Towards a Broad Coverage Named Entity Resource: A Data-Efficient Approach for Many Diverse Languages

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Outline

1. Introduction
2. Method
3. Evaluation and Analysis
4. Use cases
5. Resource
6. Conclusion

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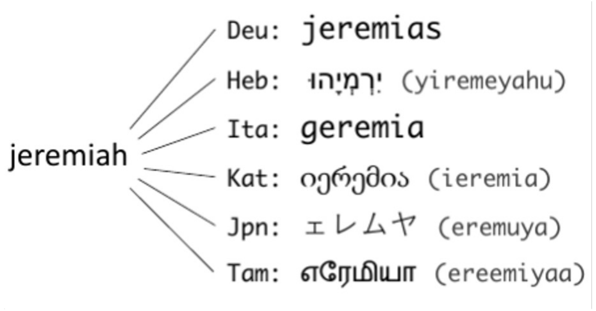
- Named entities (NEs):
  - Crucial for monolingual and cross-lingual NLP tasks
  - Multilingual NE lexicons are not available for many low-resource languages



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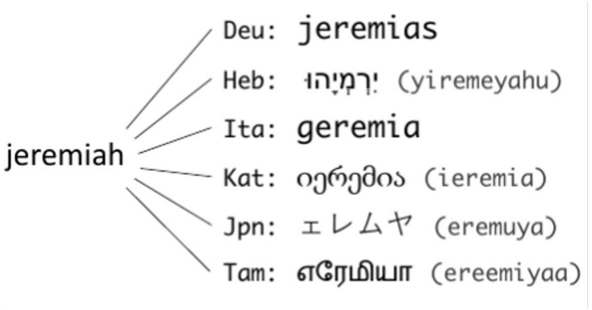

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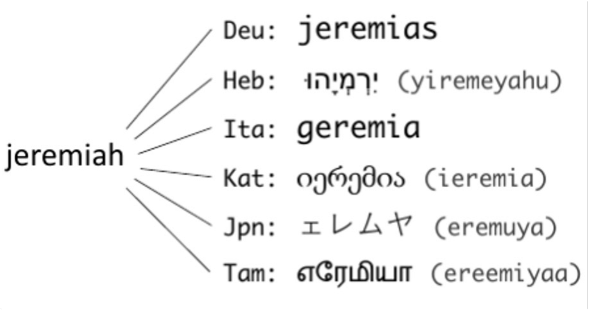

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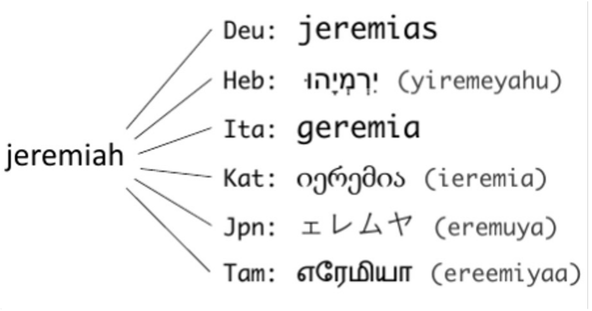

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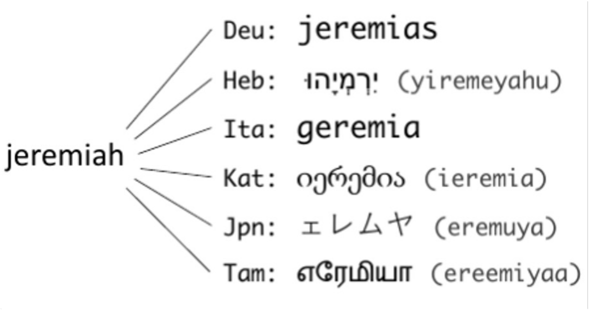
  - **Our method creates a very broad-coverage NE resource based on parallel text only**



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- We annotate a set of NEs to evaluate CLC-BN's performance on **13** languages through crowdsourcing and show a performance increase in comparison to prior work
  - We release the gold annotated sets as a resource for future work

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- We annotate a set of NEs to evaluate CLC-BN's performance on **13** languages through crowdsourcing and show a performance increase in comparison to prior work
  - We release the gold annotated sets as a resource for future work
- Using CLC-BN, we create and release a named entity resource for **1340** languages

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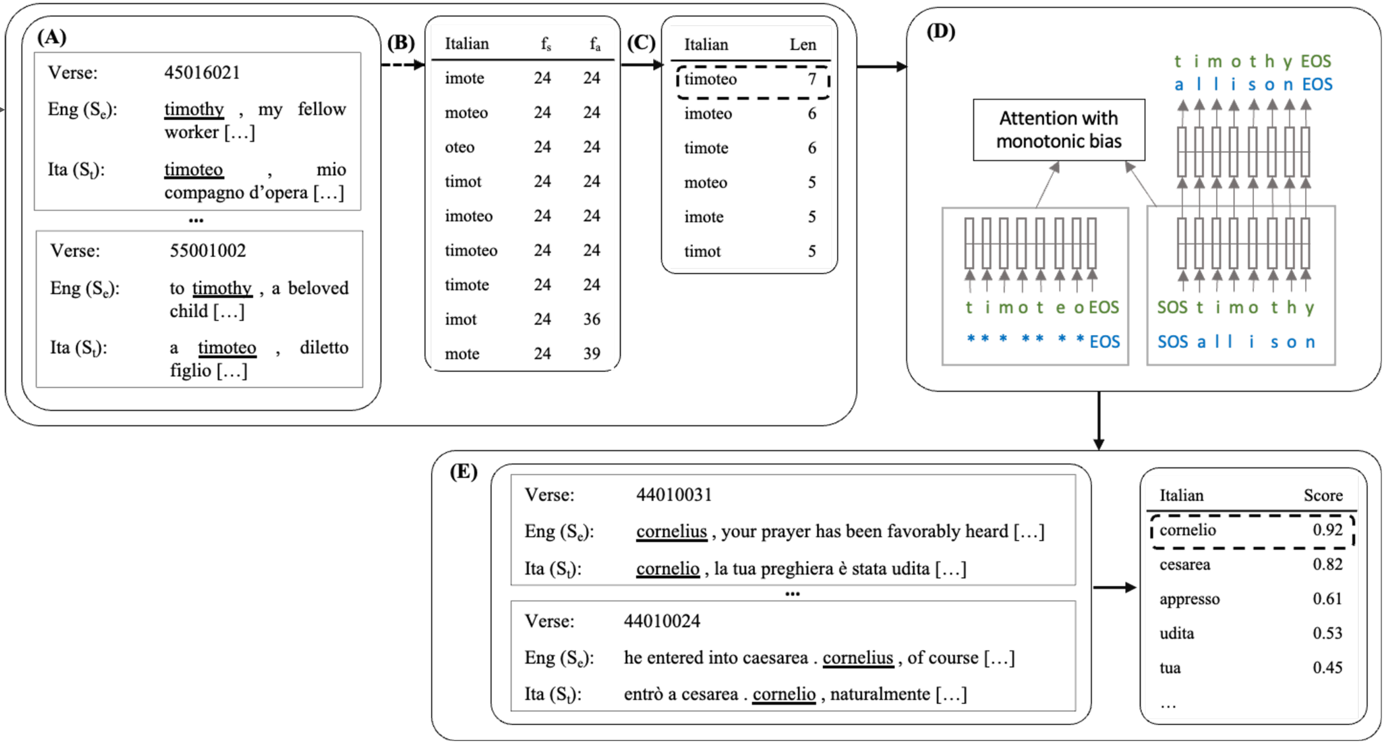
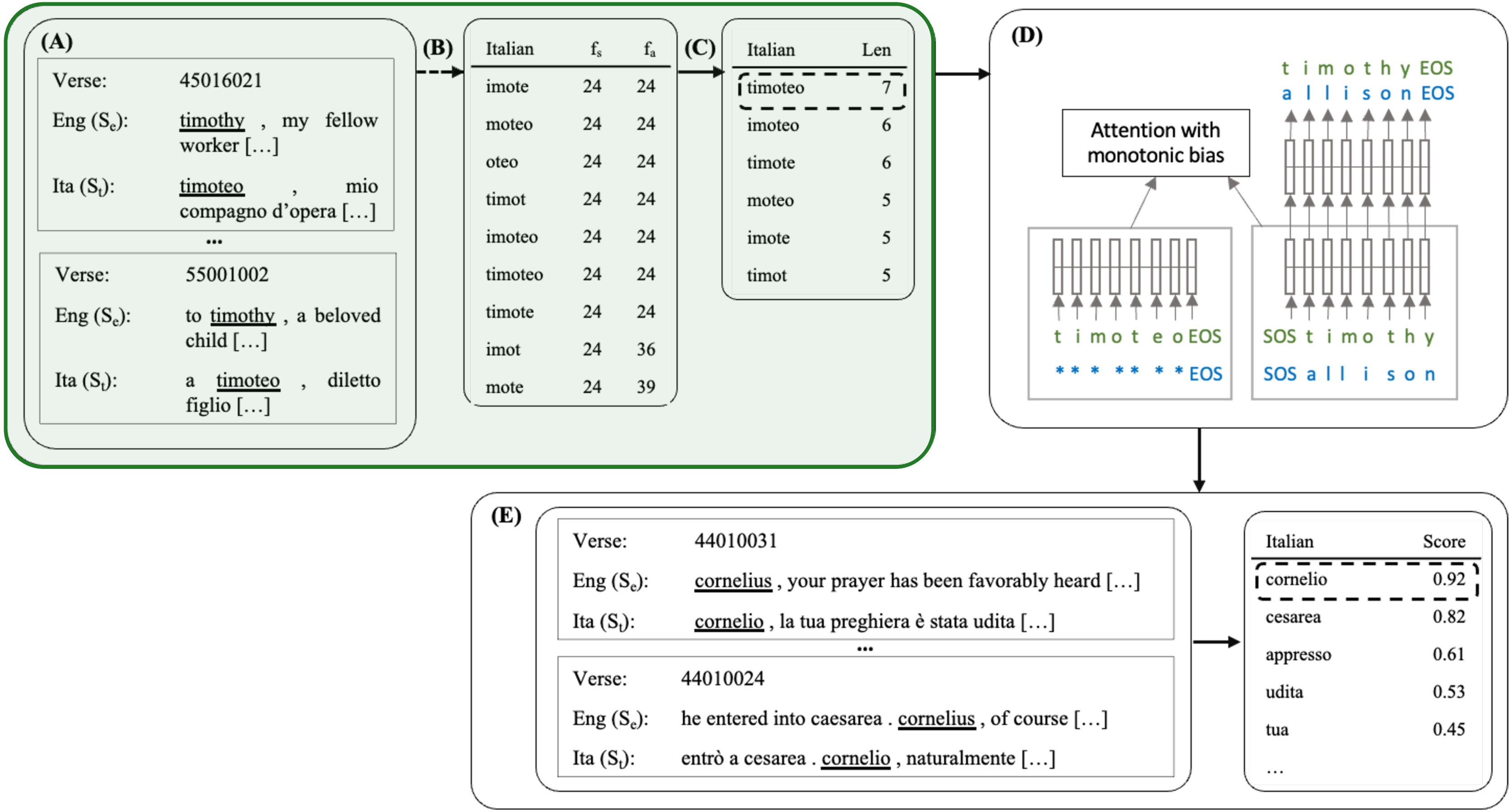
CLC-BN: CLC-Bootstraping + Neural transliteration

English NE:

Timothy



CLC-B: extract character-level correspondences



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A. Extract the parallel subcorpus that contains **Timothy**

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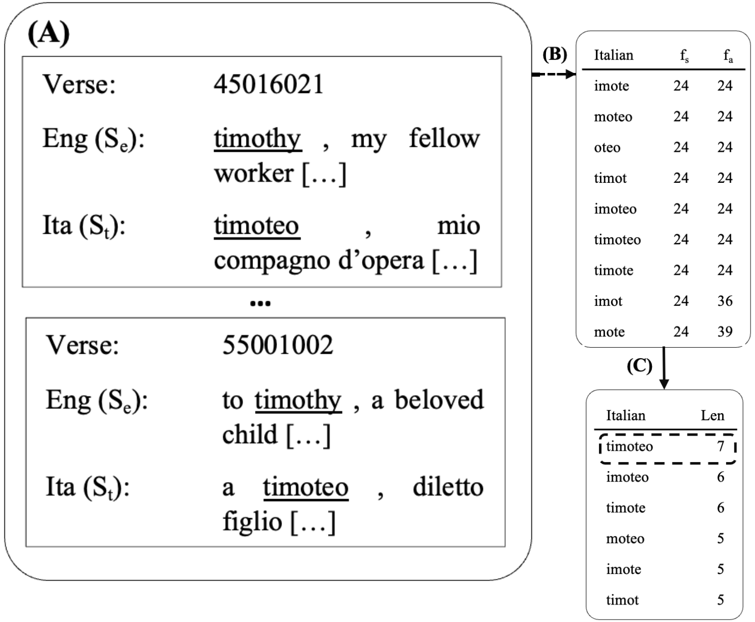

CLC-B: extract character-level correspondences

A. Extract the parallel subcorpus that contains **Timothy**

B. For all character n-grams in the target corpus, determine f_s and f_a . Discard n-grams with f_a>50

English NE: **Timothy**

(A)

Verse:	45016021
Eng (S_e):	timothy , my fellow worker […]
Ita (S_t):	timoteo , mio compagno d'opera […]

…

Verse:	55001002
Eng (S_e):	to timothy , a beloved child […]
Ita (S_t):	a timoteo , diletto figlio […]

Italian	f_s	f_a
imote	24	24
moteo	24	24
oteo	24	24
timot	24	24
imoteo	24	24
timoteo	24	24
timote	24	24
imot	24	36
mote	24	39

Italian	Len
timoteo	7
imoteo	6
timote	6
moteo	5
imote	5
timot	5

CLC-B: extract character-level correspondences

A. Extract the parallel subcorpus that contains **Timothy**

B. For all character n-grams in the target corpus, determine f_s and f_a . Discard n-grams with f_a>50

C. Filter the remaining n-grams:

  a. Keep n-grams with the highest f_s

  b. Keep n-grams with the minimum absolute difference between f_s and f_a

  c. Return the n-gram with the smallest length difference

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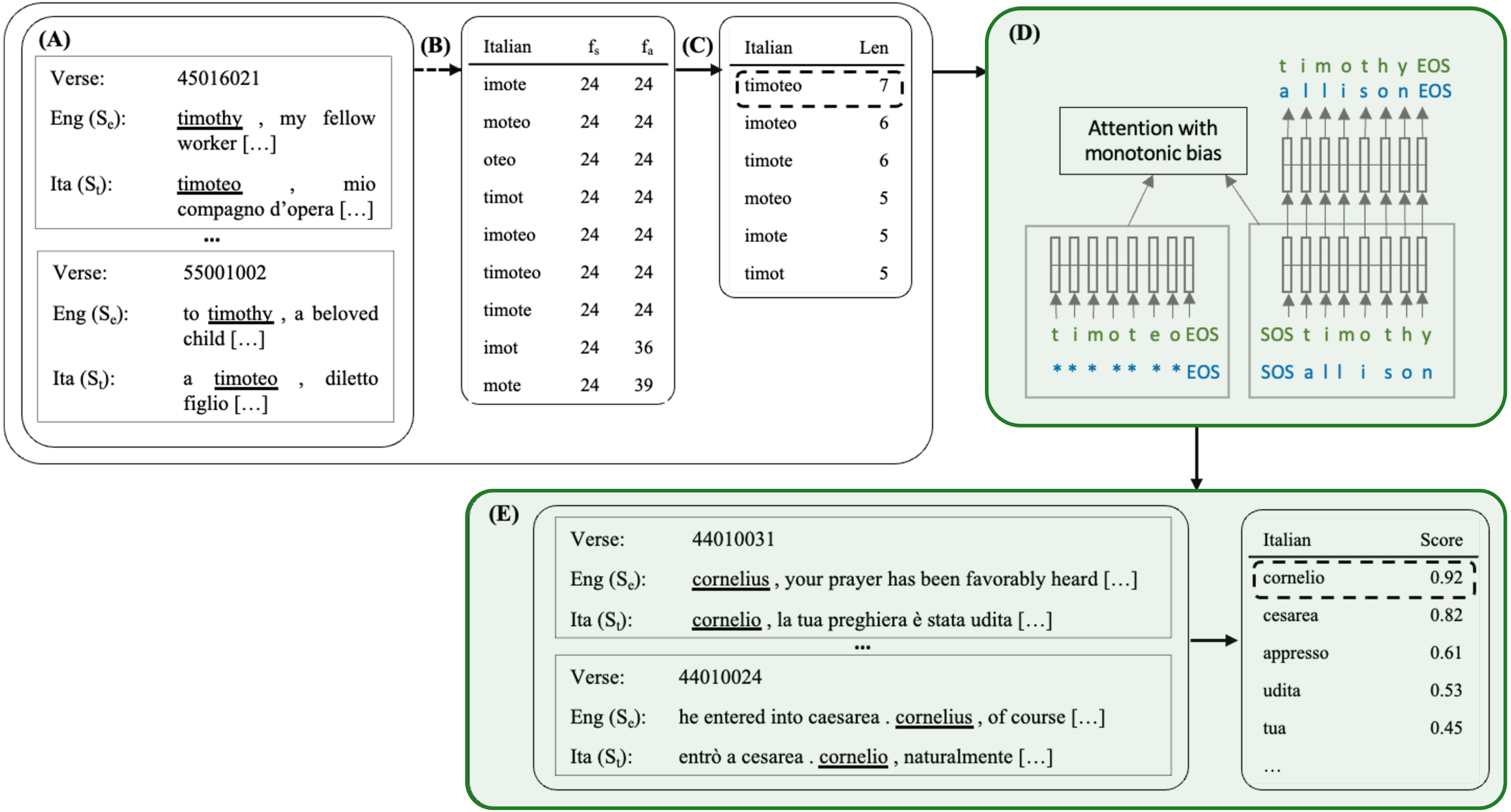
CLC-BN: Neural Transliteration model



CLC-BN: Neural Transliteration model

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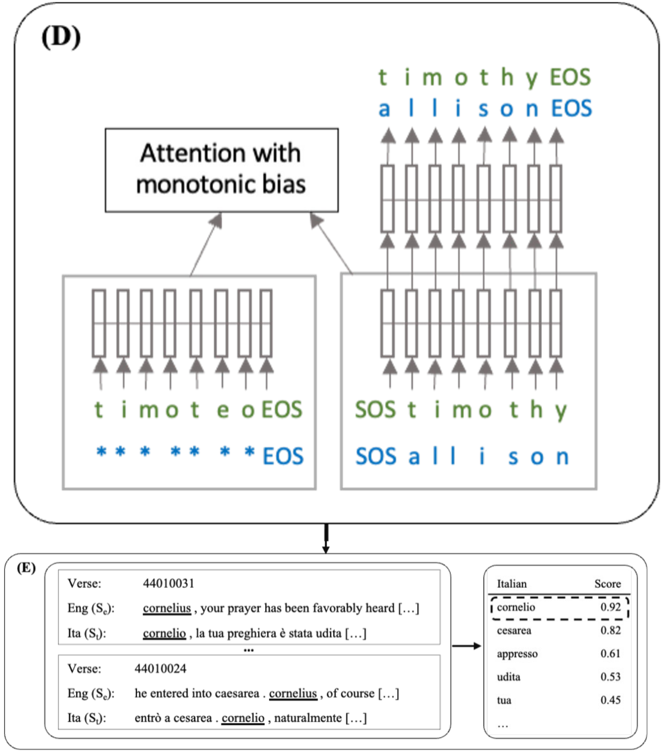
Model (D):

- Character-level Bi-GRU (Target-to-Source)
- English data augmentation with Wikipedia dump and Flair POS tagger
- Monotonic bias



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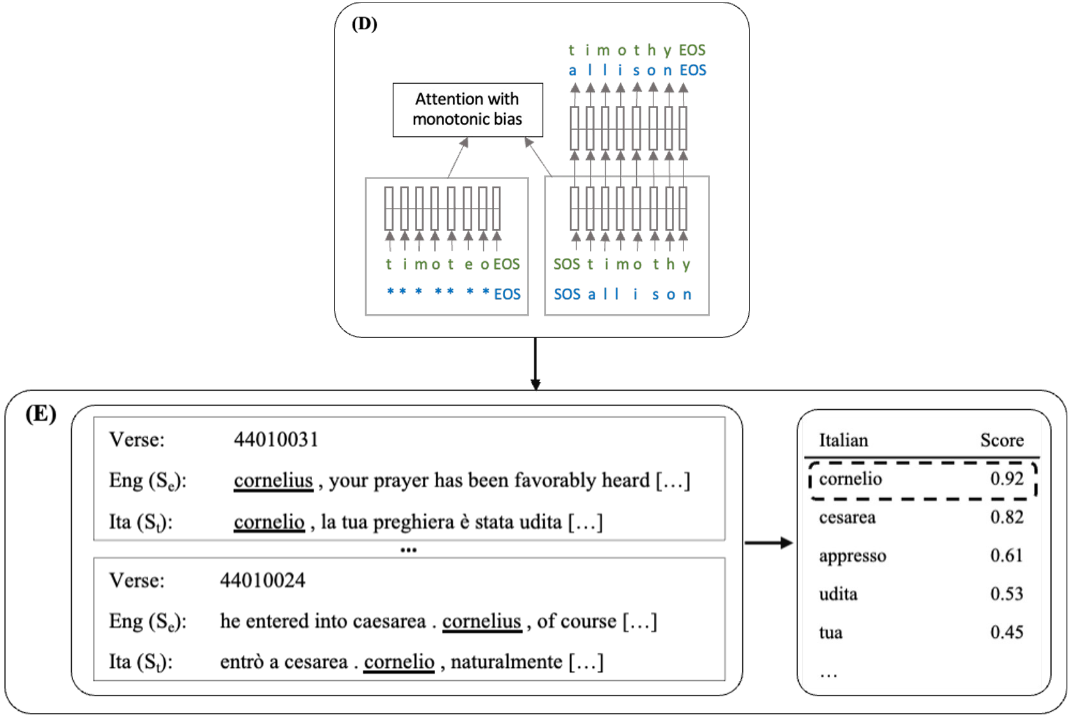

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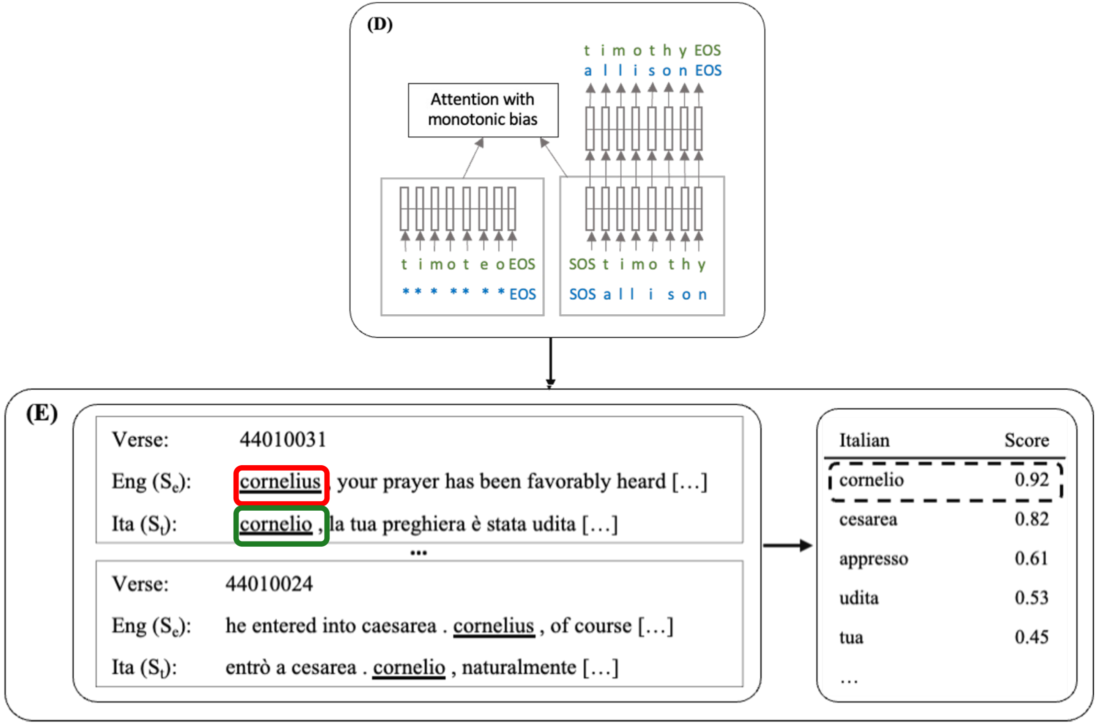

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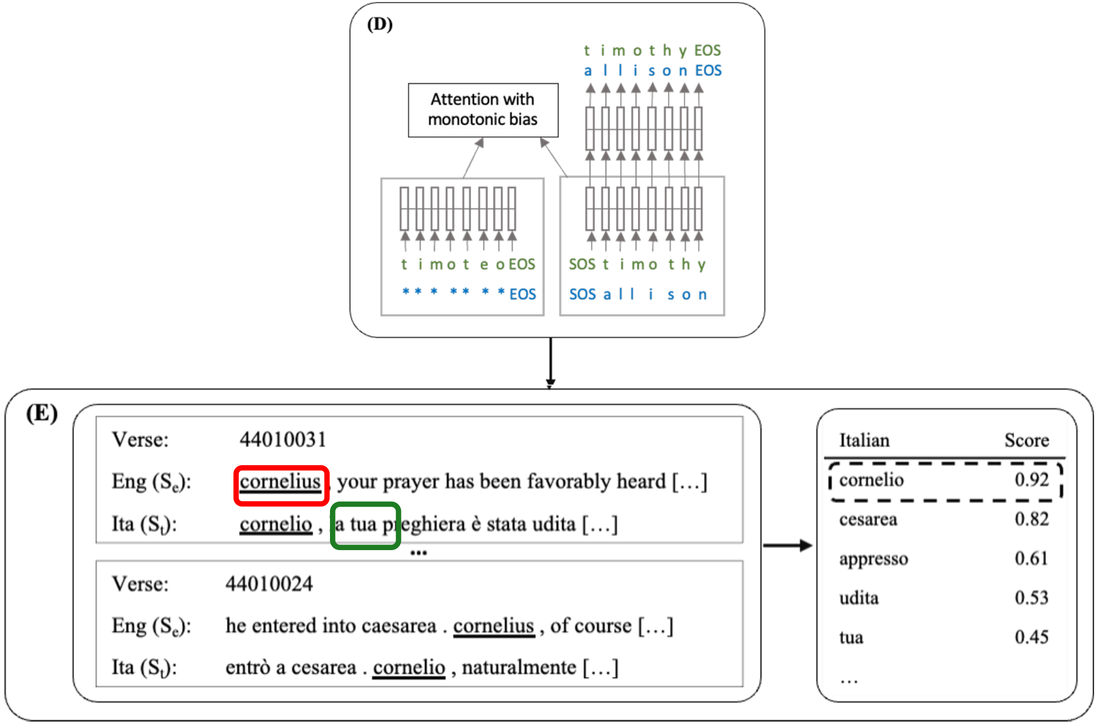

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Experimental setup

- Parallel Bible Corpus (PBC)
- Evaluation over 13 languages with different scripts, resource availabilities, and language families
- Silver evaluation using the Google translation API
- Gold human evaluation through crowd-sourcing

	Lang	ISO	# verses	# parallel
low-resource languages	Arabic	Arb	31173	31062
	Finnish	Fin	31167	31061
	Greek	Ell	31183	31062
	Russian	Rus	31173	31062
	Spanish	Spa	31167	31062
	Swedish	Swe	31167	31062
	Zulu	Zul	31167	31062
lowest-resource languages	Hebrew	Heb	7952	7917
	Hindi	Hin	7952	7917
	Kannada	Kan	7952	7917
	Korean	Kor	7913	7869
	Georgian	Kat	4904	4844
	Tamil	Tam	7942	7917

Gold human evaluation - baseline

Low-resource setting

	Arb	Ell	Fin	Spa	Swe	Rus	Zul	AVG
Wu et al. (2018)	70.0	80.0	90.0	91.7	88.3	72.9	84.8	82.5
CLC-B	56.7	45.0	50.0	48.3	48.3	57.6	74.6	54.4
CLC-BN	<u>81.7</u>	<u>91.7</u>	<u>93.3</u>	<u>96.7</u>	<u>91.7</u>	<u>84.8</u>	<u>93.2</u>	<u>90.4</u>

Lowest-resource setting

	Heb	Hin	Kan	Kat	Kor	Tam	AVG
Wu et al. (2018)	62.5	76.3*	61.7	70.0	54.2	66.1*	65.1
CLC-B	51.8	39.0*	48.3	45.0	37.3	47.5*	44.8
CLC-BN	71.4	<u>94.9</u>*	<u>93.3</u>	<u>88.3</u>	<u>78.0</u>	<u>91.5</u>*	<u>86.2</u>

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Gold human evaluation - word alignment

Low-resource setting

	Arb	Ell	Fin	Spa	Swe	Rus	Zul	AVG
Östling et al. (2016)	61.7	88.3	76.7	86.7	85.0	83.1	86.4	81.1
Sabet et al. (2020)	20.0	40.0	60.0	45.0	50.0	45.8	25.4	40.9
CLC-B	56.7	45.0	50.0	48.3	48.3	57.6	74.6	54.4
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Error Analysis

#	English	Arabic	Finnish	Greek	Hebrew	Kannada	Russian	Tamil
28	elijah	alalihaau	eliaa	elia	veaeliyahu	eliiyanaagali	elisei	eliyaavaa
12	titus	tiytusa	titus	titos	titos	titanannu	titu	tiittuvin
8	elizabeth	aaliysaabaata	elisabet	elisabet	elisheva	elisabeet	elizaveta	elicapet
3	miletus	miyliytusa	miletokseen	mileto	lemilitos	mileetakke	mileta	mileettu
2	rufus	ruwfusa	rufuksen	roufo	vishelom	uphaniguu	rufa	ruupuvukkum
2	hermes	wahirmisa	hermeeksi	epairne	heremes	meeyaniguu	germes	ermee

Error Analysis

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28	elijah	alalihaau	eliaa	elia	veaeliyahu	eliiyanaagali	elisei	eliyaavaa
12	titus	tiytusa	titus	titos	titos	titanannu	titu	tiittuvin
8	elizabeth	aaliysaabaata	elisabet	elisabet	elisheva	elisabeet	elizaveta	elicapet
3	miletus	miyliytusa	miletokseen	mileto	lemilitos	mileetakke	mileta	mileettu
2	rufus	ruwfusa	rufuksen	roufo	vishelom	uphaniguu	rufa	ruupuvukkum
2	hermes	wahirmisa	hermeeksi	epairne	heremes	meeyaniguu	germes	ermee

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Use cases

- Transliteration

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- Extending existing multilingual resources (i.e., BabelNet)

Lang.	CLC-BN	Babel	New NEs %
Arb	977	683	30.1
Fin	979	647	33.9
Ell	979	658	32.8
Rus	485	449	7.4
Spa	979	784	19.9
Swe	979	684	30.1
Zul	979	471	51.9
Heb	467	413	11.6
Hin	467	334	28.5
Kan	467	299	36.0
Kor	467	386	17.3
Kat	368	271	26.4
Tam	433	318	26.6
Jpn	979	715	27.0
Zho	979	698	28.7
Tha	467	337	27.8
AVG.	715	509	27.2

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Swe	979	684	30.1
Zul	979	471	51.9
Heb	467	413	11.6
Hin	467	334	28.5
Kan	467	299	36.0
Kor	467	386	17.3
Kat	368	271	26.4
Tam	433	318	26.6
Jpn	979	715	27.0
Zho	979	698	28.7
Tha	467	337	27.8
AVG.	715	509	27.2

Use cases

- Transliteration
- Extending existing multilingual resources (i.e., BabelNet)
- Cross-lingual mapping of word embeddings
  - VecMap
  - Bilingual Lexicon Induction (MUSE)

	Eng-Jpn	Eng-Tam	Eng-Zho
Unsupervised	0.0	0.0	0.0
Semisupervised	30.43	14.4	30.1

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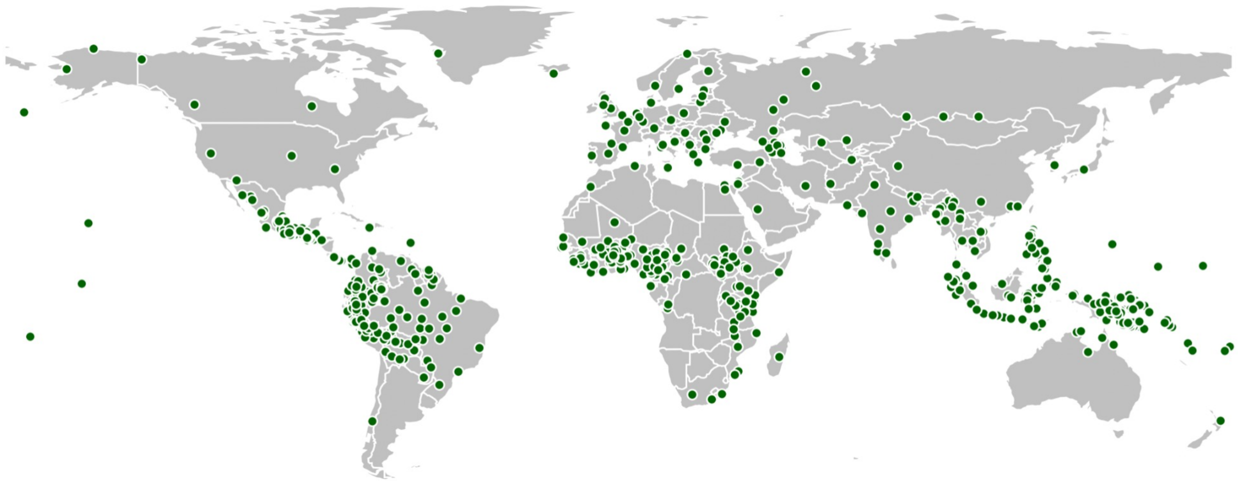
Resource

- 1340 languages, 1134 of which are lowest-resource, average of 503 NEs per language
- Best represented language families: Austronesian, Niger-Congo and Indo-European
- We cover all major areas of linguistic diversity (e.g., Amazonian, African, and Papua New Guinea)
- Our NEs resource is freely available at http://cistern.cis.lmu.de/ne_bible/



Geographical distribution of some languages in the PBC (Mayer et al., 2014) and our resource

Example: English – Italian resource

English	Italian
alexander	alessandro
deborah	debora
egypt	egitto
jahaziel	iahaziel
lucius	lucio
philadelphia	filadelfia
rachel	rachele
tiberius	tiberio

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- We showed that it outperforms prior work on human-annotated gold data
- We illustrated its utility for knowledge graph augmentation and Bilingual Lexicon Induction
- We publish a new NE resource for 1340 languages by applying CLC-BN to the Parallel Bible Corpus

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Thank you!

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