

Harnessing *Cross-lingual Features* to Improve **Cognate Detection** for Low-resource Languages

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Questions?

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Automatic Detection of Cognates

- Cognates: Words in different languages with common roots
 - Liberté - Liberty (Fr-En), Night - Nuit (En-Fr), जीवन (jeevana) - জীবন (Jībana) [meaning life], *etc.*
 - The notions of Orthographic Similarity, Phonetic Similarity, and Semantic Similarity.
 - Help NLP tasks- Machine Translation (Kondrak et. al., 2005, 2003), Cross-lingual Information Retrieval (Makin et. al., 2008; Meng et. al., 2001), Cross-lingual Question Answering, *etc.*
- Classification or Clustering based approaches for cognate detection
 - We use the binary classification-based approach.
 - Features obtained from orthographic similarity, phonetic vectors, cross-lingual embedding models.
- For low-resource Indian languages
 - Same language family for most of them (also same linguistic area).
 - The ‘Sanskrit Connection’!
 - Focus on resource constrained NLP tasks.
 - Pre-trained models on monolingual corpora to the rescue.

Previous Work

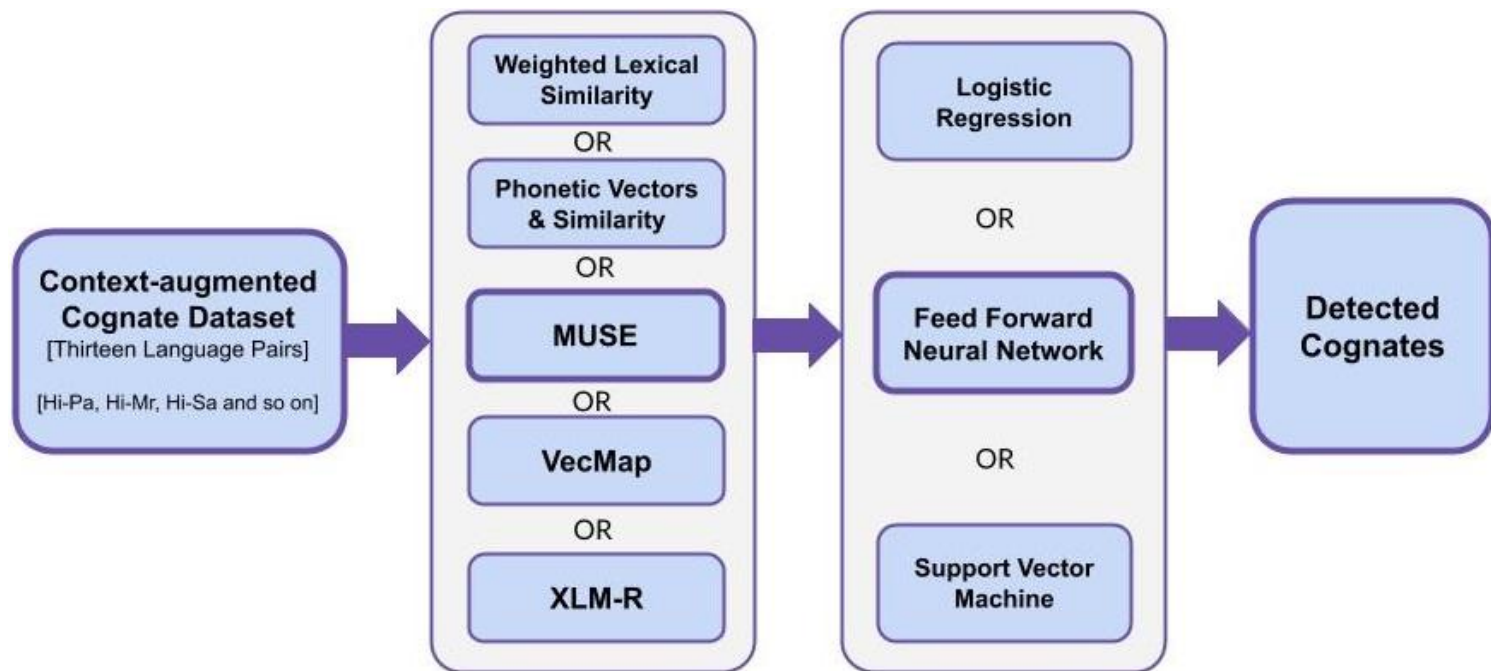
- Computation of a similarity score between potential candidate pairs.
- Orthographic similarity (Jager et al., 2017; Melamed, 1999; Mulloni and Pekar, 2006).
- Phonetic similarity (Rama, 2016; List, 2012; Kondrak, 2000).
- Distance measure with the scores learned from an existing parallel set (Mann and Yarowsky, 2001; Tiedemann, 1999).
- Rama (2016) employ a Siamese convolutional neural network.
 - Phonetic features jointly with language relatedness for cognate identification.
- Jager et al. (2017) use SVM for phonetic alignment and perform cognate detection for various language families.

Key Question & Contributions

“Can semantic information be leveraged from Cross-lingual models to improve cognate detection amongst low-resource languages?”

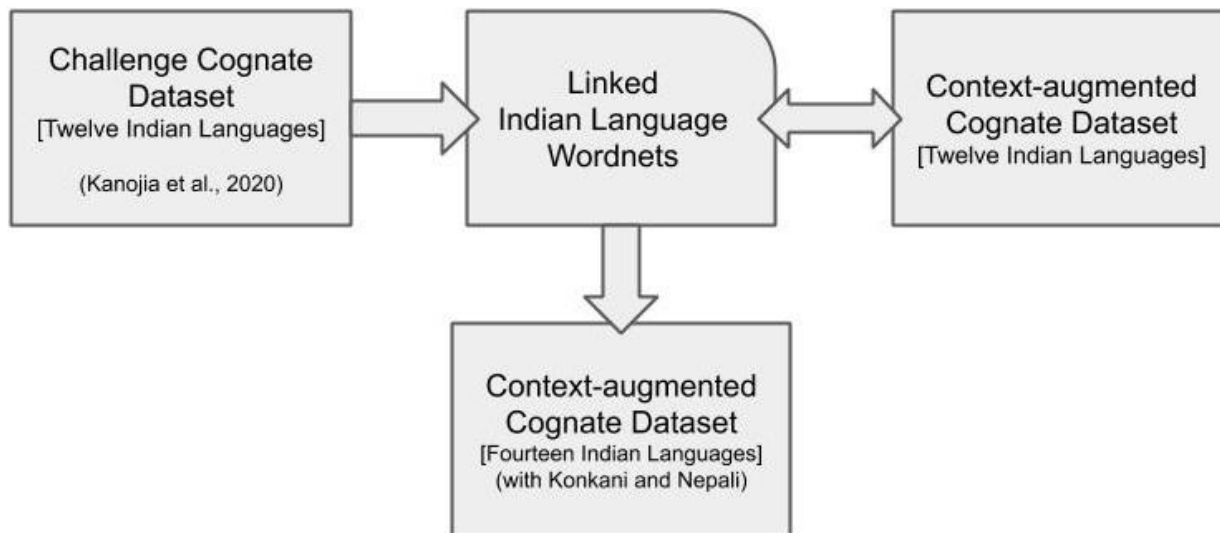
- Utilizing cross-lingual features for the automatic cognate detection task.
- Improvements shown using the cross-lingual features for all the language pairs.
- Improvements shown over baseline Neural Machine Translation (NMT-BPE) system by induction of detected cognates.

Our Idea: Cross-lingual Features For Cognate Detection



Dataset and Pre-processing

- Challenge Cognate Dataset by Kanojia et. al., 2020.
 - We add two new languages, Konkani and Nepali to this dataset.
- Indian languages are written in various scripts.
 - Preprocessing step: Unicode-offset based Transliteration



Results

LP	Baseline Approaches									Cross-lingual Embeddings based Approaches											
	WLS w/ FFNN			PVS w/ Siamese CNN (Rama, 2016)			WLS w/ RNN (Kanojia et al., 2019)			XLM-R w/ FFNN			MUSE w/ FFNN			VecMap w/ FFNN			MUSE + WLS w/ FFNN		
	P	R	F	P	R	F	P	R	F	P	R	F	P	R	F	P	R	F	P	R	F
Hi-Bn	0.51	0.28	0.36	0.68	0.62	0.65	0.67	0.69	0.68	0.81	0.76	0.78	0.77	0.75	0.76	0.72	0.74	0.73	0.80	0.75	0.77
Hi-As	0.48	0.26	0.34	0.72	0.71	0.71	0.72	0.70	0.71	0.70	0.72	0.71	0.80	0.75	0.77	0.74	0.73	0.73	0.84	0.75	0.79
Hi-Or	0.51	0.30	0.38	0.65	0.58	0.61	0.66	0.58	0.62	0.65	0.61	0.63	0.72	0.68	0.70	0.67	0.70	0.68	0.81	0.69	0.75
Hi-Gu	0.43	0.16	0.23	0.70	0.65	0.67	0.81	0.71	0.76	0.80	0.73	0.76	0.80	0.84	0.82	0.77	0.74	0.75	0.83	0.85	0.84
Hi-Ne	0.50	0.16	0.24	0.72	0.84	0.78	0.78	0.73	0.75	0.75	0.75	0.75	0.86	0.83	0.84	0.78	0.73	0.75	0.86	0.83	0.84
Hi-Mr	0.51	0.20	0.29	0.70	0.68	0.69	0.74	0.70	0.72	0.76	0.71	0.73	0.70	0.73	0.71	0.71	0.71	0.71	0.72	0.73	0.72

- Use of **cross-lingual features improves task performance**,
 - Contextual embeddings (XLM-R) are not always the best except for two language pairs (Hi - Bn and Hi-Mr).
- A **combination of MUSE + WLS features** outperforms all other feature combinations.
- Best F-scores obtained by Hi-Gu and Hi-Ne language (very linguistically close with high cognate sharing)
- *Kindly refer to paper for scores for all languages and detailed analyses*

Improving Downstream Task (Neural MT)

- Seven language pairs (Hi-Pa, Hi-Bn, Hi-Gu, Hi-Mr, Hi-Ta, Hi-Te, & Hi-Ml)
- 50k parallel sentence from the ILCI parallel corpus.
 - 46277 Sentences for *Training*, 2000 Sentences for *Test*, & 500 Sentences for *Development*.
 - Injected detected cognate pairs into corpus as training sentence (word) pairs.
- RNN-NMT model with sub-words (Bahdanau et al., 2014 + Sennrich et al., 2015)
 - 2,500 BPE Merge Operations (optimal for low-resource set; empirically determined)
 - Hidden size of the model was 500 units
 - SGD optimizer to train for 150,000 steps of 1024 sentence pair batches (8000 warm-up steps)

Approaches / LP	Hi-Pa	Hi-Bn	Hi-Gu	Hi-Mr	Hi-Ta	Hi-Te	Hi-Ml
NMT-BPE Baseline	62.79	28.75	52.17	31.66	13.78	19.18	10.4
Cognate-aware NMT-BPE	65.55	29.43	52.39	32.41	13.85	19.58	11.18

Discussion

- Consistent improvements over the strongest baseline (Kanojia et. al., 2019b)
 - 9% points (highest being 18% points for the Hi-Ta language pair)
- Improvements observed in the MT systems
 - 2.76 BLEU points for the Hi-Pa language pair (with 15001 cognate pairs)
 - With the lowest number of cognate pairs, *i.e.*, 930, an improvement of 0.4 BLEU score is observed.
 - Maximum number of cognates induced for Hi-Mr language pair (15834), but only slight improvement observed, *i.e.*, 0.75 BLEU points.
 - Probable reason: Better sub-word segmentation as BPE segmentation is cross-lingually consistent
- Examples of detected cognate pairs (undetected via previous approaches)
 - धकेलना - धकेलवुं (dhakelna-dhakelavun) (Hi-Gu) [both meaning “to push”]
 - जब्त - कुरकी (jabta-kurki) (Hi-Pa) [both meaning “seizure”]
 - कटुक - कडुप्ಪ (katuk-kaduppa) (Hi-MI) [both meaning “bitter”]

Conclusions & Future Work

- Harnessed cross-lingual embeddings to improve cognate detection- thirteen Indian language pairs.
- Used a linked knowledge graph to augment a publicly released cognate dataset.
- Significant improvements in cognate detection quality (up to 18%).
- Cognate-aware NMT-BPE results also show a consistent improvement in translation quality.
- Future work
 - Further investigation to improve the performance of contextual embeddings for this task.
 - Adding more sources for potential cognates and improving the challenge dataset.
 - Experiments within Indo-European language family to seek improvements.

Thank you! :)

Kindly reach out to us if you have queries!

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