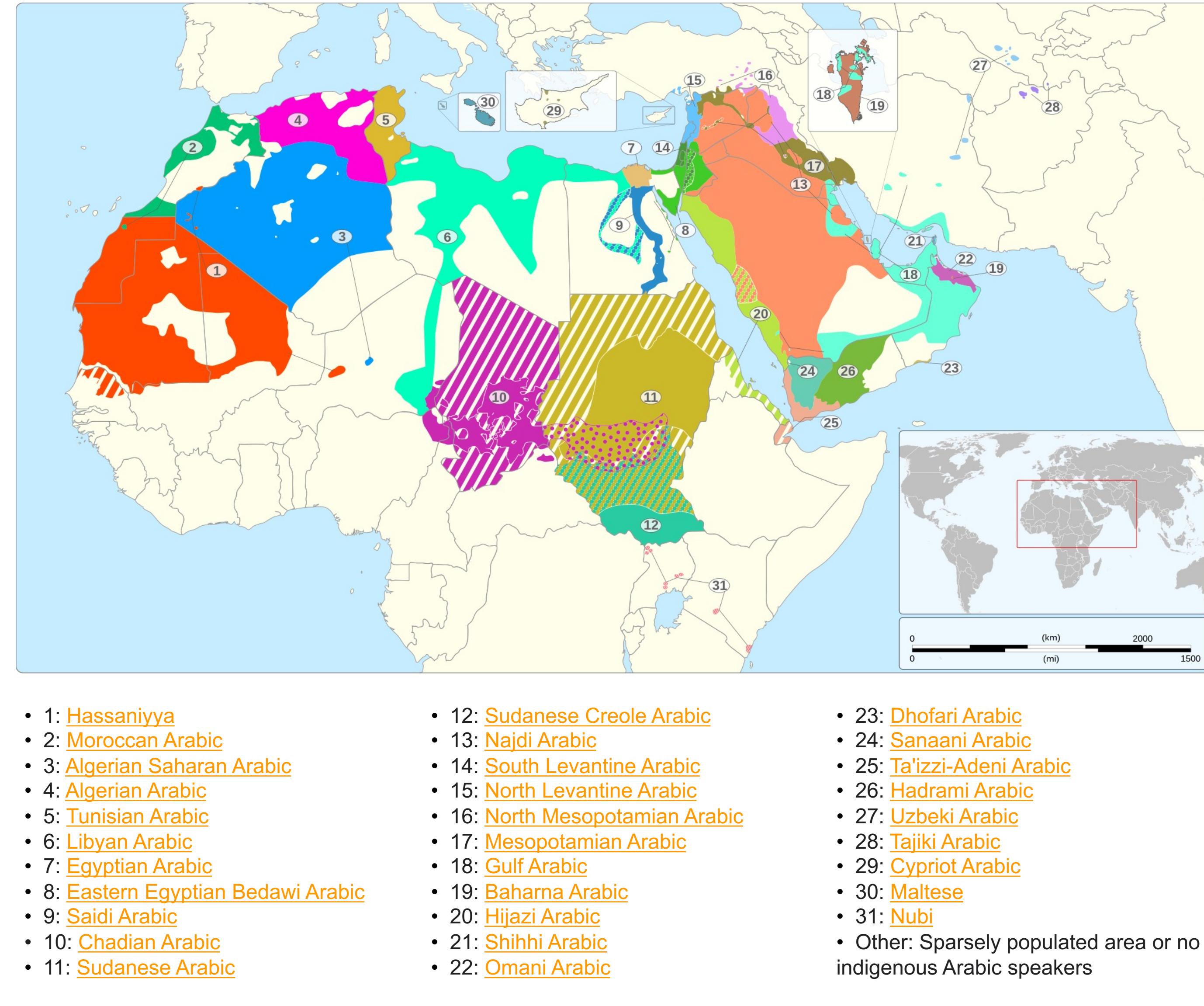


Parameter and Data Efficient Continual Pre-training for Robustness to Dialectal Variance in Arabic

Soumajyoti Sarkar, Kaixiang Lin, Sailik Sengupta, Leonard Lauen, Sheng Zha, Saab Mansour
AWS AI Labs

The Landscape of Dialects



- ❖ Dialectical variance, exhibited by differences in grammar and vocabulary, is common in many languages across the world.
- ❖ Our work focuses on Arabic, where this variance can be particularly challenging.
- ❖ Further, scanty data for all variants raises questions about how to incorporate them during pretraining?

[Q1] Continual Pre-Training (CPT) of multilingual models == monolingual model performance?

[Q2] How to incorporate sparse dialectical data alongside abundant Modern Standard Arabic (MSA) data during pretraining?

[Q3] With strategies for incorporating dialectical data, is CPT with multilingual models == CPT with monolingual models?

The Corpus

	Code	Corpora	Size
C1	Oscar Arabic	67M	
	Arabic Wiki	49M	
	Arabic CC100	111M	
	Arabic Newswire Part-1	2.3M	
	Arabic Gigaword Fifth Edition	96M	
	Gulf Arabic Conv.	4K	
	GALE (only Arabic data)	25K	
	BOLT SMS/Chat (only Arabic data)	44K	
C2	OSCAR Egyptian Arabic Corpus	102K	
C3	GALE Parallel Corpus BOLT Egyptian Arabic SMS/Chat	255K	

Figure 1: C1 – Mixed Arabic and its dialectal variants, C2 – Egyptian Arabic sentences amounting to 102K, C3 – Parallel dialectal variants to English data from the GALE Arabic Parallel datasets which are 255K in total

The Models

M-B-Ar

Multilingual BERT continually pretrained for 800K steps starting from the pretrained public checkpoint with C1 for 800K steps

B-Ar

BERT model trained from scratch (with randomly initialized weights) with C1 for 1.3M steps

t-B-Ar

BERT model trained with a custom tokenizer trained on C1

Pre-training Methodology

MLM

Masked Language Modeling Objective used with the corpus C1 and C2

TLM

Translation Language Modeling Objective used with the parallel corpus C3



The ALUE Benchmark

Task Type	Task Name	Domain
Single Sentence Classification	MDD	Travel
	OOLD	Tweet
	OHSD	Tweet
	FID	Tweet
Sentence Pair Classification	MQ2Q	Web
	XNLI	Misc.
Multi-label Classification	SEC	Tweet
	SVREG	Tweet

Experimental Results

Model	FID	MDD	MQ2Q	SVREG	SEC	OOLD	OHSD	XNLI
AraBERT	78.31	51.15	77.41	42.41	32.21	94.92	96.57	51.02
AraBERT-Twitter	79.73	52.26	77.07	39.25	31.34	94.21	97.76	39.71
mBERT	77.14	49.31	77.11	34.70	35.49	94.13	96.49	51.08
m-B-Ar	79.61	56.04	80.26	50.82	41.05	94.62	97.13	50.57
B-Ar	79.32	55.84	80.35	51.65	41.88	94.58	97.27	51.04
t-B-Ar	81.04	53.49	72.63	74.37	49.26	95.12	98.36	51.03

☺ Our models

☺ Publicly available models

☺ Monolingual models

☺ Multilingual models

Model	FID	MDD	MQ2Q	SVREG	SEC	OOLD	OHSD	XNLI
m-B-Ar	79.61	56.04	80.26	50.82	41.05	94.62	97.13	50.57
+C2	79.35	56.60	80.46	53.72	40.13	94.56	97.16	51.33
+C2+C3	78.29	56.82	80.65	51.42	40.75	95.18	97.51	52.69
B-Ar	79.32	55.84	80.35	51.65	41.88	94.58	97.27	51.04
+C2	81.20	55.84	84.73	69.72	47.66	94.53	97.75	52.13
+C2+C3	79.9	57.61	85.31	70.31	48.03	94.67	97.91	51.38

- ✓ Small dialectal data can improve dialectical robustness of finetuned multilingual and monolingual models is used cleverly!
- ✓ With C2 & C3, **monolingual models >> multilingual models**

References

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Datasets were obtained from LDC, the corpus referenced in AraBERT, OSCAR

*Corresponding author: soumajjs@amazon.com