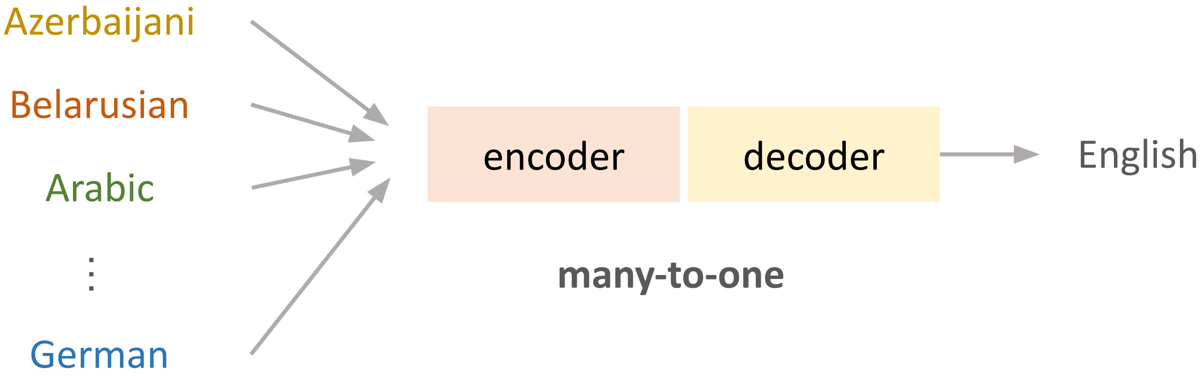
Breaking Down Multilingual Machine Translation

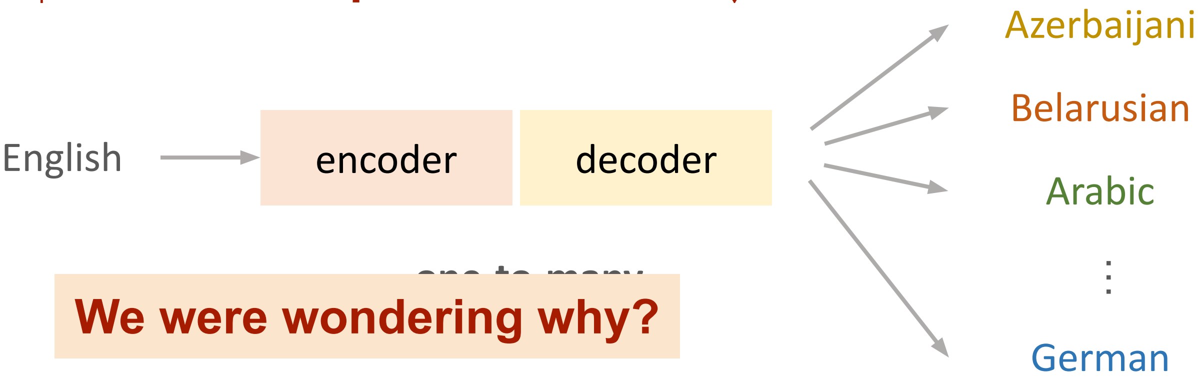
Ting-Rui Chiang[1] Yi-Pei Chen[2] Yi-Ting Yeh[1] Graham Neubig[1]
Carnegie Mellon University[1], The University of Tokyo[2]

Background: Multilingual Training for Machine Translation



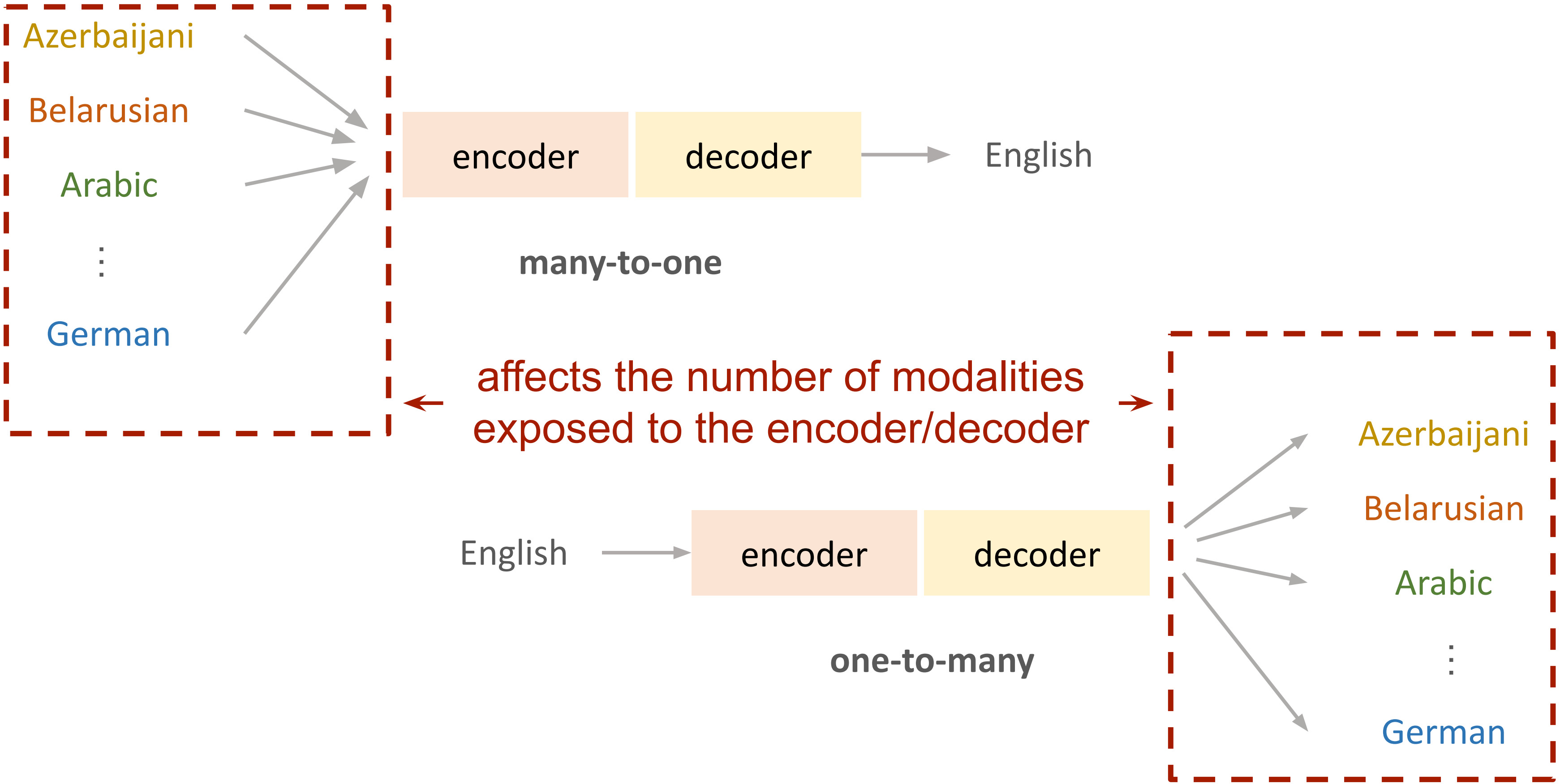
many-to-one

↑ has more improvement than ↓



We were wondering why?

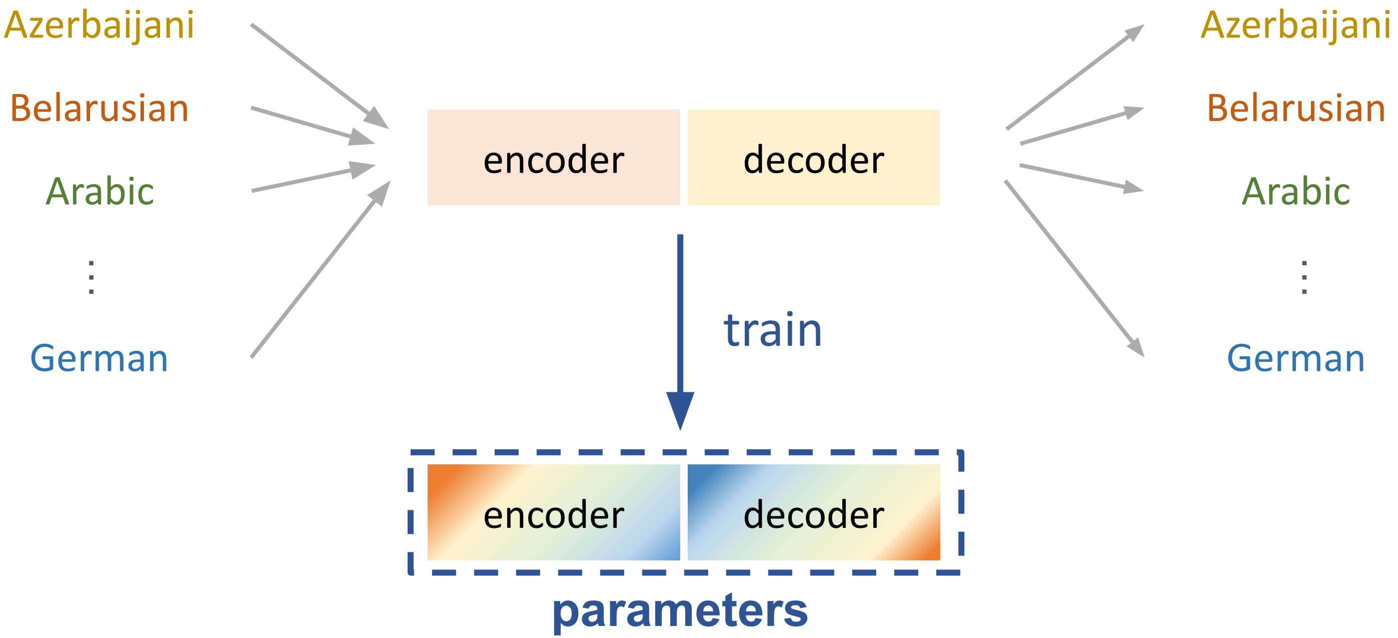
Observation



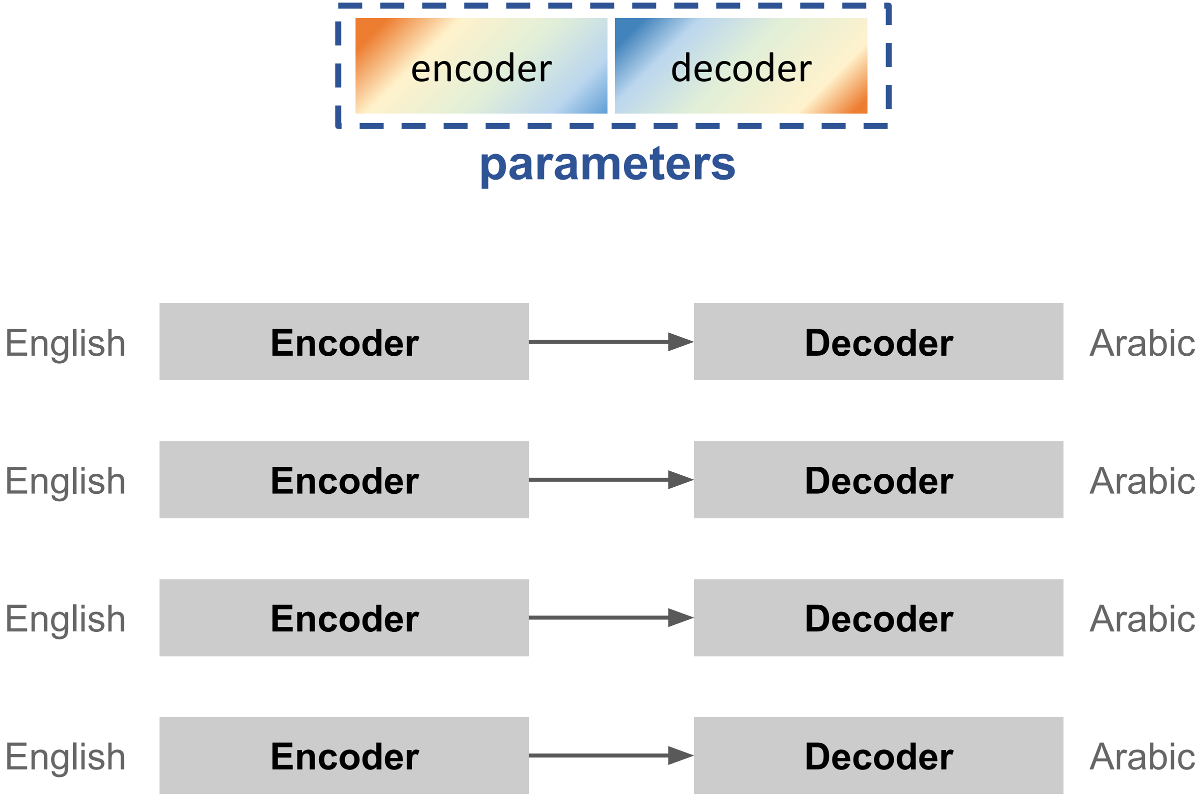
Investigation

- How does multilingual training affect the encoder/decoder?
  - i.e. How useful are the parameters learned from multilingual training?

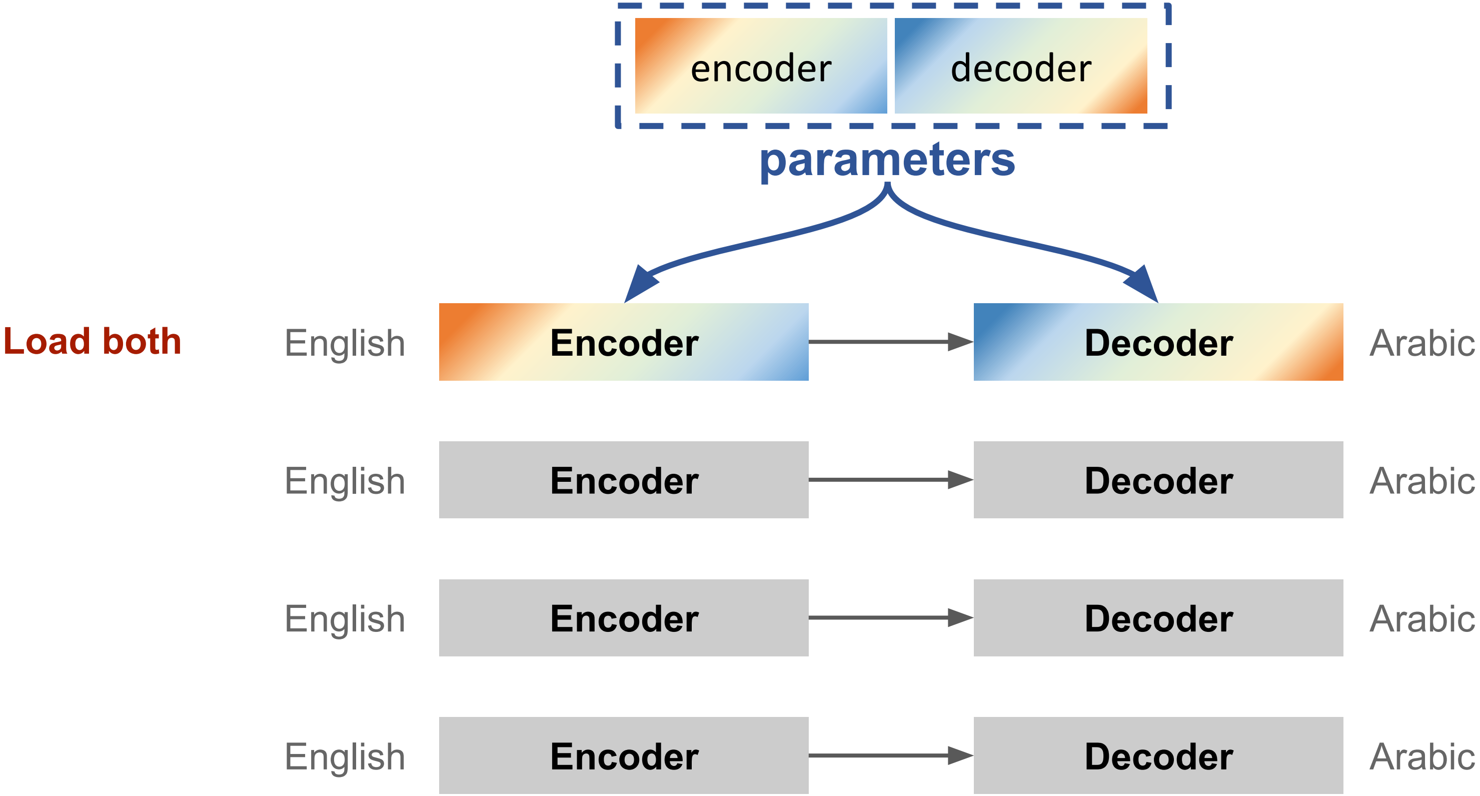
Experiment - Step 1: Train a Multilingual Model



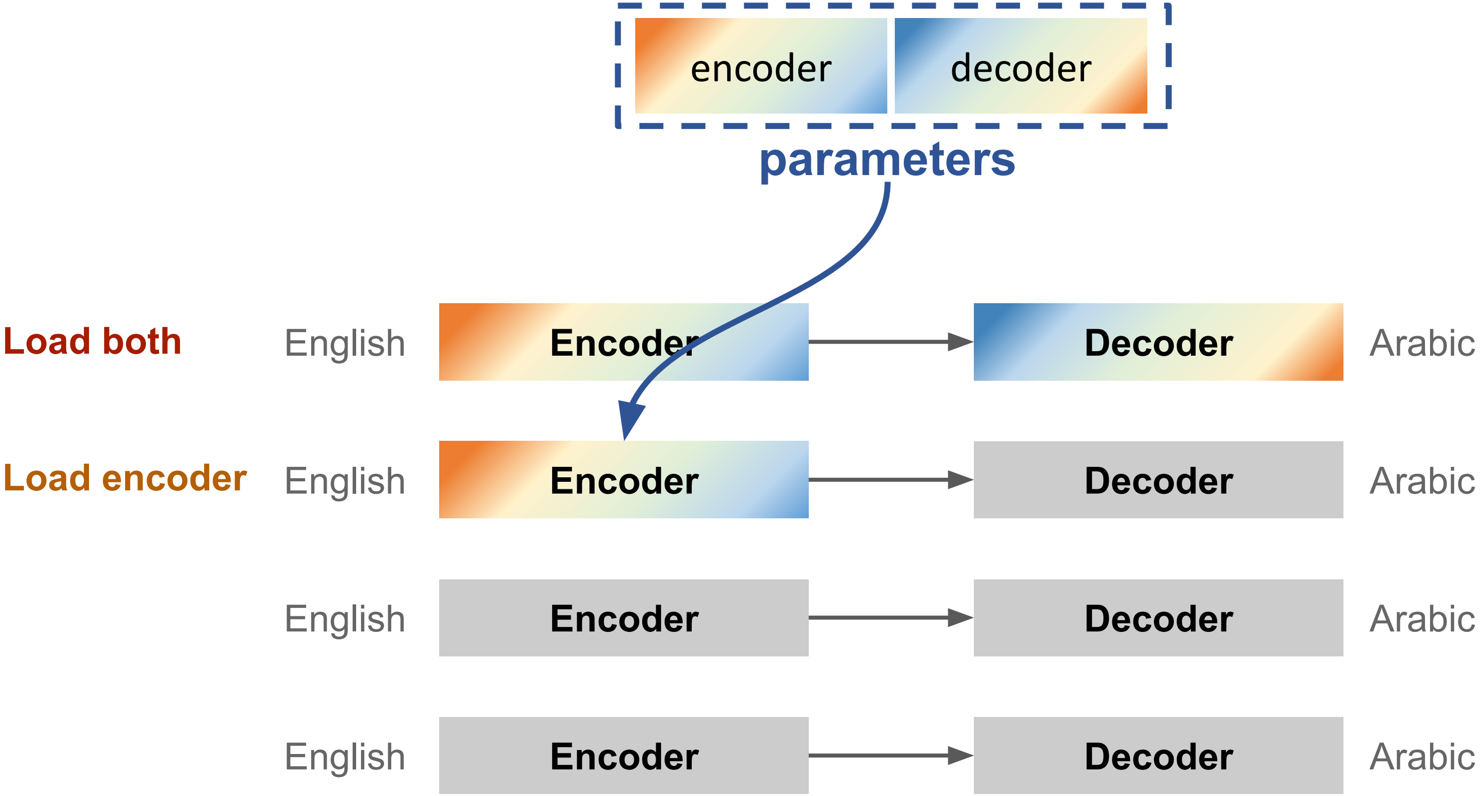
Experiment - Step 2: Initialize Several Bilingual Models



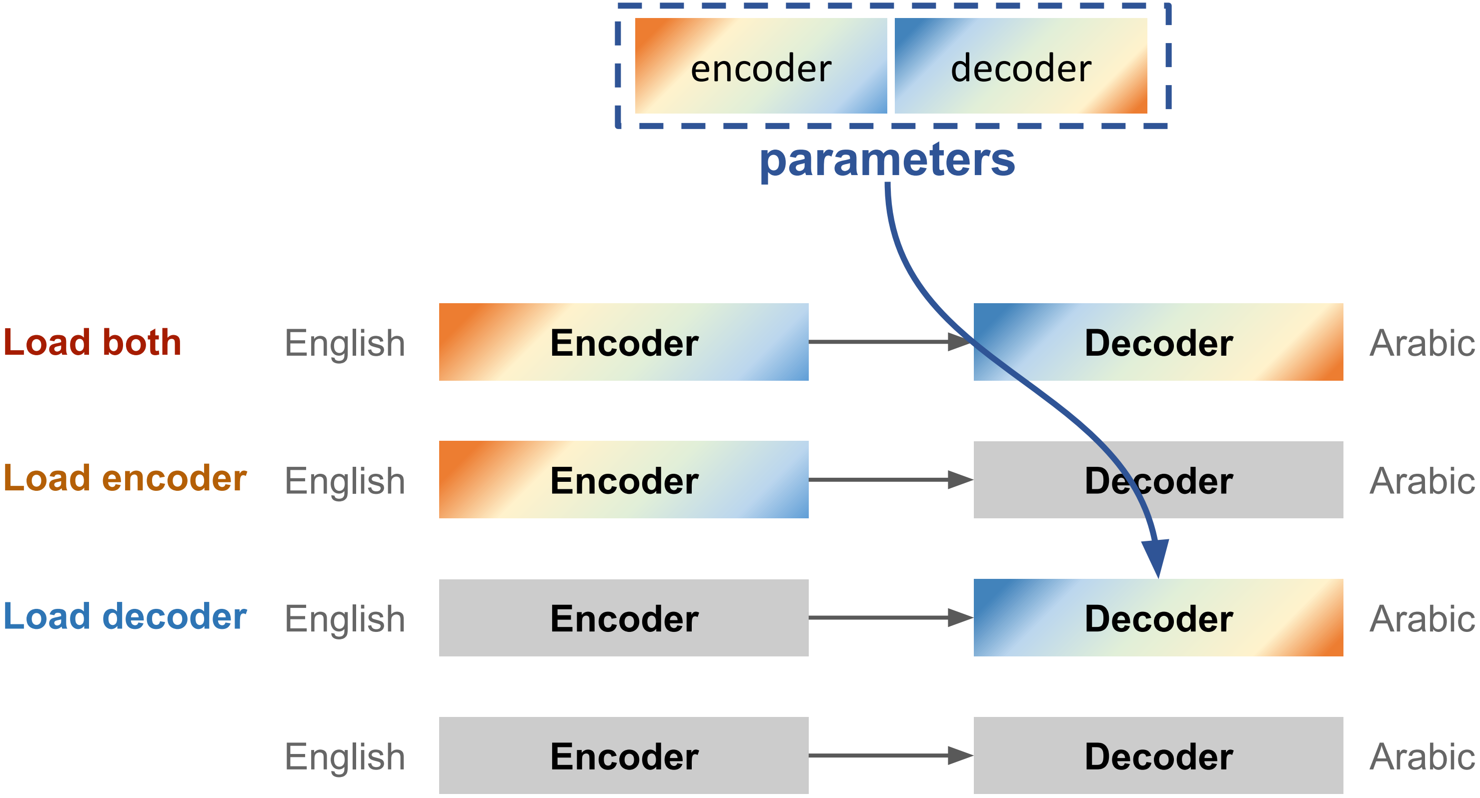
Experiment - Step 2: Initialize Several Bilingual Models



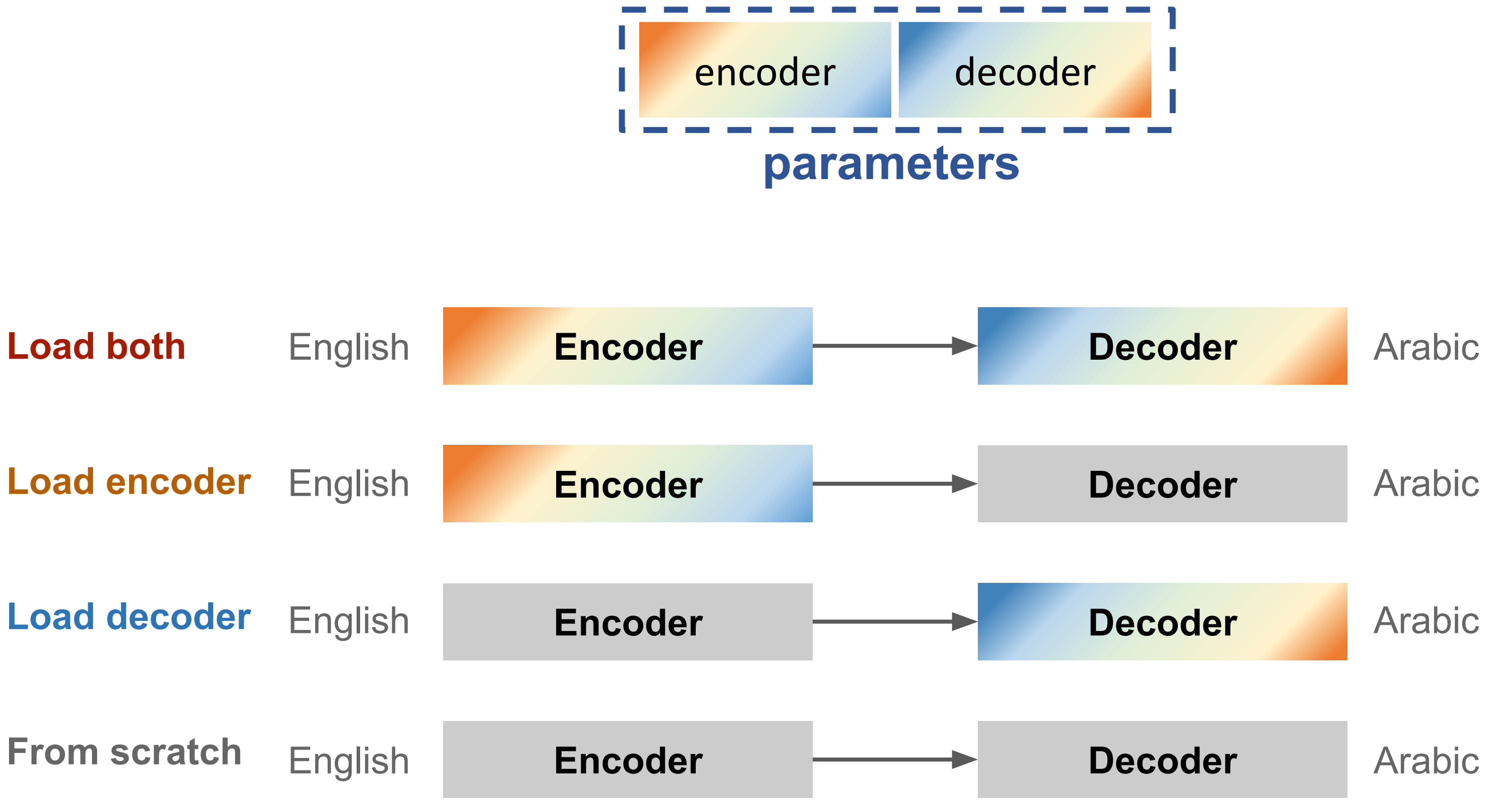
Experiment - Step 2: Initialize Several Bilingual Models



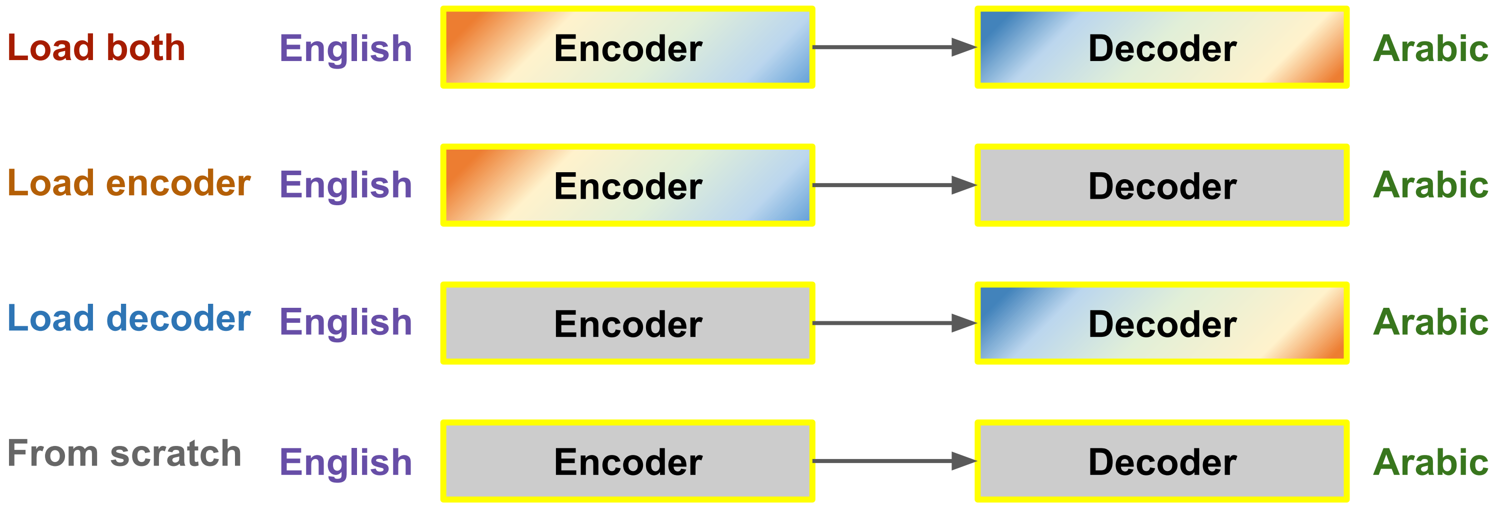
Experiment - Step 2: Initialize Several Bilingual Models



Experiment - Step 2: Initialize Several Bilingual Models

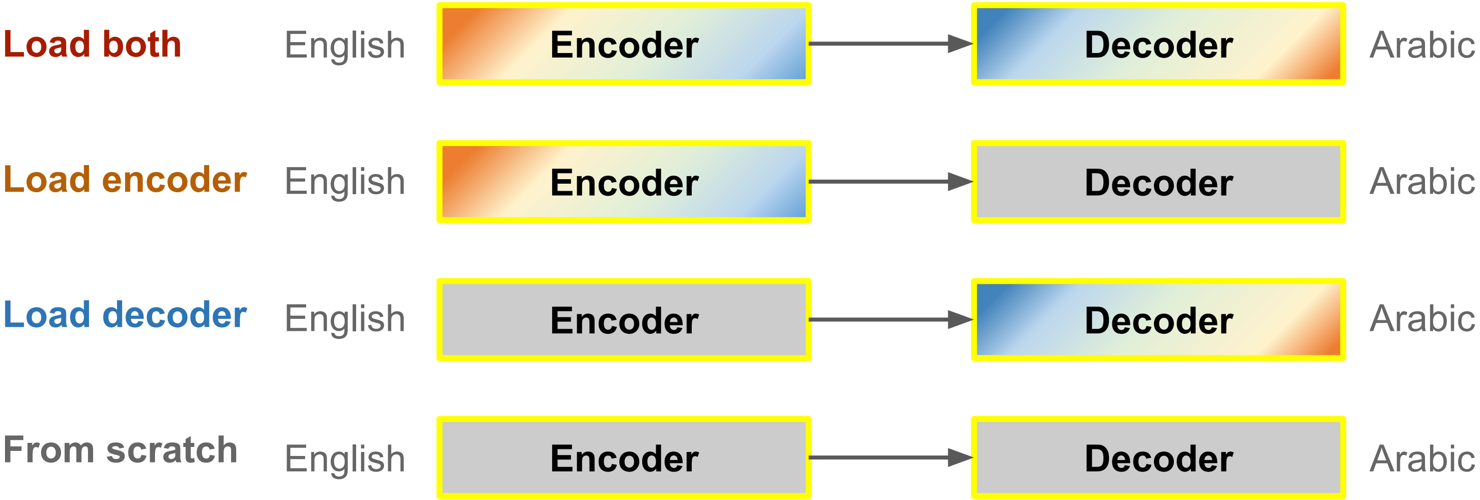


Experiment - Step 3: Train with Bilingual Data

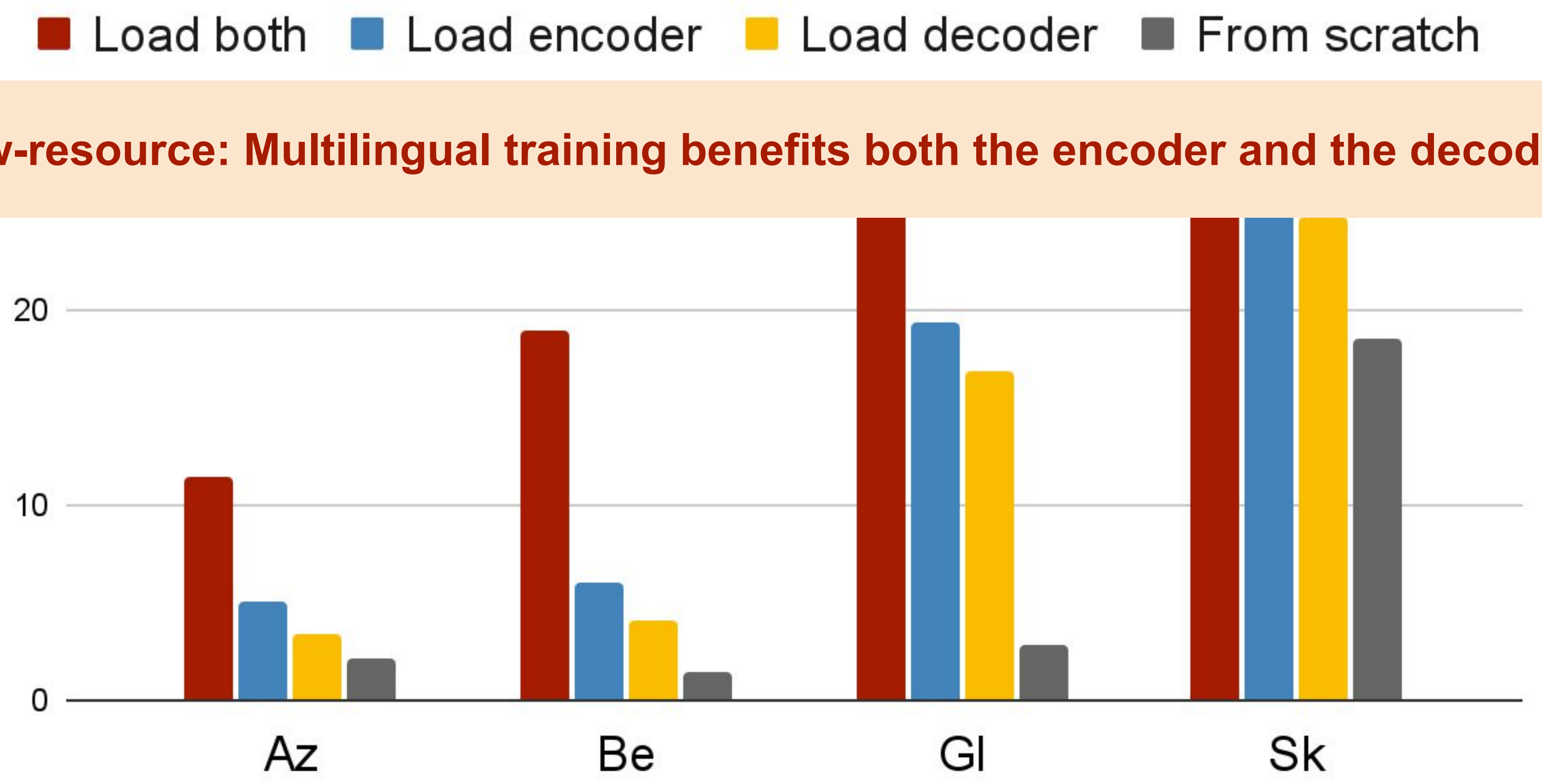


Experiment - Final Step: Compare their performance

We can infer how multilingual training benefits the encoder/decoder.

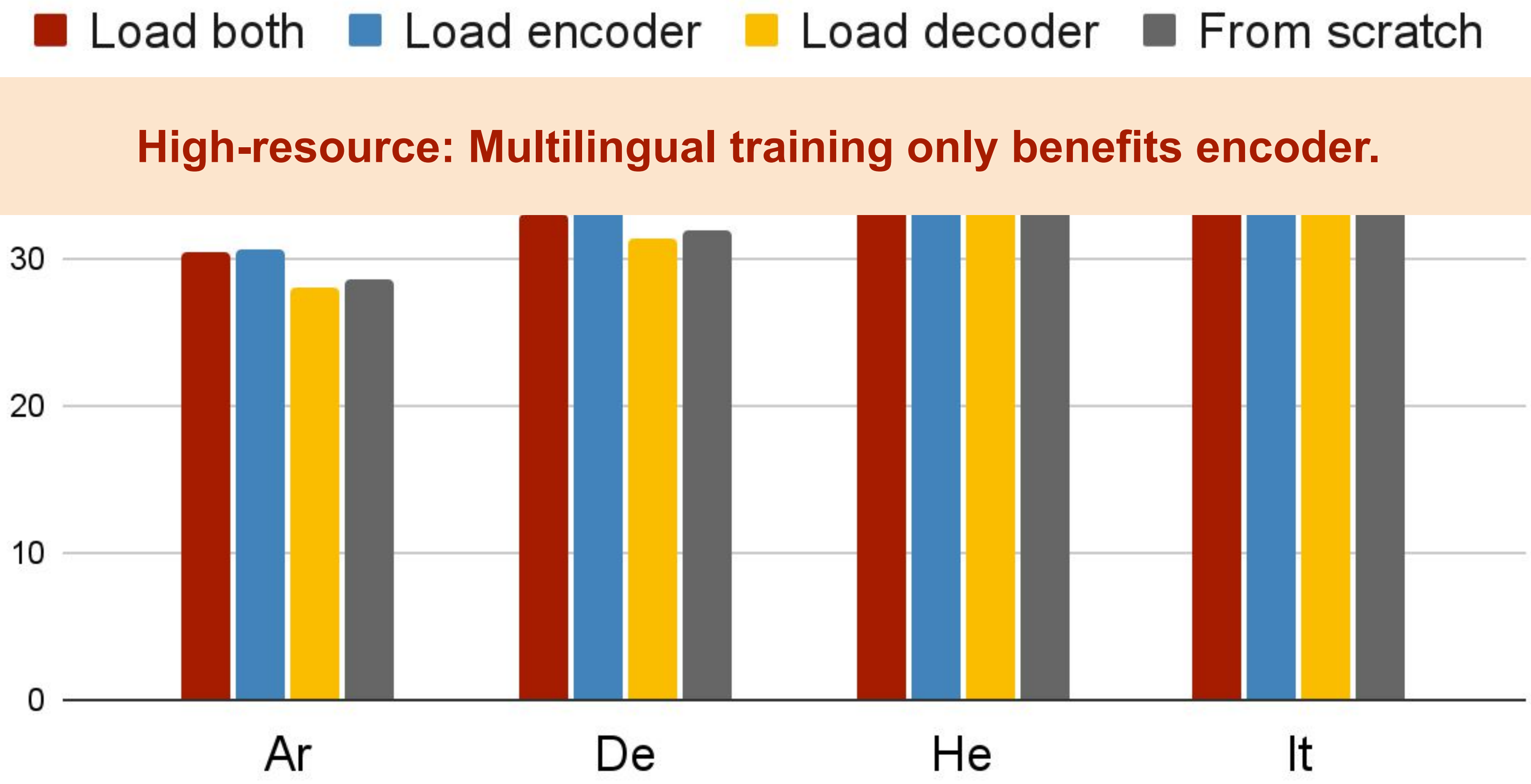


X to En - Low-resouce Languages



Low-resource: Multilingual training benefits both the encoder and the decoder.

X to En - High-resouce Languages

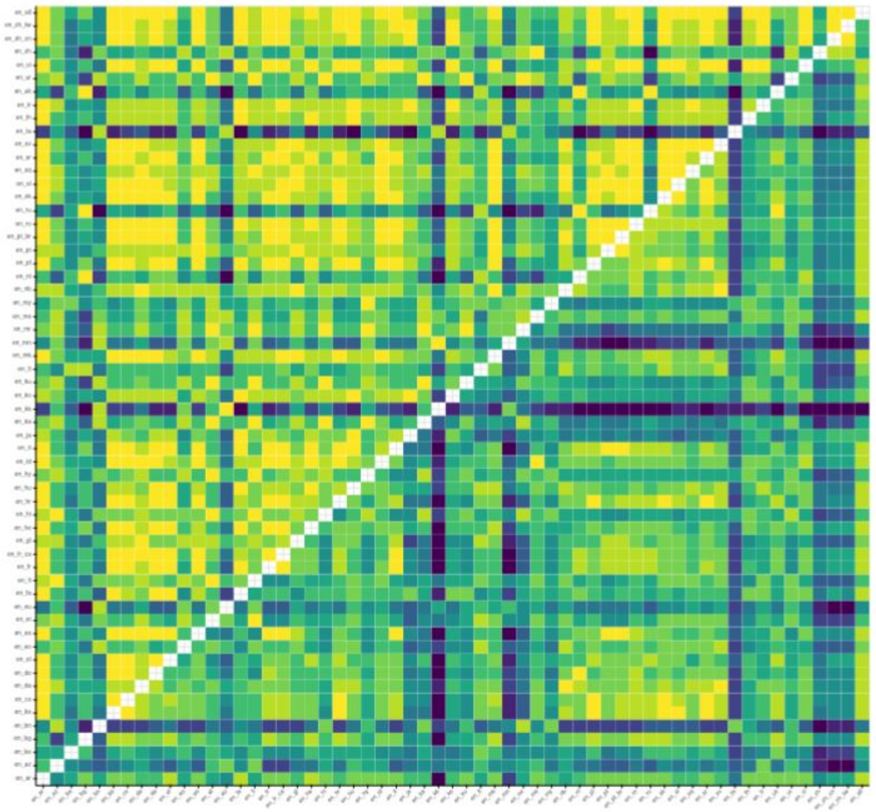


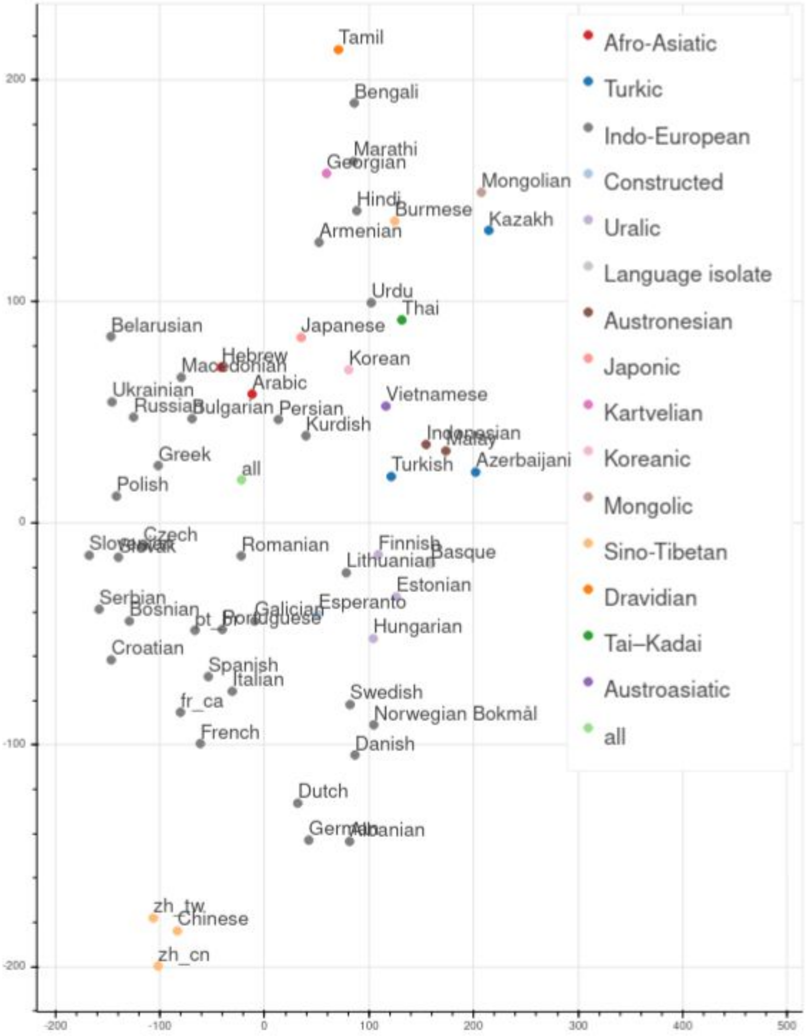
High-resource: Multilingual training only benefits encoder.

Investigating Parameter Sharing

1. Identify important attention heads for languages.
2. Compute the coherence of important heads.

Investigating Parameter Sharing



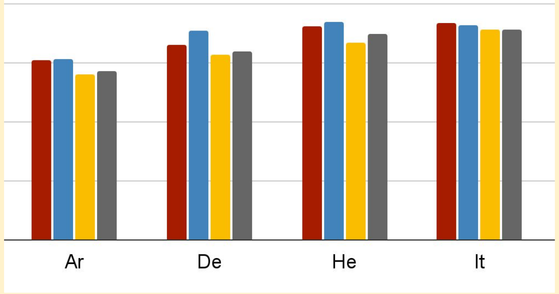

Afro-Asiatic
Turkic
Indo-European
Constructed
Uralic
Language isolate
Austronesian
Japonic
Kartvelian
Koreanic
Mongolic
Sino-Tibetan
Dravidian
Tai–Kadai
Austroasiatic
all
Tamil
Bengali
Marathi
Georgian
Mongolian
Hindi
Burmese
Kazakh
Armenian
Urdu
Thai
Belarusian
Japanese
Hebrew
Macedonian
Korean
Arabic
Ukrainian
Vietnamese
Russian
Bulgarian
Persian
Kurdish
Indonesian
Malay
Greek
all
Turkish
Azerbaijani
Polish
Czech
Slovak
Romanian
Finnish
Basque
Lithuanian
Estonian
Serbian
Bosnian
Galician
Esperanto
Portuguese
Hungarian
Croatian
Spanish
Italian
Swedish
fr_ca
Norwegian Bokmål
French
Danish
Dutch
German
Albanian
zh_tw
Chinese
zh_cn
200
100
0
-100
-200
-200
-100
0
100
200
300
400
500

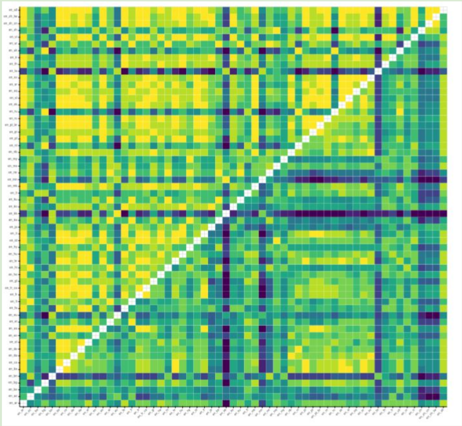
Improvement by Training with Related Languages

Model	az	be	gl	sk	ar	de	he	it
En-All (Aharoni et al., 2019)	5.1	10.7	26.6	24.5	16.7	30.5	27.6	35.9
Bilingual Baseline	1.3	1.9	3.9	13.1	15.6	27.1	25.4	32.0
All-All	3.1	6.2	20.5	18.4	12.7	24.5	21.1	30.5
All-All w/ f.t. on related clusters	7.9	12.8	27.5	24.9	-	30.2	27.0	35.4
All-All w/ f.t. on random groups	6.9	13.3	22.5	24.3	-	-	27.5	35.2
En-All	4.9	9.00	24.2	21.9	15.1	27.9	24.1	33.3
En-All w/ f.t. on related clusters	**7.9**	13.9	21.0	**26.2**	16.7	30.4	27.1	35.4
En-All w/ f.t. on random groups	7.0	13.1	23.1	24.7	-	-	27.6	35.2
Load En-All w/ f.t. on closest	7.8	**15.2**	**28.6**					

Conclusion

We found that multilingual training is more useful for the encoder.





We proposed a purely data-driven way to identify related languages.

Our experiments can serve as analysis tools for future research.