

Exploring Enhanced Code-Switched Noising for Pretraining in Neural Machine Translation

Vivek lyer, Arturo Oncevay, Alexandra Birch School of Informatics, University of Edinburgh

{vivek.iyer, a.oncevay, a.birch}@ed.ac.uk



I. INTRODUCTION

SOTA Recipe for training multilingual NMT models Aligned Augmentation (Pan et al., 2021)

SynthesizePretrain MT modelsTA DA!Code-Switched (CS) ->to "denoise" ->Better cross-lingual representationssentencesCS sentencesSuperior MT performance

- For synthesising code-switched sentences, Pan et al. (2022) use bilingual MUSE dictionaries
- These only provide non-contextual, one-to-one word-level translations
- This leads to significant noise in the pretraining corpus (polysemes, multi-word expressions, lack of linguistic agreement etc)
- This in turn might potentially harm downstream MT performance!





RQ1) Does synthesise higher quality CS text lead to better downstream MT performance? RQ2) How does CS pretraining scale to "more challenging" language families, such as agglutinative and low-resource languages? RQ3) What are the key factors to consider when pretraining on CS text, and what role do they play in performance enhancement?

III. APPROACH

To answer this, we propose CCS (Contextual Code-Switching) that extracts contextual, many-to-many substitutions for generating high-quality CS text.



IV. EXPERIMENTS

We conduct experiments on 3 different language families, comparing the dictionary-based (AA) and contextual (CCS) approaches. Results display spBLEU scores.

	En	- Es	En	- Fr	En	- It	Er	ו - Ro	A	vg.		En	- Fi	En	- Et	A	vg.		E	n - Hi	Er	า - Gu	A	Avg.
		-	\rightarrow	-		-		-				\rightarrow	-	\rightarrow	-	\rightarrow	←		\rightarrow	-	\rightarrow	←	\rightarrow	-
AA	25.0	26.2	28.8	28.7	23.8	26.8	18.7	24.1	25.7	27.0	AA	15.6	19.3	20.5	23.3	18.1	21.3	AA	28.4	24.6	10.2	11.5	19.3	18.1
CCS	30.7	29.1	33.1	30.9	29.1	29.0	25.4	30.4	29.6	29.9	CCS	21.2	21.2	25.6	25.7	23.4	23.5	CCS	28.0	24.0	12.9	12.9	20.5	18.5
Δ	+5.7	+2.9	+4.3	+2.2	+5.3	+2.2	+6.7	+6.3	+3.9	+2.9	Δ	+5.6	+1.9	+5.1	+2.4	+5.3	+2.2	Δ	-0.4	-0.6	+2.7	+1.4	+1.2	+0.4
a) Romance (High-Resource)						b) Urali	c (Ag	glutin	ative)			c) Indo	o-Arya	n (Lov	w-Res	ource	e)						
	V. ANALYSIS																							

i. Importance of Context

AA

CCS

Source45-year-old man has been remanded in
custody on a firearms charge following a
disturbance at a travellers ' site on
Monday when six people were arrested .

ii. Importance of Many-to-Many substitutions

	Rom	ance	Ura	lic	Indo-Aryan				
	En-X	X-En	En-X	X-En	En-X	X-En			
S (1-1)	28.53	28.98	21.50	21.95	18.95	18.00			

iii. Importance of CS Language Count

	Rom	ance	Ura	lic	Indo-Aryan				
	En-X	X-En	En-X	X-En	En-X	X-En			
(MLCS)	29.6	29.9	21.50	21.95	18.95	18.00			

 A 45-year-old <u>humano</u> tem been remanded in <u>gardes</u> sobre <u>one</u> arms <u>débit</u> following una necazuri at una travellers' site habilitado Monday when six people stavano arrested.
A 45-anos-old <u>homme</u> ha stato reţinut en

<u>custodia</u> on <u>a</u> firearms <u>charge</u> urma a disturbión en un viajante 'site del manhã when six persone fueron arrestadas

CCS (m-n) 29.58 29.85 23.40 23.45 20.45 18.45

CCS (BLCS) 28.2 28.6 23.40 23.45 20.45 18.45

iv. Importance of Fine-Tuning

CCS

	Ron	nance	Uralic		Indo-	Aryan	
	En-X	X-En	En-X	X-En	En-X	X-En	
CCS (mono. + parallel CS pretrain)	29.58	29.85	23.40	23.45	20.45	18.45	
CCS (mono. CS pretrain) + parallel BLFT	28.65	28.43	23.55	23.80	16.35	14.50	
CCS (mono. CS pretrain) + parallel MLFT	30.00	29.68	25.20	25.85	23.55	22.35	

KEY TAKEAWAYS!

Improvements in quality of synthetic CS text can lead to huge improvements in MT performance, even beating massive models
While improvements are observed across the board (even for low-resource langs), highest gains are for agglutinative languages
Context, many-to-many substitutions, language count etc. play a key role in enhancing performance across various families