Language Modeling for Code-Mixing: The Role of Linguistic Theory based Synthetic Data

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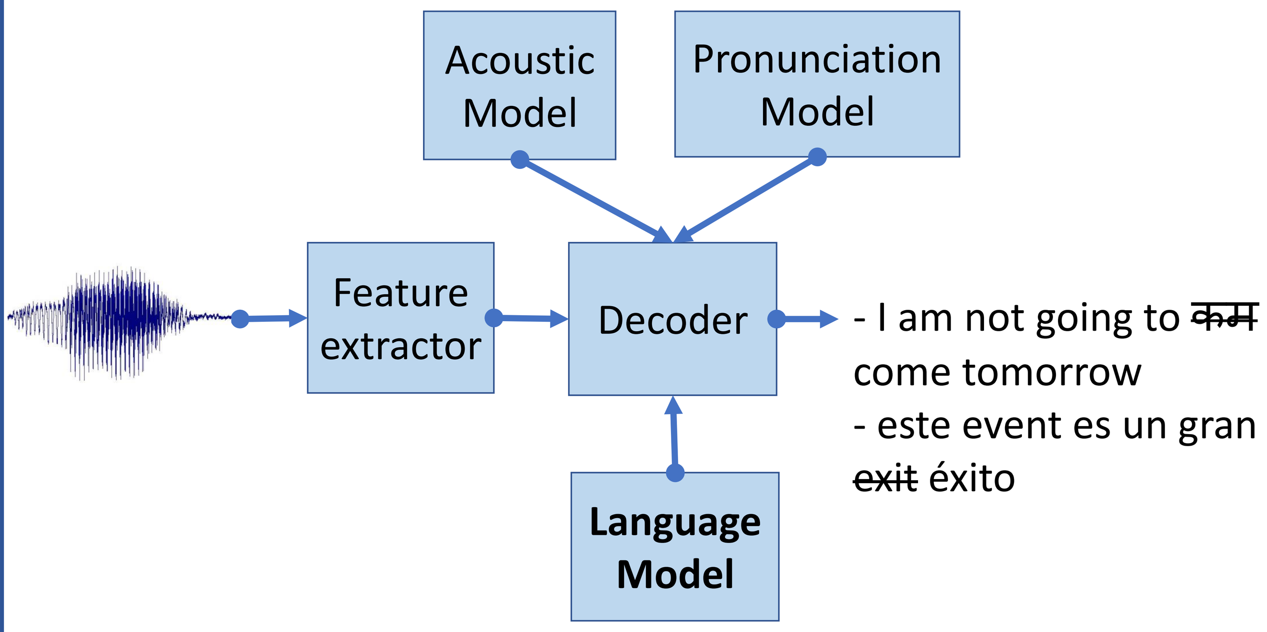
1. Introduction

- Code-Mixing (CM) refers to juxtaposition of linguistic units from two or more languages in a single conversation/utterance
- Language model (LM) has applications in ASR, Machine Translation



Challenges in modeling CM language,

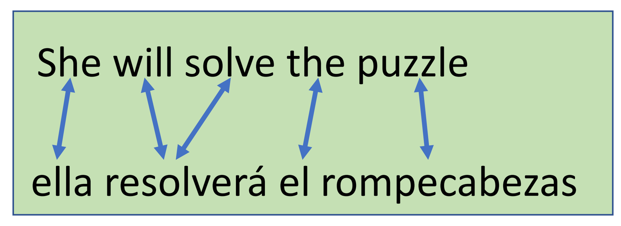
- CM is rare in formal text
- Even in the available CM data, switch points are few (~10%)

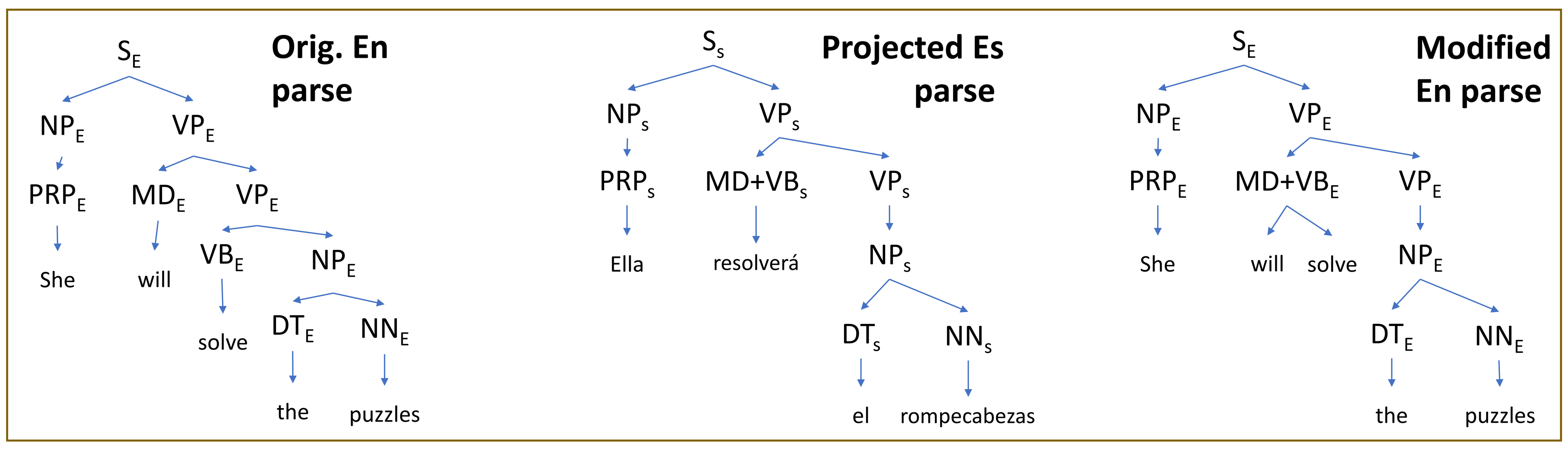
Can we leverage the readily available monolingual data?

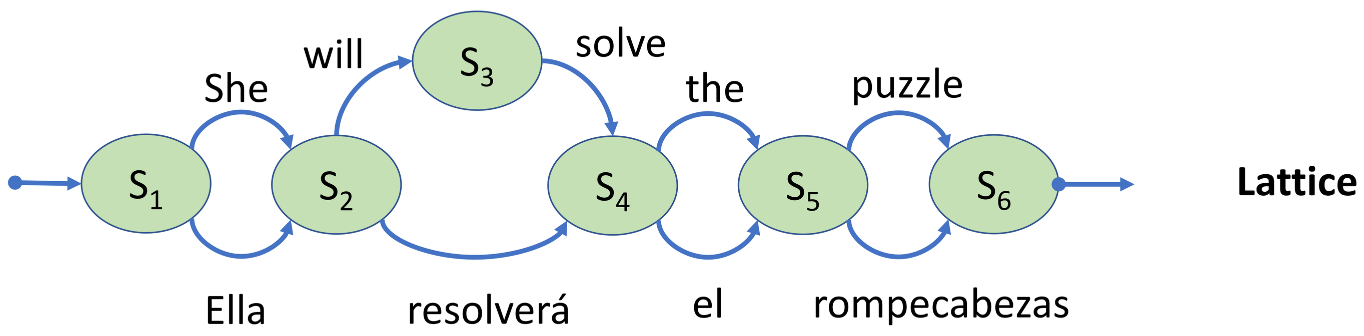
2. Linguistic Models of Code-Mixing

- *Equivalence Constraint Theory*: (*Poplack*, 1980; *Sankoff*, 1998)
  - Any monolingual fragment in CM sentence must occur in one of the monolingual sentences
  - CM sentence shouldn't deviate from both monolingual grammars
  - The two grammars must be equivalent at switch points

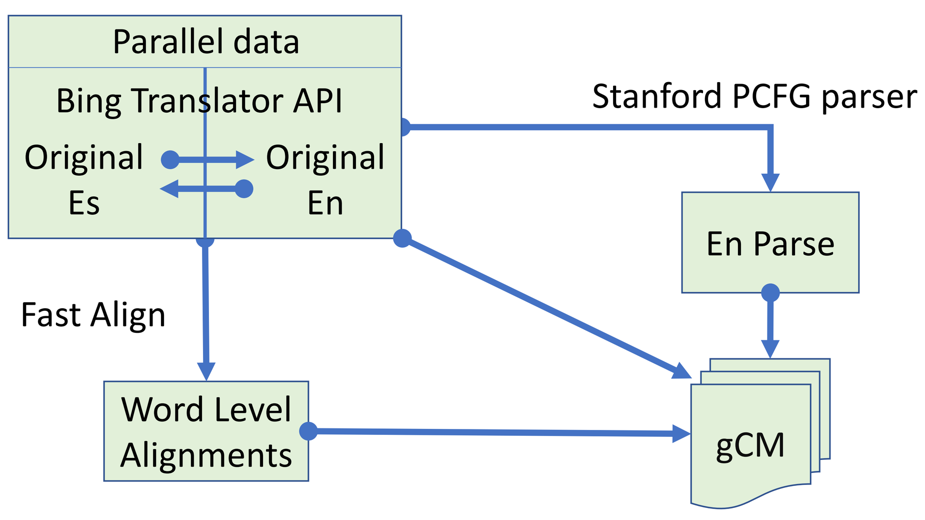
Parallel sentences with alignments







3. Generating Synthetic Data

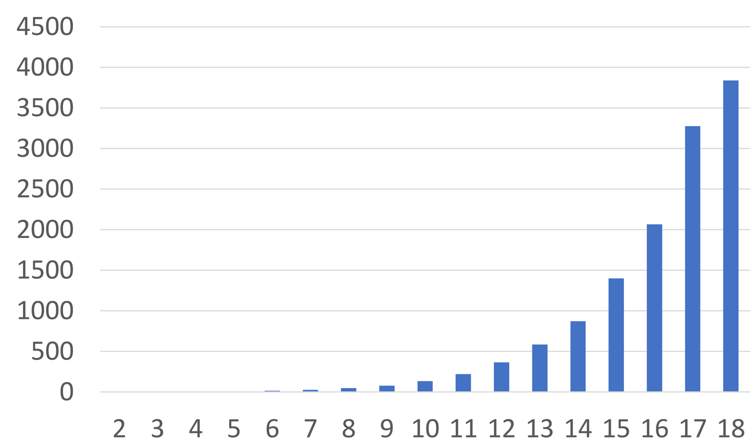


- Used Pseudo Fuzzy-match score to threshold the quality of translations
- En-parse is projected onto the Es sentence using word-level alignments
- rCM train, validation and test-17 (Rijhwani et al. 2017), test-14 (Solorio et al. 2014)

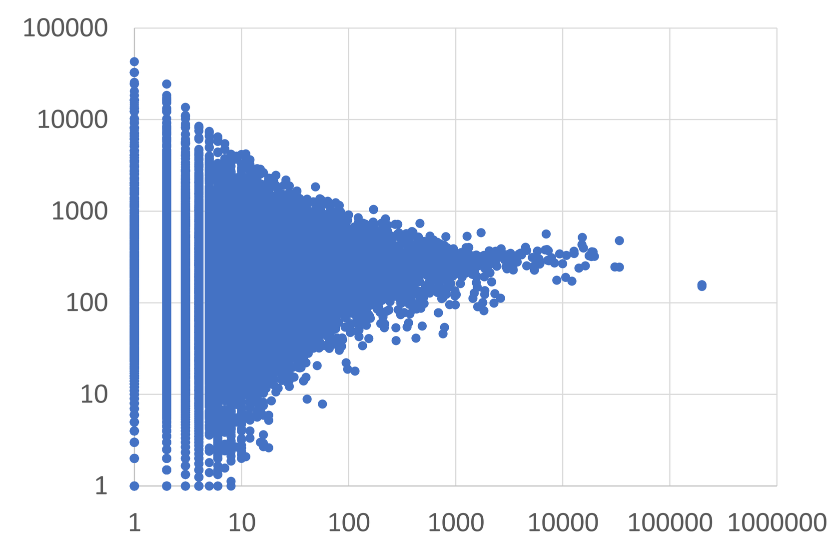
Dataset	# Tweets	# Words	CMI	SPF
English	100K	850K	0	0
Spanish	100K	860K	0	0
Train	100K	1.4M	0.31	0.105
Validation	100K	1.4M	0.31	0.106
Test-17	83K	1.1M	0.31	0.104
Test-14	13K	138K	0.12	0.06
gCM	31M	463M	0.75	0.35

4. Sampling gCM data

- A pair of monolingual sentences can give rise to a large (exponential) number of CM sentences, but only a few are observed in real data
- Even the statistical properties of this gCM data are different from real CM data



\# gCM sentences vs avg. input sentence length

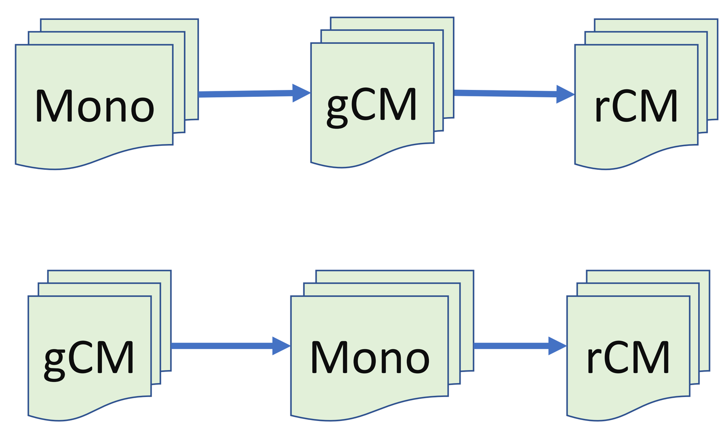


fractional increase in word freq. in gCM vs Original freq. of unigrams.

- Hence the need for sampling, based on,
  - Random (***χ-gCM***)
  - Code mixing index (CMI) (**↑*-gCM*** & **↓*-gCM***)
  - Switch point fraction (SPF) (***ρ-gCM***)

5. Training Curricula

- LM can be trained sequentially on different orderings of Mono, gCM and rCM resulting in various training curricula
- Real CM (rCM) data at the end of training is found to be most effective (*Baheti et al.* 2017)



6. Experiments and Results

Expt. ID	Training Curricula			Overall PPL		Avg. SP PPL	
				Test-17	Test-14	Test-17	Test-14
1	rCM			2018	1822	5670	8864
2	Mono			1607	892	23790	26901
3	Mono	rCM		1041	861	4824	7913
4(a)	**Mono**	**gCM**					
4(a)-χ	Mono	χ-gCM		1771	1119	5869	6065
4(a)-↑	Mono	↑-gCM		1872	1208	9167	8803
4(a)-ρ	Mono	ρ-gCM		1618	1116	6618	7293
4(b)	**gCM**	**Mono**					
4(b)-χ	χ-gCM	Mono		1680	903	21028	20300
4(b)-↓	↓-gCM	Mono		1917	973	28722	25006
4(b)-ρ	ρ-gCM	Mono		1641	871	26710	22557
5(a)	**Mono**	**gCM**	**rCM**				
5(a)-χ	Mono	χ-gCM	rCM	1038	836	4386	5958
5(a)-↑	Mono	↑-gCM	rCM	1058	961	5078	6861
5(a)-ρ	Mono	ρ-gCM	rCM	1011	830	4829	6807
5(b)	**gCM**	**Mono**	**rCM**				
5(b)-χ	χ-gCM	Mono	rCM	1019	790	4987	7018
5(b)-↓	↓-gCM	Mono	rCM	1025	800	5489	7476
5(b)-ρ	ρ-gCM	Mono	rCM	986	772	4912	6547

Rows 1–3: **Baselines**

Row 5(b)-ρ: **Best Model**

- Effect of rCM size**:**
  - As expected, PPL drops with increasing amount of rCM data
  - gCM data still helps even though diminishingly
  - In general, the baseline (Model 3) needs *twice as much amount of rCM data* to perform as good as our Model 5(b)-ρ
- Even though gCM helps, rCM data is indispensable
- SPF based sampling performs the best
- PPL at SPs is much higher than overall PPL, showing the inherent complexity of modeling CM language
- Modeling shorter run lengths is found to be challenging

# rCM / Expt.	0.5K	1K	2.5K	5K	10K	50K
3	1238	1186	1120	1041	991	812
5(b)-ρ	1181	1141	1068	986	951	808

References:

Ashutosh Baheti, Sunayana Sitaram, Monojit Choudhury, and Kalika Bali. 2017. Curriculum design for code-switching: Experiments with language identification and language modeling with deep neural networks. In Proc. of ICON-2017, Kolkata, India, pages 65–74.

Shana Poplack. 1980. Sometimes Ill start a sentence in Spanish y termino en espaol. Linguistics, 18:581– 618.

Shruti Rijhwani, R Sequiera, M Choudhury, K Bali, and C S Maddila. 2017. Estimating code-switching on Twitter with a novel generalized word-level language identification technique. In ACL.

David Sankoff. 1998. A formal production-based explanation of the facts of code-switching. Bilingualism: language and cognition, 1(01):39–50.

Thamar Solorio et al. 2014. Overview for the first shared task on language identification in codeswitched data. In 1st Workshop on Computational Approaches to Code Switching, EMNLP, pages 62– 72.

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