

Addressing Word-order Divergence in Multilingual Neural Machine Translation for Extremely Low Resource Languages

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Overview

Goal:

- Does word-order divergence affect Multilingual Neural Machine Translation?
- Improve MT performance between source language (A) and target language (B) $(A \rightarrow B)$

Assumptions:

- Very less or no parallel corpus exists between languages A and B
- However, very large parallel corpus exists between languages C and B
- Assisting source language (C) has different word-order compared to source language (A) Contribution:
 - Show word-order divergence affects Multilingual Neural Machine Translation
 - Pre-ordering assisting source language (**C**) sentences to match the word-order of source language (A) sentences leads to better Multilingual NMT performance
 - Beneficial for extremely low-resource languages with very small or no parallel data

Motivation

- Language divergence could however negate the benefits from multilingual learning leading to drop in performance
- Specifically, the word-order divergence between assisting-source and source languages

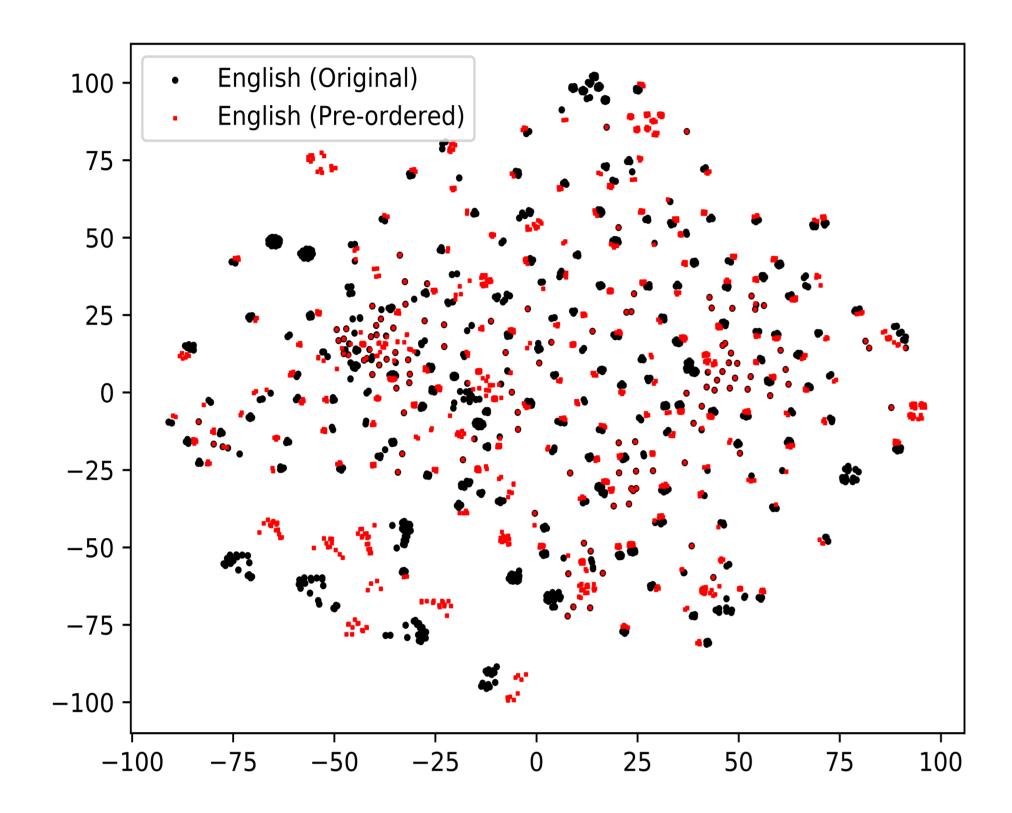
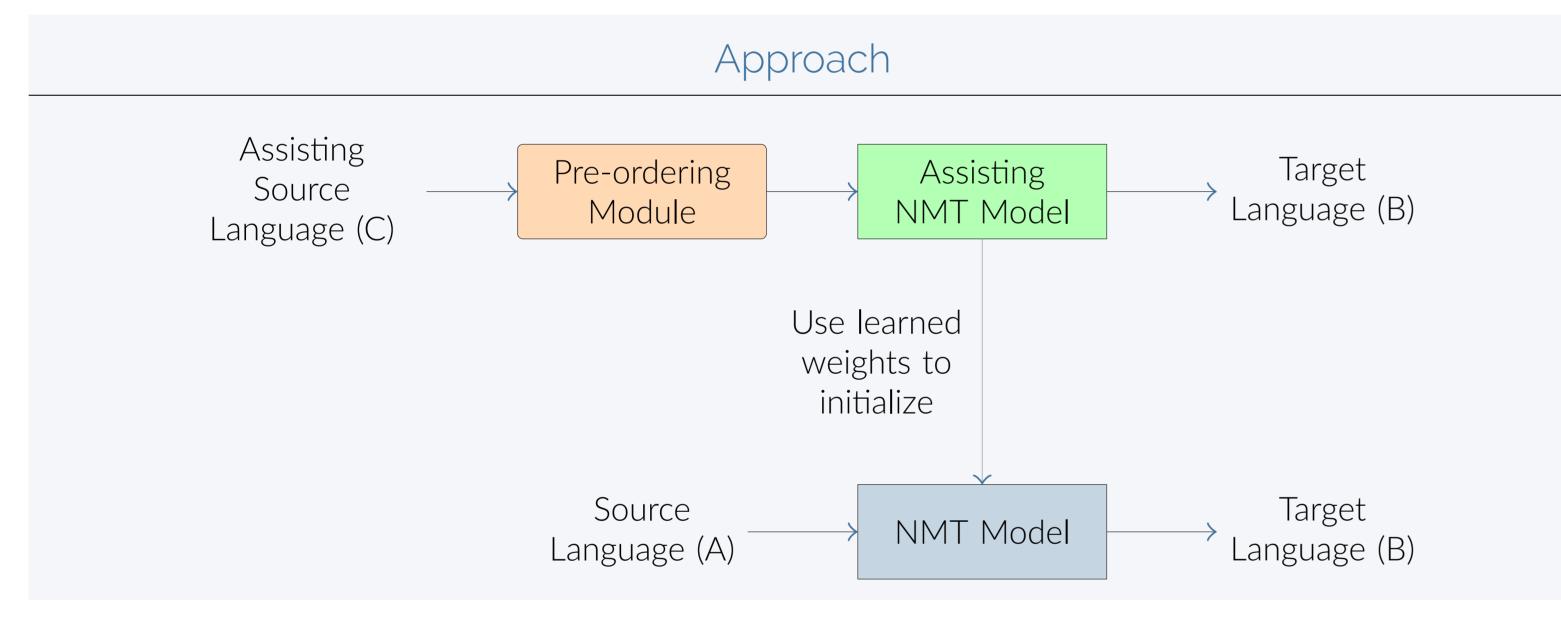
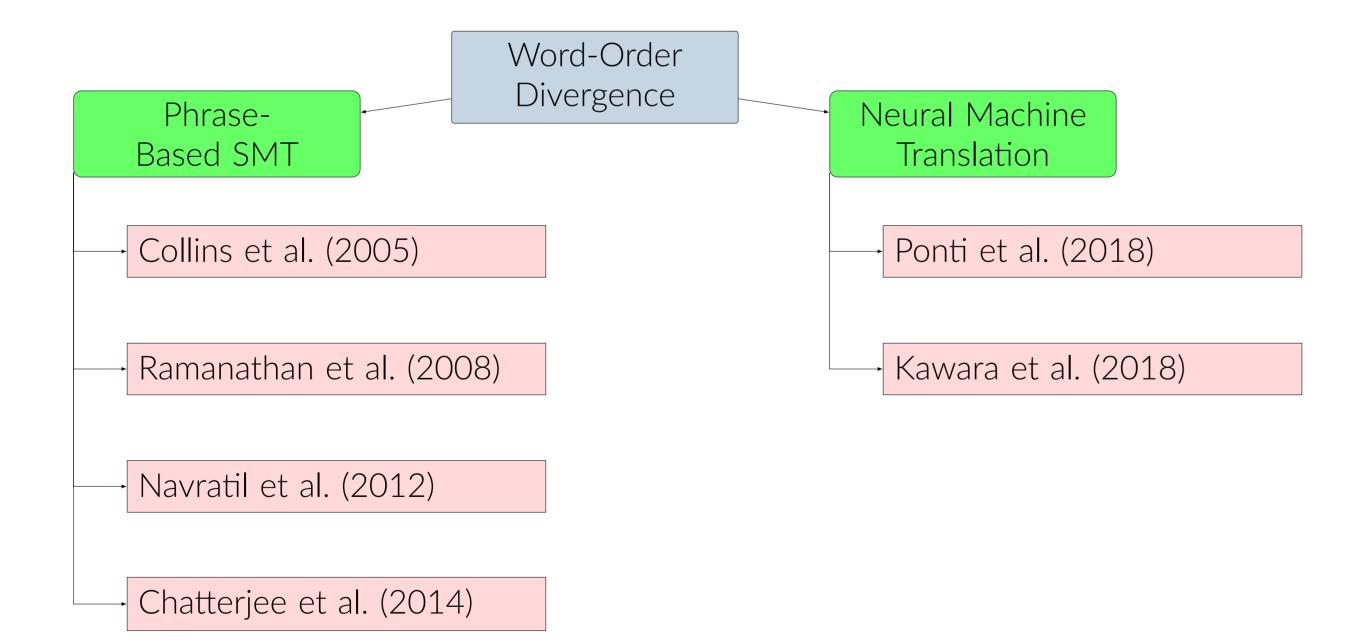


Figure 1: Encoder Representations for English sentences with and without Pre-Ordering



Related Work



We address word-order divergence between source languages as opposed to previous works which addressed divergence between source and target languages.

Experimental Setup

Task	Indian Languages → Hindi						
Source Languages Assisting Source Language	1. Bengali 2. Gujarati 3. Marathi 4. Malayalam 5. Tamil						
7 (33)3thig 30di ee Langdage	Corpus Size						
English → Hindi Indian Languages → Hindi Test Data Size	1.46 M sentences (Kunchukuttan et al. (2018)) 44.7 K sentences (Jha (2010)) 2K sentences (Jha (2010))						
Network	Experiment with both Bi-LSTMs and Transformer networks						
Pre-Ordering Rules	Generic Pre-Ordering Rules (G) (Ramanathan et al. (2008)) Hindi-Tuned Pre-Ordering Rules (HT) (Patel et al. (2013))						
Word Embeddings	English Fasttext embeddings						
	Word Translate source language data to English using Google Translate						

Results

Pre-ordering performs better than no pre-ordered system using Bi-LSTM encoder decoders.

Language	В	LEU		LeBLEU (%)			
	No	Pre-Ordered		No	Pre-Or	dered	
	Pre-Order	HT	G	Pre-Order	HT	G	
Bengali	6.72	8.83	9.19	37.10	41.50	42.01	
Gujarati	9.81	14.34	13.90	43.21	47.36	47.60	
Marathi	8.77	10.18	10.30	40.21	41.49	42.22	
Malayalam	5.73	6.49	6.95	33.27	33.69	35.09	
Tamil	4.86	6.04	6.00	29.38	30.77	31.33	

Table 1: Transfer learning results for X-Hindi pair using Bi-LSTM model, trained on English-Hindi corpus and sentences from X word translated to English. HT: Hindi-tuned Pre-ordering Rules, G: Generic Pre-ordering Rules

Pre-ordering performs better than no pre-ordered system even when Transformer networks are used.

Language	Position	al Enco	ding	No Positional Encoding			
	No	Pre-Ordered		No	Pre-Ordered		
	Pre-Order	HT	G	Pre-Order	HT	G	
Bengali	6.03	8.61	8.16	4.07	4.52	4.05	
Gujarati	8.43	12.20	11.01	4.94	5.71	5.08	
Marathi	6.96	9.16	8.68	4.40	5.07	5.03	
Malayalam	4.37	5.69	5.08	3.56	4.08	3.63	
Tamil	3.89	5.08	4.64	2.71	3.14	2.82	

Table 2: Transfer learning results (BLEU Score) for X-Hindi pair using Transformer networks, trained on English-Hindi corpus and sentences from X word translated to English. HT: Hindi-tuned Pre-ordering Rules, G: Generic Pre-ordering Rules

When Source-Target parallel corpus is available, the fine-tuned (no pre-ordered) model performs almost as good as the pre-ordered model

					•				
Corpus	No	No	Pre-Ordered		Corpus	No	No	Pre-Ordered	
Size	Transfer Learning	Pre-Order	HT G Size		Transfer Learning	Pre-Order	HT	G	
Bengali					- <u>—</u> Gujarat	 :i			
	_	6.72	8.83	9.19		-	9.81	14.34	13.90
500	0.0	11.40	11.49	11.00	500	0.0	17.27	17.11	17.75
1000	0.0	13.71	13.84	13.62	1000	0.0	21.68	22.12	21.45
2000	0.0	16.41	16.79	16.01	2000	0.0	25.34	25.73	25.63
3000	0.0	17.44	18.42†	17.82	3000	0.29	27.48	27.77	27.83
4000	0.0	18.86	19.17	18.66	4000	0.82	29.20	29.49	29.51
5000	0.07	19.58	20.15†	19.82	5000	0.0	29.87	31.09†	30.58†
10000	1.87	22.50	22.92	22.53	10000	1.52	33.97	34.25	34.08

Table 3: Transfer learning results (BLEU Score) using Bi-LSTM model for Indian Language-Hindi pair, fine-tuned with varying number of Indian Language-Hindi parallel sentences. †Indicates statistical significance between Pre-ordered and No Pre-ordered results.

English	the treatment of migraine is done in two ways								
Gujarati (Original)	भाध्त्रेननी	સારવાર	બે	રીતે	કરી	શકાય	છે.		
Gujarati (Word Translate)	migraine	treatment	two	the way	doing be	done	is the	re.	
Hindi (Reference)	माइग्रेन	का	ट्रीटमेंट	दो	तरह	से	किया	जाता	है ।
(Word Translate)	migraine	of	treatment	two	kind	from	did	go	is.
No Pre-Order	<unk></unk>	उपचार upachAra treatment	दो do two	<mark>प्रकार</mark> prakAra kind	से se from	किया kiyA did	जाता jAtA go	है hai is	
Pre-ordered (HT)	<mark>माइग्रेन</mark> mAigrena migraine	का kA of	उपचार upachAra treatment	दो do two	तरह prakAra kind	से se from	किया kiyA did	जाता jAtA go	

Table 4: Sample output generated by our Gujarati-Hindi NMT model. Text in red: phrases dropped by the no pre-ordered model.

Conclusion

- Pre-ordering the assisting language to match the word order of the source language significantly improves translation quality in an extremely low-resource setting.
- Alternatively, fine-tuning on a small source-target parallel corpus is sufficient to overcome word order divergence.

Future Work

- Validate the hypothesis on a more diverse set of languages and other word-order divergence Tarscenarios.
- Alternative methods to address word-order divergence which do not require expensive parsing.
- Apply to other multilingual NLP problems.

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