UNIVERSAL TEXT GENERATION BY PIVOTING ENGLISH DATA AND SELF-TRAINING

Ernie Chang¹, David Ifeoluwa Adelani², Xiaoyu Shen² & Vera Demberg¹
¹Department of Language Science and Technology, Saarland University, Germany
²Spoken Language Systems (LSV), Saarland Informatics Campus, Germany

{cychang,vera}@coli.uni-saarland.de

ABSTRACT

West African Pidgin English is a language that is significantly spoken in West Africa, consisting of at least 75 million speakers. Nevertheless, proper machine translation systems and relevant NLP datasets for pidgin English are virtually absent. In this work, we develop techniques targeted at bridging the gap between Pidgin English and English in the context of natural language generation. By building upon the previously released monolingual Pidgin English text and parallel English data-to-text corpus, we hope to build a system that can automatically generate Pidgin English descriptions from structured data. We first train a data-to-English text generation system, before employing techniques in unsupervised neural machine translation and self-training to establish the Pidgin-to-English cross-lingual alignment. The human evaluation performed on the generated Pidgin texts shows that, though still far from being practically usable, the pivoting + self-training technique improves both Pidgin text fluency and relevance.

1 INTRODUCTION

Pidgin English is one of the most widely spoken languages in West Africa with roughly 75 million speakers estimated in Nigeria; and over 5 million speakers estimated in Ghana (Ogueji & Ahia, 2019). While there have been recent efforts in popularizing the monolingual Pidgin English as seen in the BBC Pidgin it remains under-resourced in terms of the available parallel corpus for machine translation. Similarly, this low-resource scenario extends to other domains in natural language generation (NLG) such as summarization, data-to-text and so on (Lebret et al., 2016; Su et al., 2018; Shen et al., 2019a; Zhao et al., 2019; Hong et al., 2019; de Souza et al., 2018) where Pidgin English generation is largely under-explored. The scarcity is further aggravated when the pipeline language generation system includes other sub-modules that computes semantic textual similarity (Shen et al., 2017; Zhuang & Chang, 2017), which exists solely in English.

Previous works on unsupervised neural machine translation for Pidgin English constructed a monolingual corpus (Ogueji & Ahia, 2019), and achieved a BLEU score of 5.18 from English to Pidgin. However, there is an issue of domain mismatch between down-stream NLG tasks and the trained machine translation system. This creates a caveat where the resulting English-to-Pidgin MT systems (trained on the domain of news and the Bible) cannot be directly used to translate out-domain English texts to Pidgin. An example of the English/pidgin text in the restaurant domain (Novikova et al., 2017) is displayed in Table 1.

Nevertheless, we argue that this domain-mismatch problem can be alleviated by using English text in the target-domain as a pivot language (Guo et al., 2019). To this end, we explore this idea on the task of neural data-to-text generation which has been the subject of much recent research. Neural data-to-Pidgin generation is essential in the African continent especially given the fact that many
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Table 1: Sample parallel English-Pidgin text from the restaurant domain.

| System    | Relevance | Fluency |
|-----------|-----------|---------|
| PidginUNMT| 0.038     | 0.827   |
| model
unsup   | 0.319     | 0.788   |
| model
self    | 0.434     | 0.814   |

Table 2: PidginUNMT is trained on unparallel, out-domain English and pidgin text. model
unsup refers to unsupervised NMT trained on in-domain English text and out-domain pidgin text. model
self further augments model
unsup with pseudo parallel pairs obtained from self-training.

existing data-to-text systems are English-based e.g. Weather reporting systems (Sripada et al., 2002; Belz, 2008). This work aims at bridging the gap between many of these English-based systems and Pidgin by training an in-domain English-to-pidgin MT system in an unsupervised way. By this means, English-based NLG systems can be locally adapted by translating the output English text into pidgin English. We employ the publicly available parallel data-to-text corpus E2E (Novikova et al., 2017) consisting of tabulated data and English descriptions in the restaurant domain. The training of the in-domain MT system is done with a two-step process: (1) We use the target-side English texts as the pivot, and train an unsupervised NMT (model
unsup) directly between in-domain English text and the available monolingual Pidgin corpus. (2) Next, we employ self-training (He et al., 2019) to create augmented parallel pairs to continue updating the system (model
self).

2 APPROACH

First phase of the approach requires training of an unsupervised NMT system similar to Ogueji & Ahia (2019) (PidginUNMT). Similar to Ogueji & Ahia (2019), we train the cross-lingual model using FastText (Bojanowski et al., 2017) on the combined Pidgin-English corpus. Next, we train an unsupervised NMT similar to Lample et al. (2017); Artetxe et al. (2017); Ogueji & Ahia (2019) between them to obtain model
unsup. Then we further utilize model
unsup to construct pseudo parallel corpus by predicting target Pidgin text given the English input. We augment this dataset to the existing monolingual corpus. The self-training step involves further updating model
unsup on the pseudo parallel corpus and non-parallel monolingual corpus to yield model
self.

3 EXPERIMENTS AND RESULTS

We conduct experiments on the E2E corpus (Novikova et al., 2017) which amounts to roughly 42k samples in the training set. The monolingual Pidgin corpus contains 56,695 sentences and 32,925 unique words. The human evaluation was performed on the test set (630 data instances for E2E) by averaging over scores by 2 native Pidgin speakers on both Relevance (0 or 1 to indicate relevant or not) and Fluency (0, 1, or 2 to indicate readability). Table 2 shows that model
self outperforms direct translation (PidginUNMT) and unsupervisedly-trained model model
unsup on relevance and performing on par with PidginUNMT on fluency. We also display relevant sample outputs in Table 3 at all levels of fluency.

| Pidgin text                                                                 | Fluency |
|----------------------------------------------------------------------------|---------|
| Every money of money on food and at least 1 of 1 points.                   | 0       |
| and na one na dt best food for dt world.                                  | 1       |
| People dey feel the good food but all of us no dey available.              | 2       |

Table 3: Sampled relevant (score of 1) Pidgin outputs from model
self with various Fluency scores.
4 CONCLUSION

In this paper, we have shown that it is possible to improve upon low-resource Pidgin text generation in a demonstrated low-resource scenario. By using non-parallel in-domain English and out-domain Pidgin text along with self-training algorithm, we show that both fluency and relevance can be further improved. This work serves as the starting point for future works on Pidgin NLG in the absence of annotated data. For future works, we will also further utilize phrase-based statistical machine translation to further improve upon current work.

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