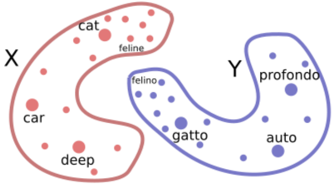
Aligning Word Vectors on Low-Resource Languages with Wiktionary

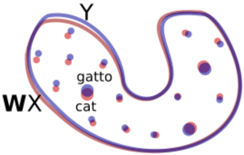
by **Mike Izbicki** (Claremont McKenna College, USA)

Background (1): What are aligned word vectors?

First train word embeddings in multiple languages:



Then map them to a common space:



Images from MUSE (Conneau et al., 2017).

Background (2): Applications of aligned word embeddings

- Transfer learning between languages

- Machine translation

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  - **Bilingual Lexicon Induction (BLI)**

    Given a word in a source language (ko):

    안녕하세요 (annyeonghaseyo)

    Find the “closest word” in the target language (en):

    hello, hi, how’s it going?, wassup?

Background (3): Lots of papers study BLI

For example:

Abdulrahim (2019), Adams et al. (2017), Ahmad et al. (2018), Alabi et al. (2020), Alaux et al. (2018), Aldarmaki and Diab (2019), Anastasopoulos and Neubig (2019), Artetxe et al. (2017b), Artetxe et al. (2017a), Artetxe et al. (2018c), Artetxe et al. (2018a), Artetxe et al. (2018b), Artetxe et al. (2020), Burdick et al. (2021), Chen and Cardie (2018), Chen and Basirat (2020), Chen and Basirat (2020), Chimalamarri et al. (2020), Chimalamarri et al. (2020), Choe et al. (2019), Conneau et al. (2017), Di Gangi and Federico (2017), Ding and Duh (2018), Dinu and Baroni (2014), Dyevre (2021), Font and Costa-Jussa (2019), Gennaro and Ash (2022), Glavaš et al. (2019), Gordon et al. (2020), Grave et al. (2018), Gupta and Jaggi (2021), Heyman and Heyman (2019), Heyman et al. (2019), Indukaev (2021), Joshi et al. (2019), Joulin et al. (2018), Kementchedjhieva et al. (2019), Kim et al. (2018), Klementiev et al. (2012), Marchisio et al. (2020), Mikolov et al. (2013), Mikolov et al. (2018), Mogadala and Rettinger (2016), Neishi et al. (2017), Ormazabal et al. (2019), Li et al. (2018), Qi et al. (2018), Rheault and Cochrane (2020), Rodriguez and Spirling (2022), Schuster et al. (2019) , Sert et al. (2021), Stringham and Izbicki (2020), Strubell et al. (2019), Vulić and Moens (2015), Vulić et al. (2019), Vulić et al. (2020), Vulić et al. (2020), Wang et al. (2020), Xia et al. (2019), Xiao and Guo (2014), Xing et al. (2015), Yang et al. (2019), Zhang et al. (2017), Zhang et al. (2019), Zhao et al. (2020)

Problem: Existing BLI datasets are machine generated

- This results in weird artifacts:

Thai "Word"	English "Translation"	
เนูเธ้เธศเธญูเธฑเธตเน่	calories	
เนฺเธ้เธกเธศเธญูเธข	lanterns	
annie	annie	proper nouns
bdfutbol	bdfutbol	HTML/code artifacts
getparent	getparent	
roca	roca	not a word

- Quality varies tremendously between languages (EN-ES pretty good... EN-TH pretty bad... others???)

- Kementchedjhieva et al. (2019) suggest that future research *"avoids drawing conclusions from quantitative results on [the MUSE] BLI dataset."*

Solution: Create BLI datasets with Wiktionary!

- “Wikipedia for dictionaries”
- Each entry contains:
  - word
  - language
  - part of speech
  - English-language translation
  - ...

  Crowd sourced data
- 1.8 million entries in 4204 languages

WIKTIONARY
the free dictionary

Limitations of Wiktionary (1)

- Most languages have few entries

  298/4204 languages "good enough" for BLI.

  Generate test sets with the following POS splits

Part of Speech	Number of Words
Adjective	50
Adverb	25
Noun	125
Verb	50
Total	250

not proper nouns

- For languages with larger vocabulary, larger test sets are created

Limitations of Wiktionary (2)

- Wiktionary dataset focuses on "dictionary forms" of words

  Korean dictionary word 가다 (gada = "to go") in the dataset

  Conjugated forms not in dictionary include:
  가, 가요, 가자, 가겠어, 가겠어요, 가겠습니다, 갑니다, 갑니까, 갑시다, 갔다, 갔어, 갔어요, 갔느냐, 갔습니다, 갔습니까

  Korean is agglutinative language, so MANY conjugated forms

- Some languages (like Spanish) DO include conjugated forms

Results (1)

Despite limitations, Wiktionary data still better:

Wiktionary Dataset	Previous Datasets
298 Languages	$\leq$ 45 languages
Human Translations	Machine Translations
Has POS tags	No POS tags

Results (2)

Align the 157 word embeddings provided by Grave et al. (2018)

- largest set of aligned word embeddings to-date

15 previously unstudied languages have "high" BLI accuracy ($> 30\%$):

Armenian (39.15)	Austurian (36.92)
Azerbaijani (37.38)	Basque (36.32)
Belarusian (35.75)	Esperanto (50.00)
Galician (46.62)	Georgian (37.30)
Malayalam (33.62)	Mongolian (31.38)
Norwegian Nynorsk (32.35)	Serbian (30.76)
Serbo-Croatian (33.17)	Urdu (37.08)
Welsh (34.84)	

Results (3): Languages Presented about Today

			BLI Accuracy	
Presenter	Language	Dataset Size	(Wiktionary)	(MUSE)
Everlyn	Swahili	6134	**18.01**	–
	Luhya	35	–	–
Mohaddeseh	Persian	10907	**39.40**	37.39
Anna	Ket	75	–	–
	Chikchi	65	–	–
	Ludic	404	–	–
	Karelian	735	–	–
	Selkup	12	–	–
	Evenki	512	–	–
	Veps	2012	–	–
Nathaniel	Jamaican	258	–	–
	Haitin Creole	1278	–	–
Amartya	Lambani	2	–	–
Vasile	Romanian	67121	48.58	**48.96**
Alberto	Indonesian	15015	**40.15**	35.20
	Malay	5989	**28.56**	27.60
Shivam	Bengali	4720	26.68	**28.34**
	Gujarati	3284	**16.81**	–
	Hindi	14234	**38.28**	33.99
	Marathay	2080	**19.82**	–
	Tamil	5357	21.20	**29.11**
Jenn	Cebuano	13176	**8.22**	–
	Tagalog	15015	**30.14**	28.24

Takeaways

- All code/data open source at

  `https://github.com/mikeizbicki/wiktionary_bli`

- Aligned word vectors might now be useful in YOUR language.
- Wiktionary can help you translate.
- You can help Wiktionary !?!?

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