



Analyzing the effect of linguistic similarity on cross-lingual transfer: Tasks and experimental setups matter

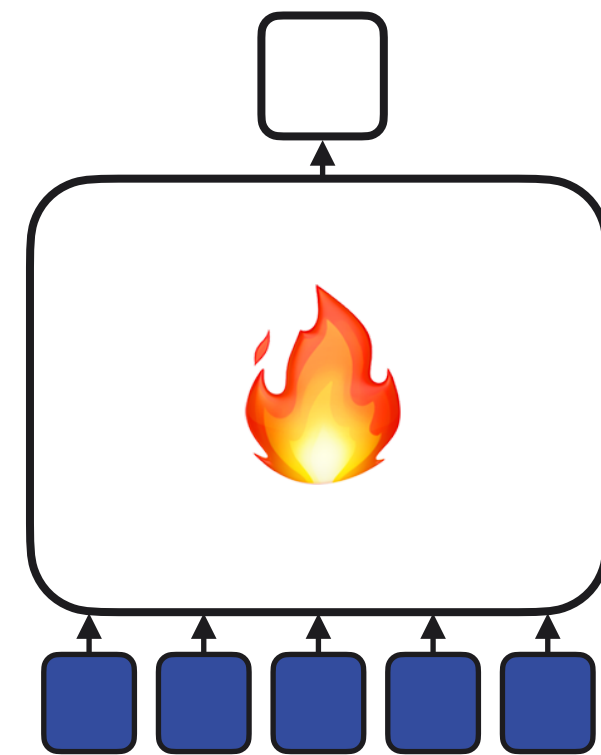
Verena Blaschke,¹ Masha Fedzechkina,² Maartje ter Hoeve²

ACL Findings | ¹LMU Munich & MCML, ²Apple | July 2025

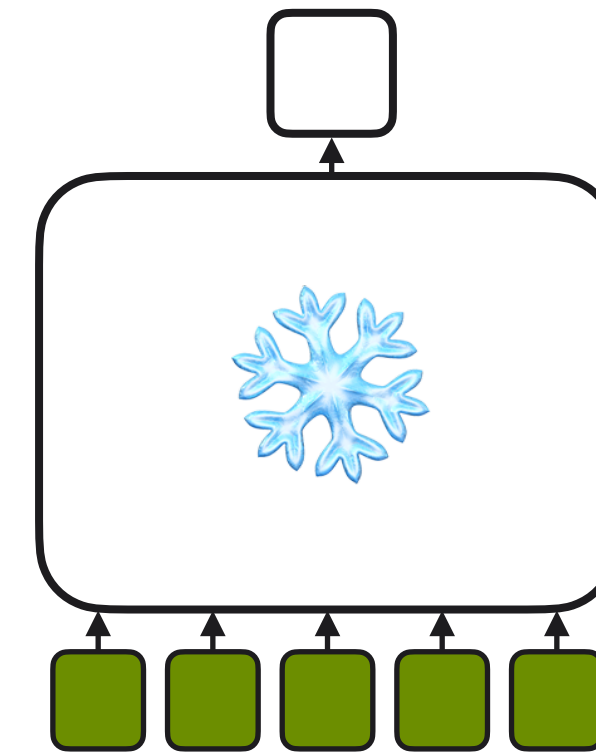
Motivation

- 7000+ languages in the world
 - Only a few of which are focused on in NLP research (Joshi+, 2020)
 - Only a few of which have training data available

→ Cross-lingual transfer



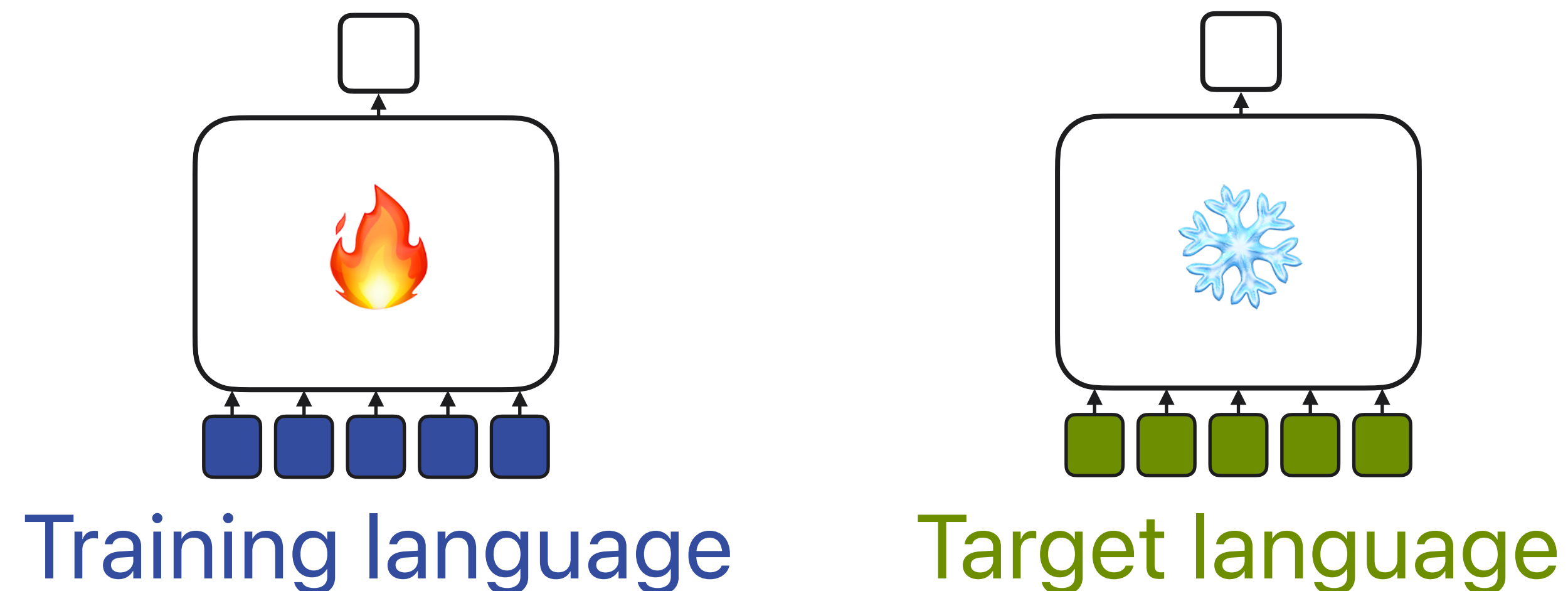
Training language



Target language

Motivation

- Given a **target language**, how do I select a good **training language**?
 - Intuitively: pick a language/dataset that is *in some way* similar...
... but in *what way*?
 - Prior work: either relatively few languages or NLP tasks (Philippy+, 2023)
 - Here: 263 languages, 3 NLP tasks, 10 similarity measures



Overview

Large-scale cross-lingual transfer experiments

Correlations with similarity measures

Practical takeaways for picking source languages

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NLP experiments

POS tagging & dep. parsing

Topic classification

NLP experiments — grammatical tasks

POS tagging & dep. parsing

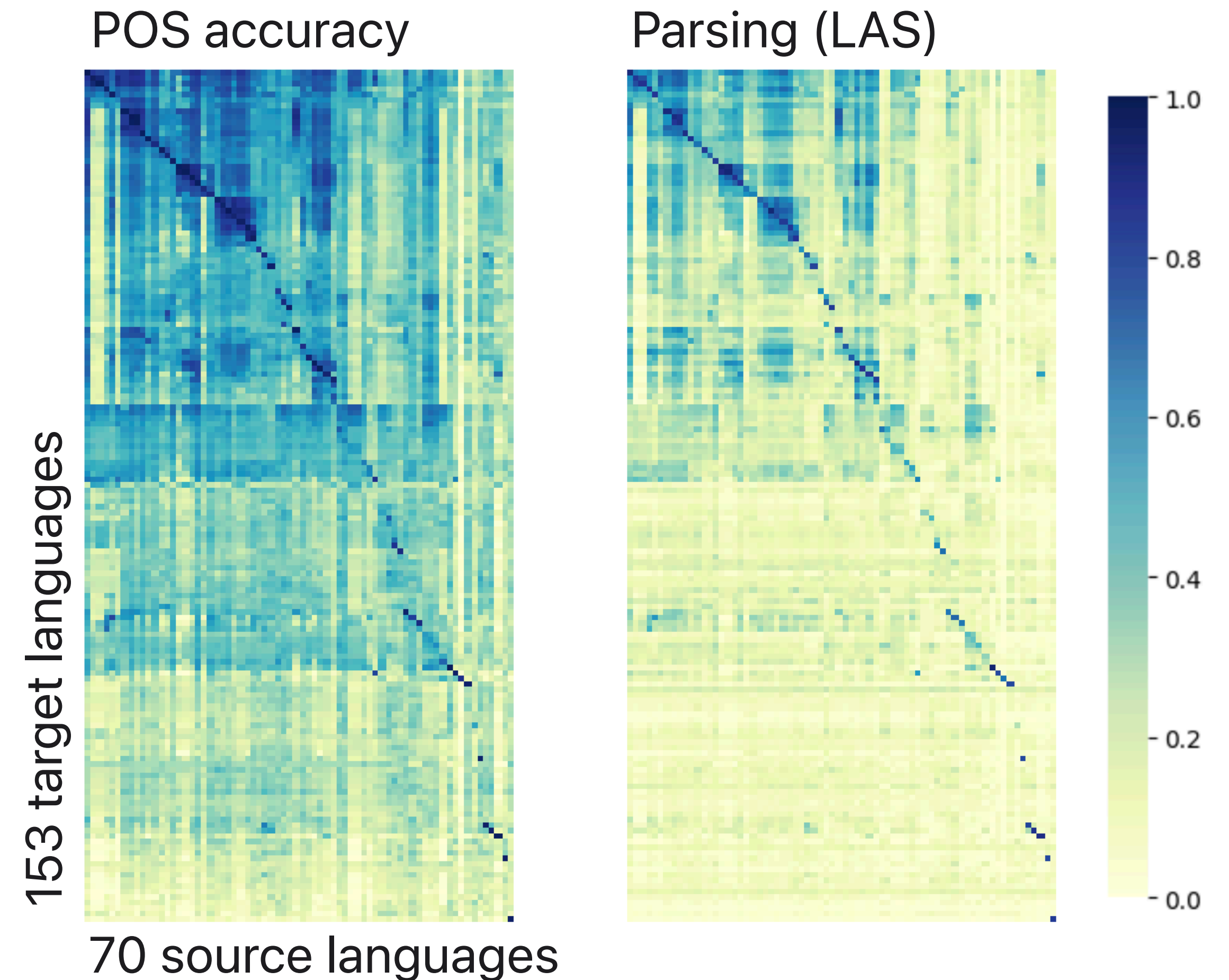
- Universal Dependencies
- 70 × 153 languages
- UDPipe 2 (mono- and multilingual char/word embeddings)

Topic classification

NLP experiments — grammatical tasks

POS tagging & dep. parsing

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LAS = labelled attachment score

NLP Experiments — topic classification

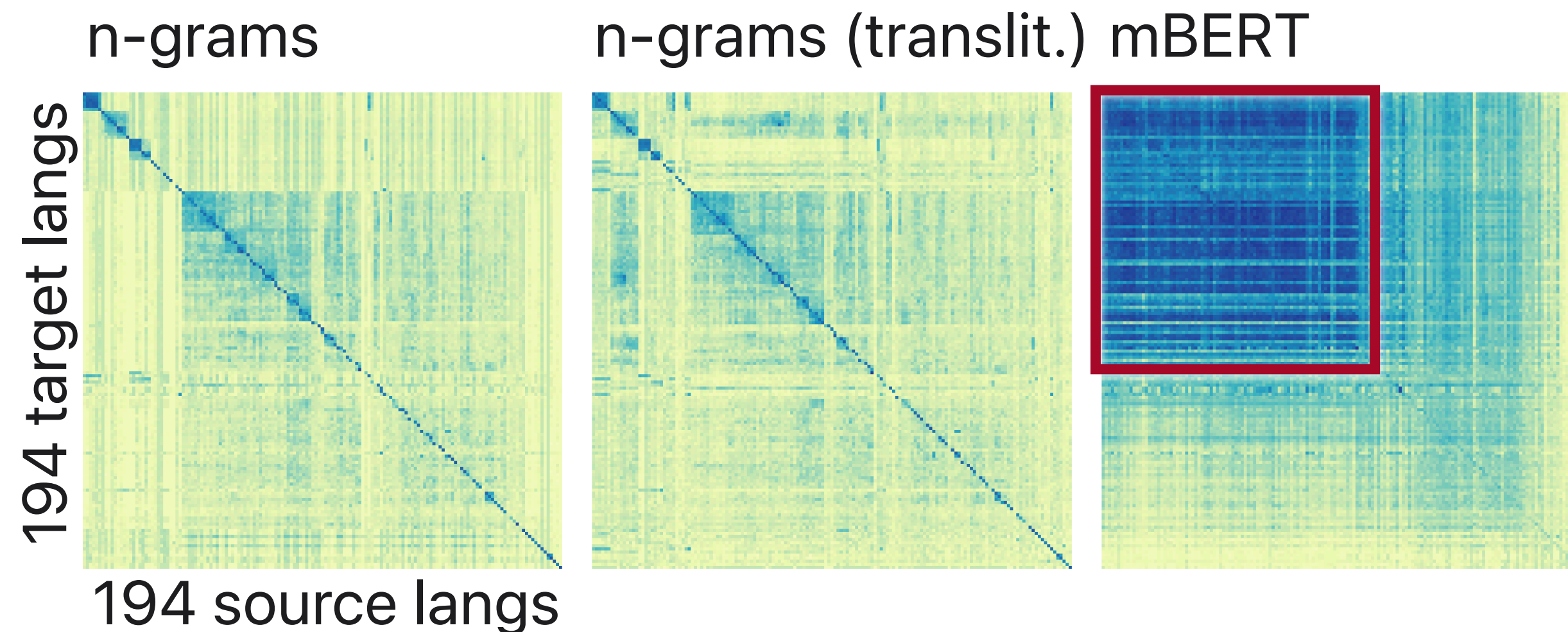
POS tagging & dep. parsing

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Topic classification

- SIB-200
- 194 × 194 languages
- MLPs → comparable & competitive
- Input representations
 - character n-grams
 - n-grams (transliterated text)
 - mBERT embeddings

NLP Experiments — topic classification



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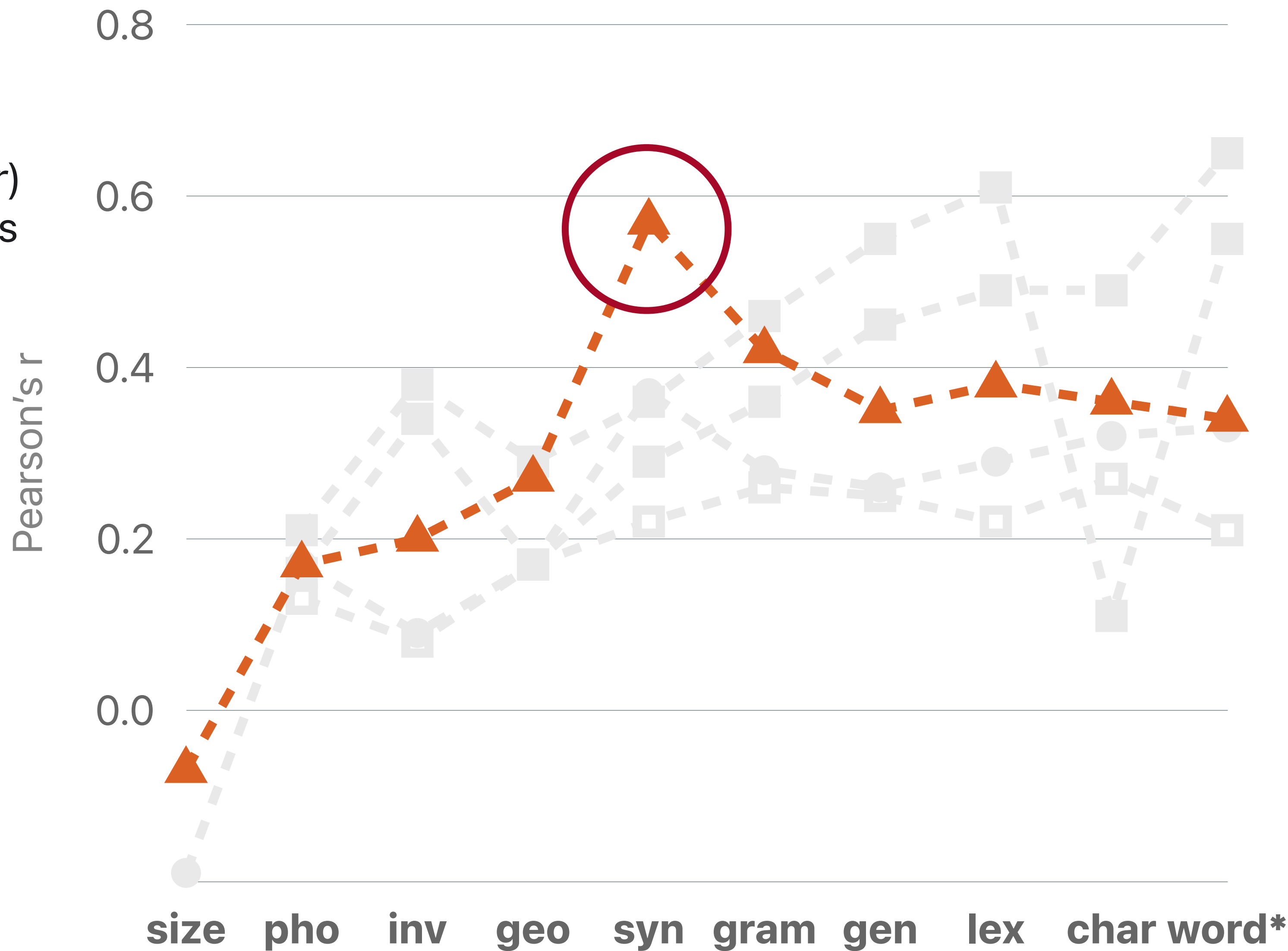
Similarity measures

- Linguistic measures
 - Structural similarities: **G**rammar, **s**yntax, **p**honology, phoneme **i**nventory
 - **L**exical similarity
 - Phylo**g**enetic relatedness
 - **G**eographic proximity
- Dataset measures
 - **C**harter overlap
 - **W**ord* overlap (words, character trigrams, subword tokens)
 - **S**ize of training split

Correlations between transfer results and similarity measures

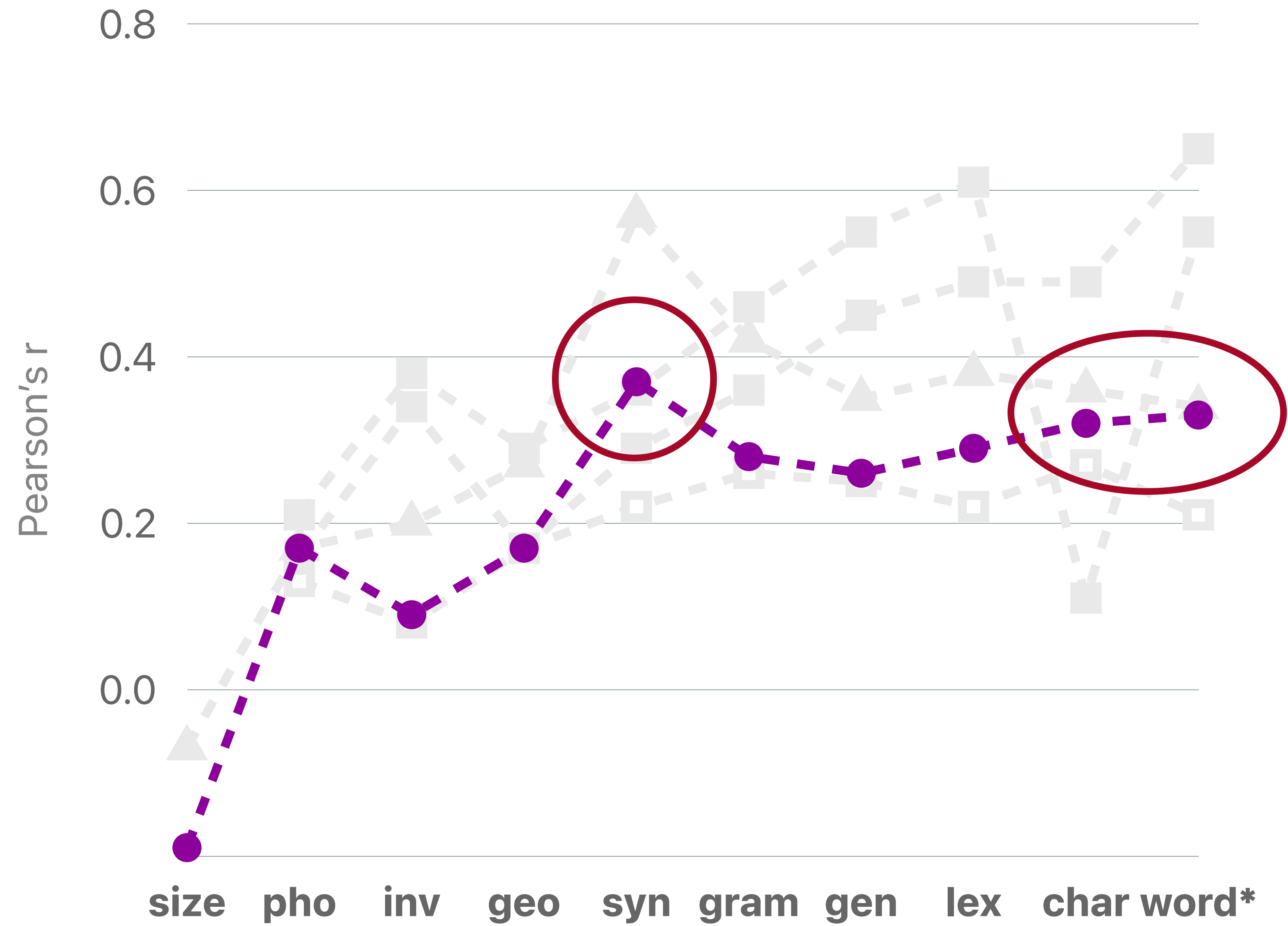
Parsing (labelled attachment score)

Mean correlation (r)
over test languages



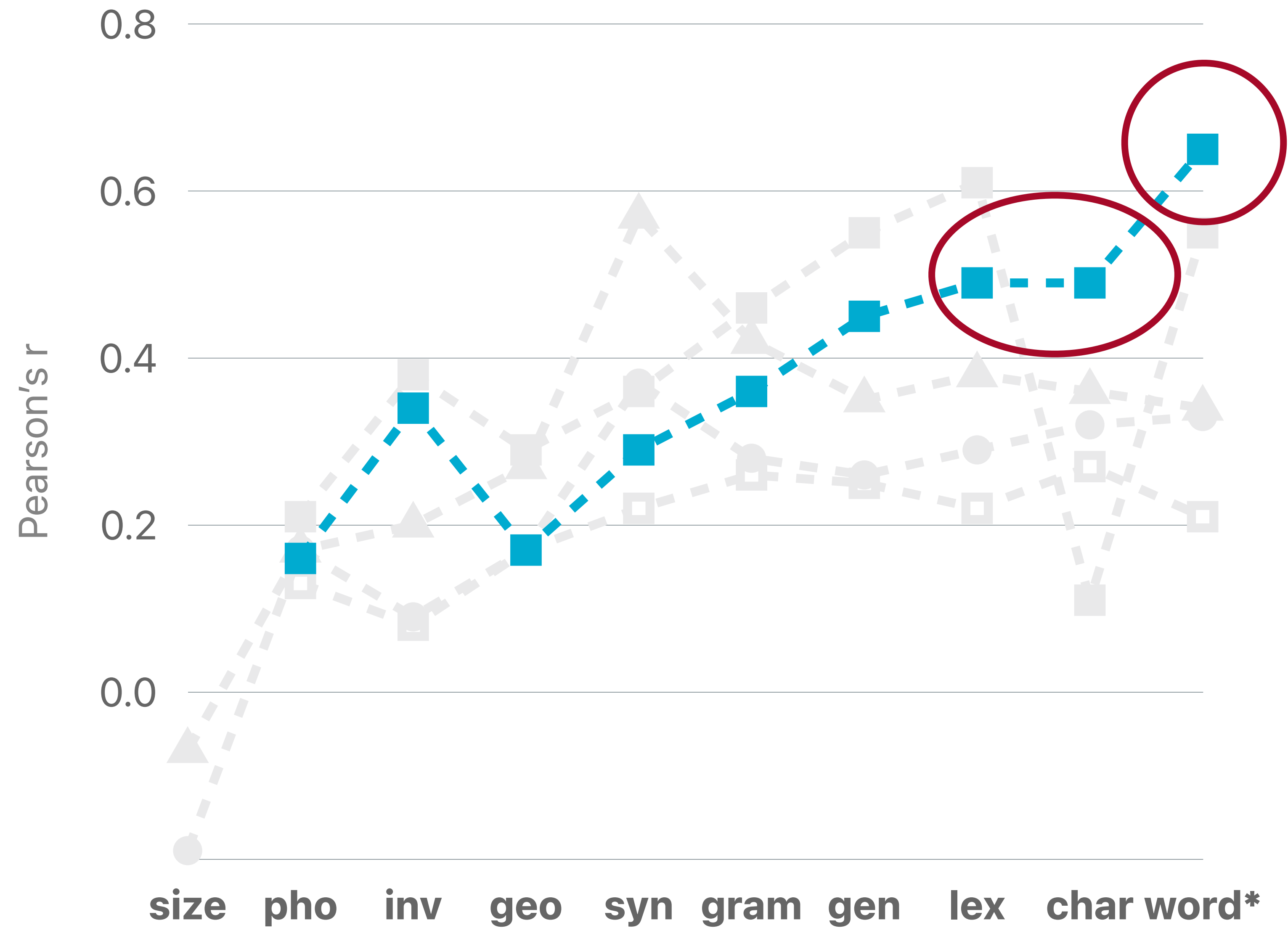
Correlations between transfer results and similarity measures

POS tagging (accuracy)



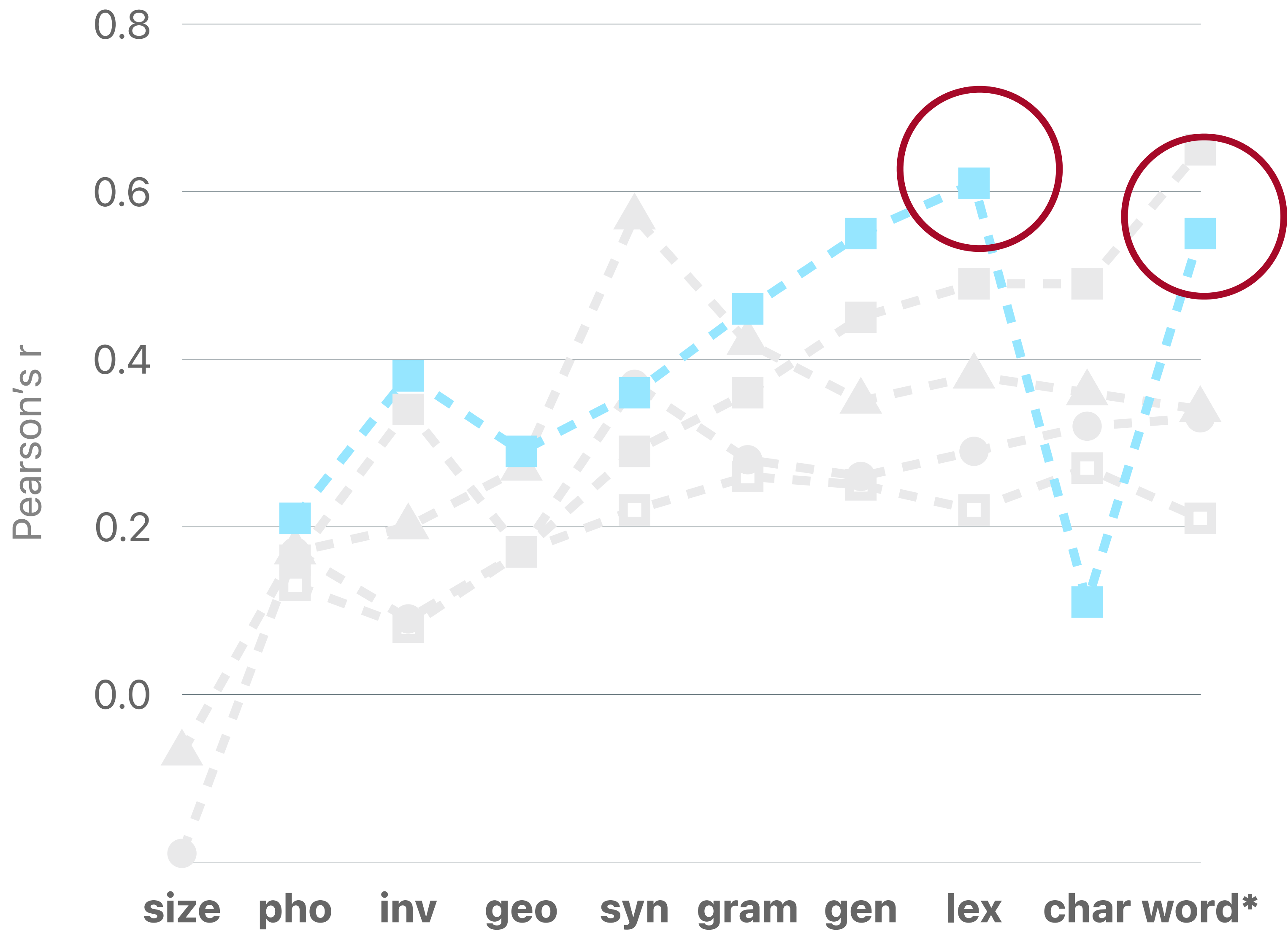
Correlations between transfer results and similarity measures

Topic classification (accuracy) — MLP with n-grams



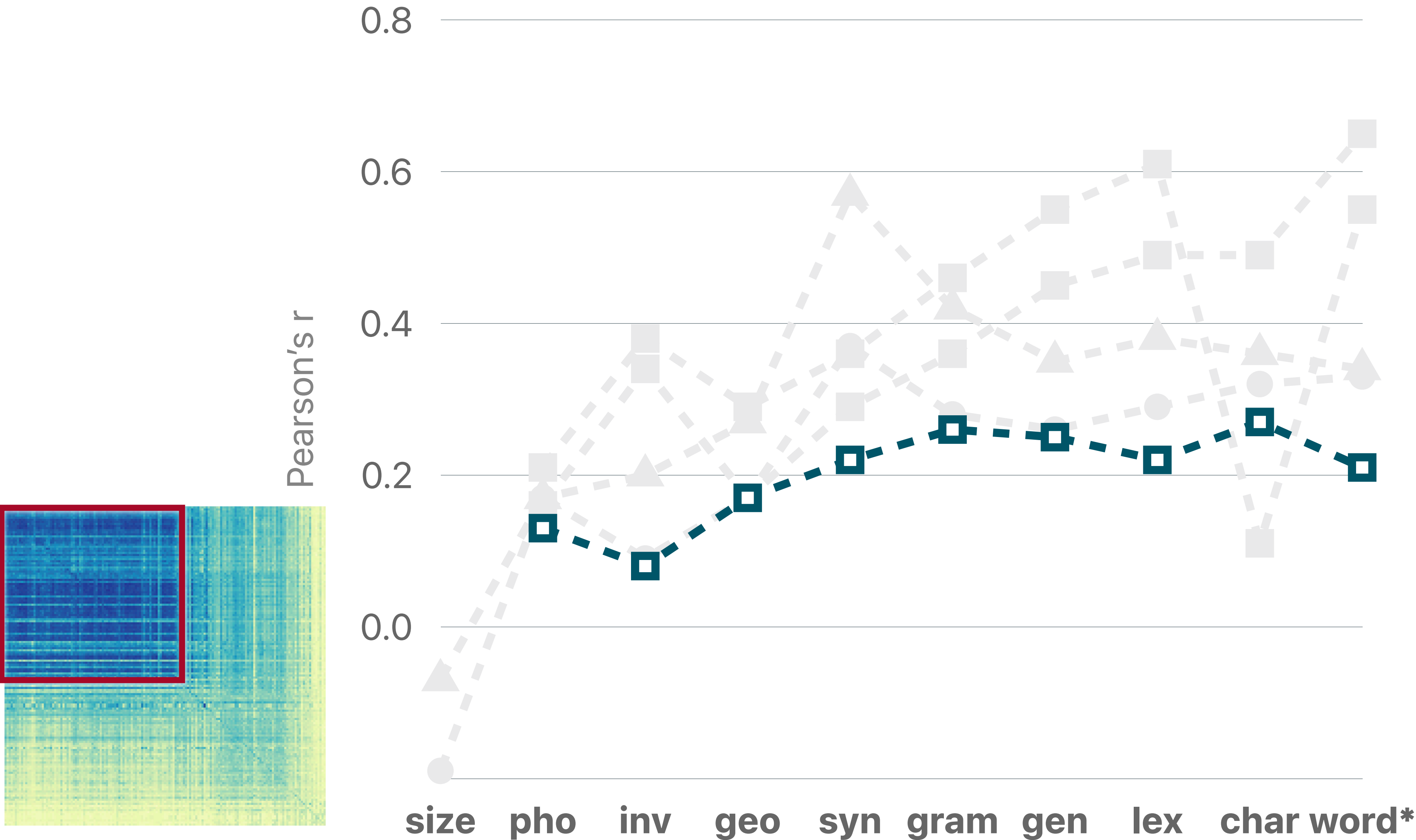
Correlations between transfer results and similarity measures

Topic classification (accuracy) — MLP with n-grams (transliterated)



Correlations between transfer results and similarity measures

Topic classification (accuracy) — MLP with mBERT embeddings



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Large-scale cross-lingual transfer experiments

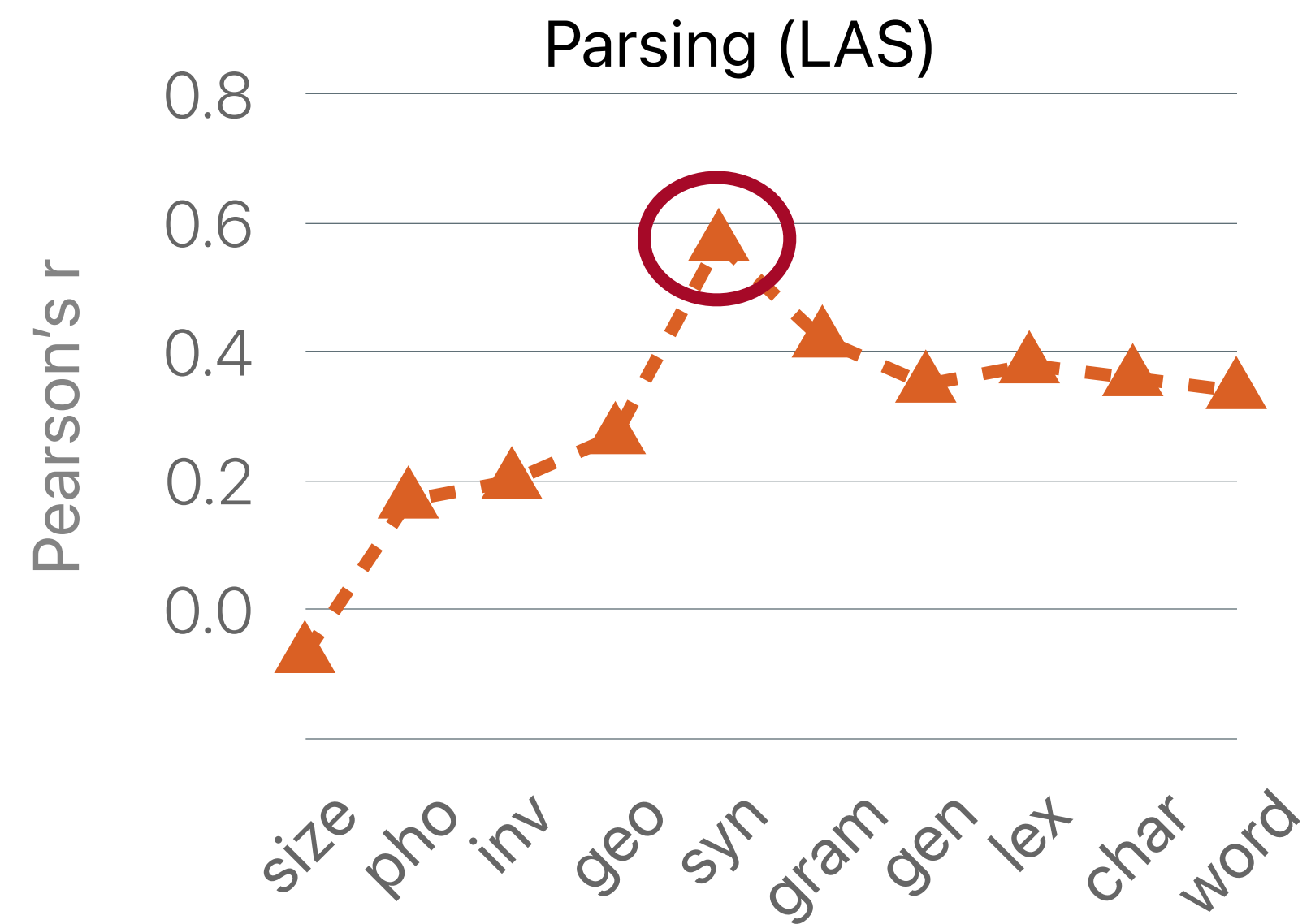
Comparing transfer trends

Practical takeaways for picking source languages

Picking source languages based on similarity measures

	size	pho	inv	geo	syn	gram	gen	lex	char	word*
<i>Top-1 source candidate (= most similar language)</i>										
POS	29	15	14	15	10	12	9	10	15	12
Parsing (LAS)	21	13	13	13	7	10	8	8	16	11
Topics (n-grams)	—	17	17	13	15	14	9	9	13	4
Topics (n-grams, translit.)	—	13	13	11	11	10	7	7	20	3
Topics (mBERT)	—	12	11	10	9	8	8	8	12	9

Mean performance loss in percentage points if picking the best training language according to one measure (instead of the overall best one)



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Topics (mBERT)	—	12	11	10	9	8	8	8	12	9
<i>Top-3 source candidates</i>										
POS	25	7	7	5	3	4	5	4	7	5
Parsing (LAS)	18	8	7	5	3	4	4	3	8	6
Topics (n-grams)	—	10	9	5	6	6	5	3	8	2
Topics (n-grams, translit.)	—	8	7	4	5	5	3	3	14	1
Topics (mBERT)	—	6	5	4	4	4	4	4	5	6

Mean performance loss in percentage points if picking the best training language according to one measure (instead of the overall best one)

Picking source languages based on other transfer experiments?

	Topics				
	POS	LAS	n-grams	n-grams (translit.)	mBERT
<i>Top-1 source candidate (= best src in another experiment)</i>					
POS	—	2	9	10	16
Parsing (LAS)	1	—	11	10	18
Topics (n-grams)	10	11	—	3	19
Topics (n-grams, translit.)	8	8	3	—	18
Topics (mBERT)	4	5	7	6	—
<i>Top-3 source candidates</i>					
POS	—	1	4	4	7
LAS	0	—	5	5	9
Topics (n-grams)	5	5	—	1	12
Topics (n-grams, translit.)	5	4	2	—	12
Topics (mBERT)	2	2	3	3	—

Mean performance loss in percentage points if picking the best training language according to the results of another transfer experiment (instead of the overall best one)

Conclusions

- Different tasks/input representations
→ different similarity measures matter
- Selecting training languages based on relevant similarity measures (or on similar experiments) works well
 - If possible: compare multiple promising training languages

More details in the paper :)

