word order
Arabic	5,000	208,932	Semitic	VSO
Hebrew	5,000	161,685	Semitic	SVO
Estonian	5,000	60,393	Finnic	SVO
Finnish	5,000	67,258	Finnic	SVO
Croatian	5,000	109,965	Slavic	SVO
Russian	5,000	90,170	Slavic	SVO
Italian	5,000	113,825	Romance	SVO
Spanish	5,000	154,844	Romance	SVO
Dutch	5,000	75,796	Germanic	No dom. order
Norwegian	5,000	76,622	Germanic	SVO

Dataset characteristics

Parameter sharing

Parameter sharing



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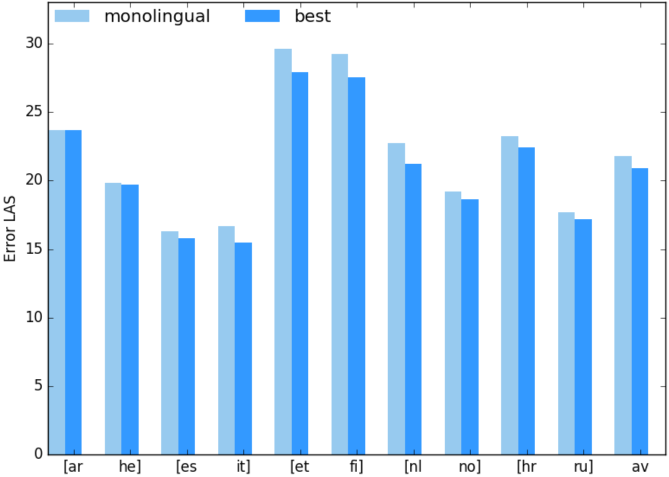

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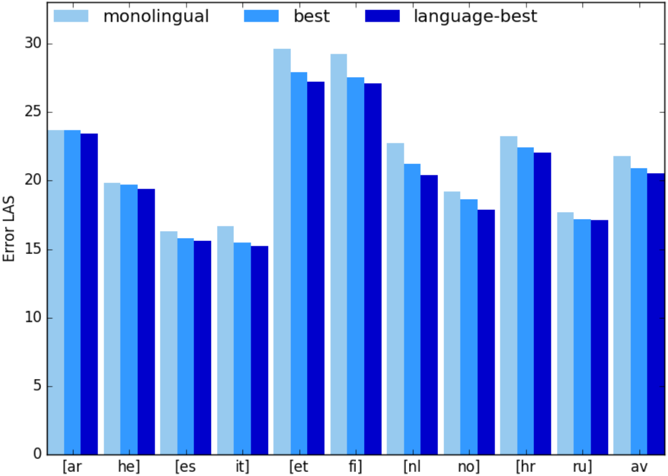

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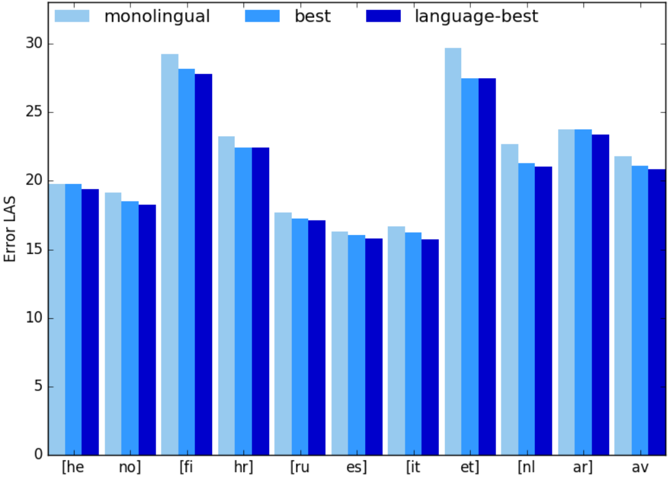

Parameter sharing

Findings

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- Sharing MLP helps for all pairs

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- Sharing MLP helps for all pairs
- Sharing word and character depends on language pair

Polyglot parsing

Polyglot parsing exploiting language relatedness:

- Vania et al. (2019)
- Meechan-Maddon and Nivre (2019)
- Barry et al. (2019)

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We can do cross-lingual without using POS tags!
We can improve parsing for low-resource languages if there is a related high-resource language.

Polyglot parsing without using relatedness

Basirat et al. (2019)

Training			Test	
Afrikaans	Finnish	Russian	Arabic	OCSlavonic
Bulgarian	Hungarian	Slovenian	Belarusian	Serbian
Catalan	Indonesian	Spanish	Coptic	Telugu
Danish	Italian	Swedish	Gothic	Urdu
English	Polish	Turkish	Hindi	Uyghur
Estonian	Portuguese	Ukrainian	Marathi	Vietnamese

Polyglot parsing without using relatedness

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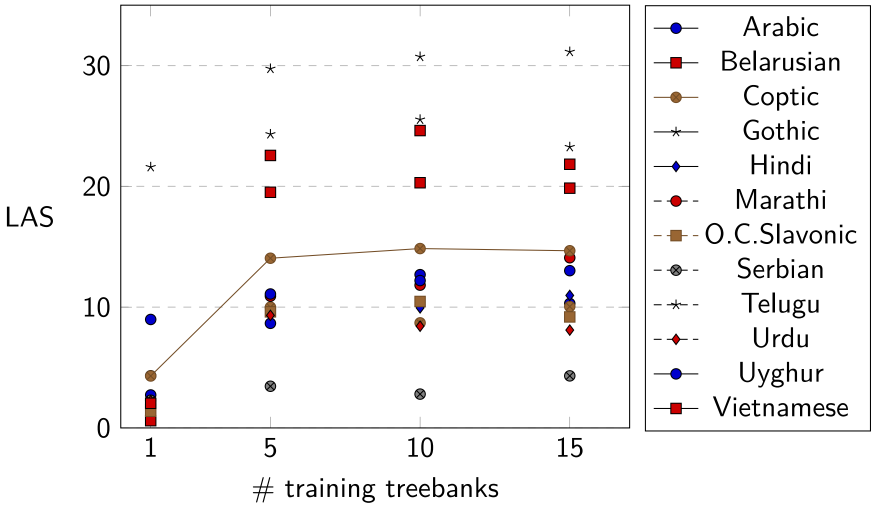
- Pretrained language embeddings
- Multilingual word embeddings

Polyglot parsing without using relatedness



Mind the relatedness gap!

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- LSTMs vs Transformers (Ahmad et al., 2019)

Mind the relatedness gap!

- LSTMs vs Transformers (Ahmad et al., 2019)
- Transfer works best between typologically similar languages in mBERT (Pires et al., 2019)

Typology

Typological features in WALS: cover many languages

Typology

Typological features in WALS: cover many languages

Mixed results with gold POS tags

- Ammar et al. (2016)
- Scholivet et al. (2019)
- Fisch et al. (2019)

Typology

Typological features in WALS: cover many languages

More promising

Üstün et al. (2020)

	be	br*	bxr*	cy	fo*	gsw*	hsb*	kk	koi*	krl*	mdf*	mr	olo*	pcm*	sa*	tl	yo*	yue*	AVG
multi-udify	**80.1**	**60.5**	26.1	53.6	68.6	43.6	53.2	**61.9**	20.8	**49.2**	24.8	**46.4**	42.1	36.1	19.4	62.7	41.2	30.5	45.2
udapter-proxy	69.9	-	-	-	64.1	23.7	44.4	45.1	-	45.6	-	29.6	41.1	-	15.1	-	-	24.5	-
udapter	79.3	58.5	**28.9**	**54.4**	**69.2**	**45.5**	**54.2**	60.7	**23.1**	48.4	**26.6**	44.4	**43.3**	**36.7**	**22.2**	**69.5**	**42.7**	**32.8**	**46.2**

Conclusion

Take-away

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- UD parsing is at the forefront of multilingual NLP

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Open questions

- Are we reaching the limits of implicit cross-lingual transfer?

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Open questions

- Are we reaching the limits of implicit cross-lingual transfer?
- Can we explicitly transfer structure? With typological features?

Thanks to my collaborators!

Joakim Nivre

Sara Stymne

Aaron Smith

Ali Basirat

Anders Soegaard

Johannes Bjerva

Isabelle Augenstein

And more!

Questions?

Thanks for listening! Questions?

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