CODE-SWITCHING TEXT AUGMENTATION FOR MULTILINGUAL SPEECH PROCESSING

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ABSTRACT

The pervasiveness of intra-utterance Code-switching (CS) in spoken content has enforced ASR systems to handle mixed input. Yet, designing a CS-ASR has many challenges, mainly due to the data scarcity, grammatical structure complexity and mismatch along with unbalanced language usage distribution. Recent ASR studies showed the predominance of E2E-ASR using multilingual data to handle CS phenomena with little CS data. However, the dependency on the CS data still remains. In this work, we propose a methodology to augment the monolingual data for artificially generating spoken CS text to improve different speech modules. We based our approach on Equivalence Constraint theory while exploiting aligned translation pairs, to generate grammatically valid CS content. Our empirical results show a relative gain of 29-34\% in perplexity and \approx 2\% in WER for two ecological and noisy CS test sets. Finally, the human evaluation suggests that 83.8\% of the generated data is acceptable to humans.

Index Terms— code-switching, data augmentation, multilingual, speech recognition

1. INTRODUCTION

Code-switching (CS) is a prevalent phenomenon in multi-cultural and multi-lingual society due to the advent of globalization and also as a result of colonization. Code-switching is a phenomena, where speakers alter between two or more languages during the spoken discourse, has attracted the attention of speech researchers to address and model this highly unpredictable mixed input for Automatic Speech Recognition (ASR) systems.

Efforts has been given to design CS ASR to cover handful of language pairs, such as – Mandarin-English \cite{1}, Hindi-English \cite{2}, French-Arabic \cite{3}, Arabic-English \cite{4,5} and English-(Dialectal) Arabic-French \cite{6}. Some studies also showed the complexities and the need for dialectal code-switching ASR \cite{7}. Despite the aforementioned efforts, CS ASR still face challenges due to the scarcity of transcribed resources, with skewed coverage of languages or dialects.

Therefore, to address the data scarcity, we propose to augment the monolingual text with artificially generated CS data to improve the speech component performance – such as language model (LM). For this task, we choose Arabic due to its rich morphological properties along with more than 20 mutually in-comprehensive dialectal variation with modern standard Arabic (MSA) being the only standardised dialect \cite{8}. However, we believe the proposed system can be generalized to other languages, based on the availability of the respective monolingual resources.

Generating synthetic code-mixed data is a large and growing body of linguistic research. There has been many attempts to explain the grammatical constraints on code-switching based on Embedded-Matrix theory \cite{9}. Equivalence Constraint \cite{10} and Functional Head Constraint \cite{11}. In \cite{12}, authors proposed creation of grammatically valid artificial code-switching data based on the Equivalence Constraint Theory (EC), since it explains a range of interesting CS patterns beyond lexical substitution and suitable for computational modeling. On the other hand, \cite{13} proposed to model the CS with a sequence to sequence recurrent neural network (RNN) with attention, that learns when to switch and copy words from parallel sentences. However, this approach still requires having considerable amount of CS data for adaptation.

In this work, we propose to generate CS data based on EC theory. First, we build parallel data by translating original Arabic content into English. Later, we generate the CS content by mixing the pair of parallel sentences guided by the data alignments and different sampling techniques. Our method can be applied without the need for any CS speech data. Arabic language is a morphologically complex language with a high degree of affixation and derivation – it is very challenging to obtain accurate alignments with the corresponding English translation. To address the alignment challenge, we propose to segment the Arabic text into morphemes. The segmentation allows to align single morphemes with their English translation \cite{14}. We used Farasa \cite{15} Arabic segmenter for our task.

We show that our novel pipeline is an effective method for realistic CS generation and substantially improves over the baseline ASR and LM models. Moreover, we evaluate the well-formedness and acceptability of the generated sentences through subjective evaluation. We compare the mean opinion score (MOS) of the generated text data with ecological transcribed CS speech data, showing majority of the generated utterance are acceptable according to human judgements.

In summary, the key contributions are:

- Developing a novel pipeline for Arabic code-switching text generation based on EC theory.
- Comprehensive subjective analysis on the generated Arabic-English code-switching data with human evaluation.
- Comprehensive objective evaluation showing the efficacy of the generated Arabic-English code-switching data in language modeling and in hybrid ASR evaluation.

2. THE PROPOSED APPROACH

In this section, we describe our proposed approach to generate synthetic Arabic-English CS based on the EC theory.

\footnote{A single word could represent multiple tokens. For example, the Arabic segment "وسيدروهما في حقولهم" ("And they will plant it in their fields") map the first Arabic word to five English tokens, the last word represent the last two. Such 1-to-n mapping makes it difficult to build natural CS data.}
2.1. Equivalence theory

In the Equivalence theory both languages $S_1$ and $S_2$ are defined by context-free grammars $G_1$ and $G_2$. Every non-terminal category $c_1$ in $G_1$ has a corresponding non-terminal category $c_2$ in $G_2$ and every terminal word $w_1$ in $G_1$ has a corresponding terminal word $w_2$ in $G_2$. These assumptions imply that intra-sentential code-mixing can only occur at places where the surface structures of two languages map onto each other, hence implicitly following the grammatical rules of both languages. In this work, we build our approach on top of the EC implementation in the GCM toolkit.

2.2. Code-switching Text Generation

The input to the generation pipeline is a pair of parallel sentences $S_1$ and $S_2$, along with the word alignments. The $S_1$ and $S_2$ in our experiments are the English and Arabic languages respectively. The proposed CS generation pipeline includes four major components (also shown in Figure 1):

1. **Parallel text translation**: We generate the parallel English text from the Arabic transcription using a public Machine Translation System. The system is built on transformer-based seq2seq model implemented in OpenNMT. The Neural translation system is capable of translating Modern Standard Arabic as well as dialectal content. It was fine-tuned on a large collection of coarse and fine-grained city-level dialectal data from diverse genres, such as media, chat, religion and travel with varying level of dialectness. Such richness of the system makes it suitable for our task.

2. **Aligning the two sentences**: To generate word level alignments between the two sentences we use “fast-align” which is simple and fast unsupervised aligner. Arabic language is agglutinative and morphologically complex and hence very challenging to align with other Latin languages like English. To overcome this challenge we segmented Arabic words into their stem, prefix(es) and affix(es) using Farasa segmeter. Segmentation was proven to be beneficial to help reduce alignment complexity and improve tasks such as Machine Translation. Figures 2a and 2b shows an example of complex alignment with several 1-to-n alignments. After using segmentation, such cases almost disappeared. Further, the segmentation allowed to resolve complex construction that were caused by language re-ordering like “الله يكره” that is aligned with “her opinion” in the reverse order; as well as making it easy to resolve co-references such as the case of “الله” that is mapped to both “she” and “her”.

3. **Generating the Parse**: In this stage we use Stanford Parser to generate a sentence level constituent parse tree for one of the source languages. We generate the parse for English text and use the alignments to generate the equivalent parse for the Arabic text.

4. **CS text Generation**: Applying EC theory (as described in [12]) to generate Arabic-English CS text. The high level steps are described as following:

- **Replace every word in the Arabic parse tree with its English equivalent.**
- **Re-order the child nodes of each internal node in the Arabic tree such that their right-to-left order is as in the original Arabic language.**

   In case of deviation between grammatical structures of the two languages, the following steps are followed:
   - **Replace unaligned English words for any Arabic words with empty strings.**
   - **Collapsed contiguous word sequences in English, aligned with same Arabic word(s), to a single multi-word node.**
   - **Flattened the entire sub-tree, between the above collapsed nodes and their closest common ancestor, to accommodate the difference.**

2.3. Improved Naturalness through Sampling

In order to generate more natural CS sentences we experiment with two sampling methods: random sampling and Switch Point Fraction (SPF) sampling. For random sampling, we arbitrarily pick number of CS sentences from the generated data. For SPF sampling we estimate the distribution of the number of switch points in a sentence, based on empirical observations mentioned in [6, 23] and then we rank the generated CS sentences based on that distribution. In addition, to make the generated data more acceptable to a bilingual speaker we impose two constrains: 1) the sentence should start with an Arabic word 2) the number of English words should not exceed 45% of the total words in a sentence.

3. CORPUS

For our empirical analysis of the proposed augmentation method, we trained the language models and speech recognition systems. For the systems, we use several monolingual Arabic and English datasets.

3.1. Monolingual Datasets

**MSA and Dialectal Arabic data**: We use MSA and multidialectal training data collected from QASR, GALE, MGB3, MGB5, and an internal 156h Kanari multi-dialectal dataset.

**English**: To incorporate variety of English data we use Tedlium 1 training set and a subset of 300h of SPIGispeech dataset.

3.2. Evaluation code switching sets:

For comprehensive code-switching evaluation we use three evaluation sets: Arabic language with MSA and multiple dialects (Egyptian, Gulf, Levantian, North Africa), English languages, ESCWA and Kanari internal code-switching data.

1. **Validation set**: for diverse performance evaluation on both English and Arabic languages we combine MGB3-test 2h, QASR-test 2h, SPGI-test 1h, and Tedlium3-test 1h.

2. **ESCWA-CS [4]**: 2.8 hours of speech code-switching data collected over two days of United Nations meetings.

3. **Kanari-CS**: 4.8 hours of code-switching data from different dialects including Levantine, Egyptian, Gulf and Moroccan.

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2. [https://github.com/microsoft/CodeMixed-Text-Generator](https://github.com/microsoft/CodeMixed-Text-Generator)
3. API access available from [https://mt.qcri.org/api](https://mt.qcri.org/api)
4. For CS augmentation, we use Arabic monolingual data.
5. [https://openslr.magicdatatech.com/51/](https://openslr.magicdatatech.com/51/)
6. [https://datasets.kensho.com/datasets/spgispeech](https://datasets.kensho.com/datasets/spgispeech)
7. [https://arabicspeech.org/escwa](https://arabicspeech.org/escwa)
4. EXPERIMENTS

We evaluated the quality of the augmented CS textual data, using both objective and subjective evaluation. For objective evaluation, we tested the efficacy of the data in language modeling and in speech recognition tasks. We use human ratings, as subjective test, evaluating the naturalness/acceptability of the generated utterances.

4.1. Language Modeling Evaluation

We assess the quality of the generated text and its efficacy in handling CS in language modeling (LM), we use both n-gram and neural LM. For this, we build standard trigram LM using Kneser-Ney smoothing using SRILM toolkit [26] and for the neural LM, we train TDNN-LSTM using Kaldi-RNNLM toolkit [27] for 5 epoch only. We evaluate the efficacy using tradition perplexity (PPL), where the lower the number, the better it is.

4.2. Speech Recognition Evaluation

The hybrid HMM-DNN ASR architecture based on the weighted finite-state transducers (WFSTs) outlined in [28]. The training, development, and testing are the same as the Arabic MGB-2 [29] and the English TED-LIUM3 [30]. For the hybrid ASR, we trained a Time Delay Neural Network (TDNN) [31] using sequence discriminative training with the LF-MMI objective [32] with the alignments from a context-dependent Gaussian mixture model-hidden Markov model (GMM-HMM). The input to the TDNN is composed of 40-dimensional high-resolution MFCC extracted from 25 msec frames and 10 msec shift along with 100-dimensional i-vectors computed from 1500 msec. Five consecutive MFCC vectors and the chunk i-vector are concatenated, forming a 300-dimensional features vector each frame.

Modeling graphemes implicitly models spelling, which reduced the amount of entries in the lexicon. However, graphemes can differ immensely from language to language, and languages may have nothing in common in terms of graphemes (e.g. Arabic and English in our case). Thus, we propose a multilingual architecture that merges all graphemes from multiple languages, keeping the language identity at the grapheme level. A multilingual n-gram language model is learned over the transcription for all the languages along with the augmented data.

4.3. Human Evaluation

In order to perform quality assessment of the generated data and compare it with natural CS data, we designed several crowdsourcing...
5. RESULTS AND DISCUSSION

5.1. Objective Evaluation:

The perplexity (PPL) along with out-of-vocabulary (OOV) are present in Table 2. We observed a significant gain when using Farasa alignments with both sampling methods. Our results indicate the importance of considering the code-alteration distribution (i.e., SPF) with a relative gain of ≈ 9% and ≈ 3.5% in PPL wrt random sampling in n-grams for both the test sets. A similar pattern is seen in RNNLMs. Table 3 presents the WER on the two different test sets in the three experimental settings. In aligned with the PPL from language models, we noticed an decrease in WER when augmented CS data is added with SPF sampling.

Table 2: Perplexity and Out-of-Vocabulary (OOV) on the test sets. F: Farasa, SPF: Switch Point Fraction.

|               | Perplexity | Kanari | ESCWA |
|---------------|------------|--------|-------|
| #Total Tokens | 20,902     | 37,416 |       |
| n-gram       |            |        |       |
| NLM OOV      |            |        |       |
| Baseline     | 4,173      | 2,341  | 3,216 |
| Random       | 4,071      | 2,257  | 3,228 |
| F+ SPF       | 3,719      | 2,298  | 3,177 |

Table 3: Word Error Rates (WER) on the test sets. F: Farasa, SPF: Switch Point Fraction.

|               | Hybrid ASR | WER in % |
|---------------|------------|----------|
|               | Kanari ESCWA |         |
| Baseline     | 50.3  47.7 | 50.0  47.5 |
| Random       | 50.0  47.5 | 49.5  47.2 |

Table 4: Averaged MOS on generated and human-transcribed CS data.

| MOS | Generated data (# 1170) | Kanari-CS (# 1921) |
|-----|------------------------|---------------------|
| 1 <= * <= 2 | 1.29% 16.15% | 4.22% 37.74% |
| 2 <= * <= 3 | 14.96% | 37.74% 41.96% |
| 3 <= * <= 4 | 54.36% 83.85% | 43.68% 58.04% |
| 4 <= * <= 5 | 29.49% 14.37% |

5.2. Subjective Evaluation:

The average judgment scores for each quality categories are presented in Table 4. From MOS, we observed that ≈ 83.8% of the generated data is acceptable to human judges. Hence, reflecting the importance of the proposed pipeline for enriching CS data. Our result also suggests that generated CS data is more clean than natural CS transcription, which contains overlapping speech, disfluency, repetition among others. We further discuss this in the following Section.

5.3. Key Observations and Discussion:

Human evaluation of the generated CS indicates the potential of the proposed method to generate natural CS data. Moreover, addition of CS-augmented data to LM shows a significant improvement in perplexity performance when combining Farasa and SPF settings. This is to be noted that such gain is not due to changes in OOV rate. As seen from the Table 2, CS-augmented data does not help much with unknown words above the monolingual sets. Moreover, we noticed a small gain in WER. One of the biggest challenge of evaluating CS ASR is its measure. As shown in previous CS studies, WER is not robust against paratactic/full transliteration of a correctly recognised word, hence no reflects improvement in CS-ASR properly, as seen below example where the words “International” and “Pharmatech” use a mixed scripts between the ASR output and the Reference:

While the above combination of scores confirms the validity of the approach. Inspecting some of the results with low MOS and/or high PPL allows to enumerate the shortcomings of the proposed approach. A number of sentences that were scored lower than 3 had one common issue which was the original sentences was not complete. Speech fragments such as “وكان الأردن و حكومة” (“And was Jordan, people and government”) or “is support” (“There is not support and the proof is”) despite that the CS algorithm choose the correct word to be replaced, the context seems missing or incomplete/broken and hence these sentences ended up with a low score from the human judges. Additional issue was inherent from the MT system itself. Wrong lexical choice created further ambiguity in the resulting CS sentences and results in turn in a low score. Some instances were also the results of the Neural MT generating more fluent output from less fluent input, this caused misalignment between the original and the translation pairs and impacted the quality of the generated CS. Such exercise allowed to pin point shortcomings of the proposed framework. Restricting the generation on complete sentences in the step (3), while parsing the sentences would allow to avoid some of the aforementioned problems. Additionally, using additional MT systems can also help to avoid the low quality translation that will degrade the CS generation.

6. CONCLUSION

In this paper, we have proposed a novel text augmentation pipeline for code-switching speech modules. We show that segmentation is crucial to obtain accurate alignments and hence generate more realistic CS. Through objective evaluation we show that the proposed approach substantially improves both LM and ASR systems with 29-34% and 1-2% relative improvement in perplexity and WER respectively compared to the baseline. In addition, our subjective evaluation to measure the naturalness of the generated CS text suggests that 83.8% of the generated sentences are acceptable according to human judgements. The proposed method can generalized for other language pairs, depending on the available monolingual resources.
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