DUAL LANGUAGE MODELS FOR CODE MIXED SPEECH RECOGNITION

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ABSTRACT

In this work, we present a new approach to language modeling for bilingual code-switched text. This technique, called dual language models, involves building two complementary monolingual language models and combining them using a probabilistic model for switching between the two. The objective of this technique is to improve generalization when the amount of code-switched training data is limited. We evaluate the efficacy of our approach using a conversational Mandarin-English speech corpus. Using our model, we obtain significant improvements in both perplexity measures and automatic speech recognition error rates compared to a standard bilingual language model.

Index Terms— Code-switching, language modeling, speech recognition

1. INTRODUCTION

Code-switching is a commonly occurring phenomenon in multilingual communities, wherein a speaker switches between languages within the span of a single utterance. Code-switched speech presents many challenges for automatic speech recognition (ASR) systems, in the context of both acoustic models and language models. Our focus in this paper is on building language models for code-switched speech from bilingual speakers, especially when only a limited amount of training data is available.

A naïve approach towards this problem would be to simply use a bilingual language model. However, the complexity of a full-fledged bilingual language model is significantly higher than that of two monolingual models, and is unsuitable in a limited data setting. More sophisticated approaches relying on translation models have been proposed to overcome this challenge (see Section 2), but they rely on external resources to build the translation model. In this paper, we introduce an alternate — and simpler — approach to address the challenge of limited data in the context of code-switched text.

At the heart of our solution is a dual language model (DLM) that has roughly the complexity of two monolingual language models combined. A DLM combines two such models and uses a probabilistic model to switch between them. Its simplicity makes it amenable for generalization in our low-data context. Further there are several other benefits of using DLMs. (1) The DLM construction is language-agnostic and does not rely on any prior information about the underlying languages. (2) Since the structure of our combined model is derived from monolingual language models, it can be implemented as a finite-state machine and easily incorporated within an ASR system. (3) The monolingual language model for the primary language can be trained further with large amounts of monolingual text data (which is easier to obtain compared to code-switched text).

Our main contributions can be summarized as follows:

• We formalize the framework of DLMs (Section 3).
• We observe improvements in perplexity on unseen test sets using DLMs when compared against smoothed n-gram language models estimated on code-switched text (Section 4.2).
• We also show improvements in ASR performance using DLMs when combined with state-of-the-art acoustic models (Section 4.3).

2. RELATED WORK

Prior work on building ASR systems for code-switched speech can be broadly categorized into two sets of approaches: (1) Detecting code-switching points in an utterance, followed by the application of monolingual acoustic and language models to the individual segments [1, 2, 3]. (2) Employing a universal phone set to build acoustic models for the mixed speech and pairing it with standard language models trained on code-switched text [4, 5, 6, 7, 8].

There have been many past efforts towards enhancing the capability of language models for code-switched speech using additional sources of information such as part-of-speech (POS) tags and statistical machine translation (SMT) systems. Yeh et al. [7] employed class-based n-gram models that cluster words from both languages into classes based on POS and perplexity-based features. Vu et al. [9] used an SMT system to enhance the language models during decoding. Li et
al. [10] propose combining a code-switch boundary predictor with both a translation model and a reconstruction model to build language models. Adel et al. [11] investigated how to effectively use syntactic and semantic features extracted from code-switched data within factored language models. Combining recurrent neural network-based language models with such factored language models has also been explored [12].

3. DUAL LANGUAGE MODELS

We define a dual language model (DLM) to have the following 2-player game structure. A sentence (or more generally, a sequence of tokens) is generated via a co-operative game between the two players who take turns. During its turn a player generates one or more words (or tokens), and either terminates the sentence or transfers control to the other player. Optionally, while transferring control, a player may send additional information to the other player (e.g., the last word it produced), and also may retain some state information (e.g., cached words) for its next turn. At the beginning of the game one of the two players is chosen probabilistically.

In the context of code-switched text involving two languages, we consider a DLM wherein the two players are each in charge of generating tokens in one of the two languages. Suppose the two languages have (typically disjoint) vocabularies \( V_1 \) and \( V_2 \). Then the alphabet of the output tokens produced by the first player in a single turn is \( V_1 \cup \{\langle \text{sw} \rangle, \langle /\text{s} \rangle\} \); \( \langle \text{sw} \rangle \) denotes the switching – i.e., transferring control to the other player – and \( \langle /\text{s} \rangle \) denotes the end of sentence, terminating the game. We shall require that a player produces at least one token before switching or terminating, so that when \( V_1 \cap V_2 = \emptyset \), any non-empty sentence in \( (V_1 \cup V_2)^* \) uniquely determines the sequence of corresponding outputs from the two players when the DLM produces that sentence. (Without this restriction, the players can switch control between each other arbitrarily many times, or have either player terminate a given sentence.)

In this paper, we explore a particularly simple DLM that is constructed from two given LMs for the two languages. More precisely, we shall consider an LM \( L_1 \) which produces \( \langle /\text{s} \rangle \)-terminated strings in \( (V_1 \cup \{\langle \text{sw} \rangle\})^* \) where \( \langle \text{sw} \rangle \) indicates a span of tokens in the other language (so multiple \( \langle \text{sw} \rangle \) tokens cannot appear adjacent to each other), and symmetrically an LM \( L_2 \) which produces strings in \( (V_2 \cup \{\langle \text{sw} \rangle\})^* \). In Section 3.1 we will describe how such monolingual LMs can be constructed from code-switched data. Given \( L_1 \) and \( L_2 \), we shall splice them together into a simple DLM (in which players do not retain any state between turns, or transmit state information to the other player at the end of a turn). Below we explain this process which is formally described in Fig. 1 (for bi-gram language models).

We impose conditions (1)-(4) on the given LMs. Condition (1) which disallows empty sentences in the given LMs (and the resulting LM) is natural, and merely for convenience. Condition (2) states the requirement that \( L_1 \) and \( L_2 \) agree on the probabilities with which each of them gets the first turn. Conditions (3) and (4) require that after switching at least one token should be output before switching again or terminating. If the two LMs are trained on the same data as described in Section 3.1 all these conditions would hold.

To see that \( P[w' \mid w] \) defined in Fig. 1 is a well-defined probability distribution, we check that \( \sum_{w'} P[w' \mid w] = 1 \) for all three cases of \( w \), where the summation is over \( w' \in V_1 \cup V_2 \cup \{\langle /\text{s} \rangle\} \). When \( w = \langle \text{s} \rangle \), \( \sum_{w'} P[w' \mid w] \) equals

\[
\sum_{w' \in V_1} P_1[w' \mid \langle \text{s} \rangle] + \sum_{w' \in V_2} P_2[w' \mid \langle \text{s} \rangle] = (1 - P_1[\langle \text{sw} \rangle \mid \langle \text{s} \rangle]) + (1 - P_2[\langle \text{sw} \rangle \mid \langle \text{s} \rangle]) = 1
\]

where the first equality is from (1) and the second equality is from (2).
4. EXPERIMENTS AND ANALYSIS

4.1. Data description

We make use of the SEAME corpus [13] which is a conversational Mandarin-English code-switching speech corpus.

4.1.1. Preprocessing of data

Apart from the code-switched speech, the SEAME corpus comprises a) words of foreign origin (other than Mandarin and English) b) incomplete words c) unknown words labeled as (unk), and d) mixed words such as bleach跟, cause就是, etc.. Since it was difficult to obtain pronunciations for these words, we removed utterances that contained any of these words. (There were a few occurrences of non-ASCII space/bracket characters and some cases of unmatched parentheses in the corpus, which we also fixed.) A few utterances contained markers for non-speech sounds like laughing, breathing, etc. Since our focus in this work is to investigate language models for code-switching, ideally without the interference of these non-speech sounds, we excluded these utterances from our task. After adopting our preprocessing steps, we saw an overall reduction of ≈ 15% compared to the original corpus.

4.1.2. Data distribution

We construct training, development and test sets from the preprocessed SEAME corpus data using a random 60-20-20 split. Table 1 shows detailed statistics of each split. We made the development and test sets fairly large for more accurate evaluations of our language models. We also did not want to assign a larger split to the training data as it is common to have to work with smaller amounts of training data for code-switching tasks. The out-of-vocabulary (OOV) rates on the development and test sets are 3.3% and 3.7%, respectively.

4.2. Perplexity experiments

We used the SRILM toolkit [14] to build all our LMs. The baseline LM is a smoothed bigram LM estimated using the code-switched text which will henceforth be referred to as mixed LM. Our DLM was built using two monolingual bigram LMs. We used bigram LMs instead of trigram LMs as the latter did not provide any significant improvements in perplexity (or ASR performance, which we will describe in

|                  | Train | Dev | Test |
|------------------|-------|-----|------|
| # Speakers       | 90    | 37  | 30   |
| Duration (hrs)   | 56.6  | 18.5| 18.7 |
| # Utterances     | 54,020| 19,976| 19,784|
| # Tokens         | 539,185| 195,551| 196,462|

Table 1: Statistics of the dataset
| Smoothing Technique | Dev        | Test       |
|---------------------|------------|------------|
|                     | mixed LM   | DLM        | mixed LM   | DLM        |
| Good Turing         | 338.2978   | 329.1822   | 384.5164   | 371.1112   |
| Kneser-Ney          | 329.6725   | 324.9268   | 376.0968   | 369.9355   |

Table 2: Perplexities on the dev/test sets using mixed LMs and DLMs with different smoothing techniques.

Section 4.3. Table 2 shows the perplexities on both the validation and test sets using both Good Turing and Kneser-Ney smoothing techniques. We observe that DLMs outperform mixed LMs on both the datasets. All subsequent experiments use Kneser-Ney smoothed bigram LMs.

To test the generalization abilities of DLMs, we also evaluate perplexities by reducing the amount of training data to $\frac{1}{2}$ or $\frac{1}{3}$ of the original training data (shown in Table 3). We observe that the improvements in perplexity of DLMs over mixed LMs increases as we reduce the amount of training data, thus validating our hypothesis about DLMs’ ability to generalize better in low-data settings.

We further analyze the frequency of code-switched bigrams in the training data. Code-switched bigrams with counts of $\leq 10$ occupy 87.5% of the total number of code-switched bigrams in the training data. Of these, 55% of the bigrams are singletons (i.e. with a count of 1). This analysis provides further evidence for the need for LMs that generalize better at code-switching boundaries.

### 4.3. ASR experiments

All the ASR systems were built using the Kaldi toolkit [15]. We used standard MFCC+delta+double-delta features with fMLLR transforms to build speaker-adapted triphone models with 4200 tied-state triphones, henceforth referred to as “SAT” models. We also build time delay neural network (TDNN)-based acoustic models using i-vector based features (referred to as “TDNN+SAT”). The pronunciation lexicon was constructed using English pronunciations from CMUdict [16] and Mandarin pronunciations from the THCHS30 dictionary [17]. Mandarin words that did not appear in THCHS30 were mapped into Pinyin using a freely available Chinese to Pinyin converter [18]. We manually merged the phone sets of Mandarin and English (by mapping all the phones to IPA) resulting in a combined phone inventory of size 105.

![https://www.chineseconverter.com/en/convert/chinese-to-pinyin](https://www.chineseconverter.com/en/convert/chinese-to-pinyin)

| Training data | mixed LM | DLM | mixed LM | DLM |
|---------------|----------|-----|----------|-----|
| Full          | 329.6725 | 324.9268 | 376.0968 | 369.9355 |
| 1/2           | 362.5966 | 350.5860 | 400.5831 | 389.7618 |
| 1/3           | 368.6205 | 356.012 | 408.562 | 394.2131 |

Table 3: Kneser-Ney smoothed bigram dev/test set perplexities using varying amounts of training data.

To evaluate the ASR systems, we treat English words and Mandarin characters as separate tokens and compute token error rates (TERs). Table 4 shows TERs on the dev/test sets using both mixed LMs and DLMs. We find DLMs to be comparable in performance to mixed LMs. However, DLMs capture a significant amount of complementary information which we leverage by combining lattices from both systems. We observe statistically significant improvements in TER (at $p < 0.001$, highlighted in Table 4) using a combined LM for both the SAT and TDNN+SAT systems. Using either a trigram LM or a recurrent neural network-based LM rescoring led to worse TERs on our mixed LM systems, compared to bigram LMs; hence we adopted the latter in all our models. This also demonstrates that obtaining significant performance improvements via LMs on this task is very challenging.

Table 5 shows all the TER numbers by utilizing only $\frac{1}{2}$ of the total training data. The combined models continue to give significant improvements over the individual models. We also observe that the DLMs consistently produce lower TERs compared to mixed LMs in the $\frac{1}{2}$ training data setting.

| ASR system  | Data    | mixed LM | DLM | combined |
|-------------|---------|----------|-----|----------|
| SAT         | Dev     | 45.59    | 45.59 | 44.93*   |
|             | Test    | 47.43    | 47.48 | 46.96*   |
| TDNN+SAT    | Dev     | 35.20    | 35.26 | 34.91*   |
|             | Test    | 37.42    | 37.35 | 37.17*   |

Table 4: TERs using mixed LMs and DLMs

| ASR system  | Data    | mixed LM | DLM | combined |
|-------------|---------|----------|-----|----------|
| SAT         | Dev     | 48.48    | 48.17 | 47.67*   |
|             | Test    | 49.07    | 49.04 | 48.52*   |
| TDNN+SAT    | Dev     | 40.59    | 40.48 | 40.12*   |
|             | Test    | 41.34    | 41.32 | 41.13*   |

Table 5: TERs with $\frac{1}{2}$ training data

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### 5. CONCLUSIONS

We introduced DLMs and showed how they can improve ASR performance for code-switched speech, especially when the training data is limited. While the performance improvements are modest, they are achieved without the aid of any external resources and with little computational overhead. Currently, ASR improvements with DLMs are achieved when they are combined with standard mixed LMs. A future direction would be to design DLMs that can bring about these improvements on their own.

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