Can Cognate Prediction Be Modelled as a Low-Resource Machine Translation Task?

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What are cognates?	Data	Methods	Observations
Cognates are evolutions, in re- lated languages, of the same word from their common ancestor. (+ ancestor)	BILINGUALLA-ITLA-ESES-IT $\#$ words5,1094,2711,804 $\#$ phones77,77163,13124,576 $\#$ Unique phones343938Avg. word length7.627.406.81	 Baseline (S): Neural MT: Recurrent neural networks (orange - 1) Transformers (blue - 2) Statistical MT (green - 3) 	 SMT > NMT for smallest datasets' baseline, RNN > otherwise Best data augmentation for RNNs: multilinguality Combining data augmentation methods is not very conclusted and the set of the set of
Latin bonus 'good' Vulgar Latin ?	MONOLINGUALESITLA#words78,41299,94918,639#phones626,175815,562142,955#Unique phones384029Word length7.988.247.67	 Data augmentation: Pre-training (P) Backtranslation (B) 	



- Multilingual neural translation (M)

Bilingual results

Table 1:Dataset statistics for our lexicons.



Multilingual results



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Language choice for multilingual setups

ES→IT	IT→ES
53.9 ± 3.4	66.6 ± 4.2
ES→IT	IT→ES
62.5 ± 2.5	71.8 ± 1.7
57.1 ± 1.8	67.4 ± 3.3
58.5 ± 2.0	67.0 ± 2.8
58.8 ± 1.1	66.9 ± 2.9
fferent mul	tilingual set
	$ES \rightarrow IT$ 53.9 ± 3.4 $ES \rightarrow IT$ 62.5 ± 2.5 57.1 ± 1.8 58.5 ± 2.0 58.8 ± 1.1 ferent multiplication of the second states

Best is to add data from current languages. If unavailable, add data from a parent language to source and target. If unavailable, add data from a language closest to the source.

Goals

Cognate prediction produces likely cognates in related languages. Can be modelled as learning seq2seq correspondences from very little data.

 \rightarrow Can cognate prediction be modelled as a low-resource machine translation task?

We study:

- their theoretical differences • the efficiency of MT architectures for cognate prediction
- the transferability of data augmentation techniques (from low resource MT)

Error analysis

- BLEU prediction error repartition (for resp. SMT/RNN/Transformer):
- 84.6/81.4/79.5% : ambiguous sound correspondence
- 10.3/13.4/11.6% : rare sound correspondences
- 0.9/0.9/0.9% : data error • 4.3/4.3/8.0% : model error

Conclusion

For our studied languages and methods: Yes, as long as you take into account its specificities regarding ambiguity and nbest prediction.

Theoretical differences

- Representation units
- Reordering, alignment
- Sample length
- Modelled relations
- Ambiguity management
- Impact of extra data for data augmentation

Figure 1:BLEU when comparing all methods

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