The ASRU 2019 Mandarin-English Code-Switching Speech Recognition Challenge: Open Datasets, Tracks, Methods and Results

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Abstract

Code-switching (CS) is a common phenomenon and recognizing CS speech is challenging. But CS speech data is scarce and there’s no common testbed in relevant research. This paper describes the design and main outcomes of the ASRU 2019 Mandarin-English code-switching speech recognition challenge, which aims to improve the ASR performance in Mandarin-English code-switching situation. 500 hours Mandarin speech data and 240 hours Mandarin-English intra-sentential CS data are released to the participants. Three tracks were set for advancing the AM and LM part in traditional DNN-HMM ASR system, as well as exploring the E2E models' performance. The paper then presents an overview of the results and system performance in the three tracks. It turns out that traditional ASR system benefits from pronunciation lexicon, CS text generating and data augmentation. In E2E track, however, the results highlight the importance of using language identification, building-up a rational set of modeling units and spec-augment. The other details in model training and method comparison are discussed.

Index Terms: automatic speech recognition, code-switching, end-to-end ASR

1. Introduction

Code-Switching (CS), the alternating use of more than one languages inside a single utterance [1], is a special and complicated language phenomenon, which has become an important field of both linguistics and ASR research. For instance, the InterSpeech 2020 workshop on speech technologies for code switching is a recent platform particularly focusing on CS related research [2].

Code-switching has many varieties, and a classification method based on mixed position is often used, which classifies CS into two primary categories: inter-sentential (switch happens at the sentence boundaries) and intra-sentential (switch happens in the middle of a sentence).

An ASR system usually contains the ability of modeling linguistic information and acoustic information at the same time. In CS situation however, language switching happens at unpredictable positions makes it difficult to train a multilingual language model (LM) while the varied accent of non-native speakers and mixing of phonemes from different language bring difficulty to acoustic model (AM) training.

Previous work has made continuous progress in Code-switching area, and a variety of modeling methods are proposed, which can be roughly divided into three categories. The first kind of optimization aims at modeling units, which turns out that both phone merging methods and new modeling units building methods [6,7] are helpful to code-switching ASR.

The second kind of methods focus on the neural network structure, making deep neural networks-hidden Markov model (DNN-HMM) based ASR system more competent for CS tasks by optimizing the neural network and training strategy [8,9]. The third kind of efforts is explored on End-to-End (E2E) speech recognition [10,11]. E2E ASR framework enables lexicon-free recognition, which is an important advantage over traditional hybrid system, especially for CS tasks. An encoder-decoder based CS ASR system was built by Hiroshi et al. [10]. Zhang et al. [11] built a bilingual Mandarin-English acoustic model by putting two separately pre-trained DFSMN-CTC-sMBR together. Li et al. [12] added a frame-level language identification (LID) loss to bilingual CTC model, assisting CTC to distinguish the language ID of frames. Although those efforts have improved the performance of CS ASR, robust ASR system that supports arbitrary switching of languages still remains a challenging goal.

This paper describes the design and outcomes of the ASRU 2019 Mandarin-English Code-Switching Speech Recognition Challenge, a special event of IEEE Automatic Speech Recognition and Understanding Workshop (ASRU 2019). Actually, the difficulties discussed above also reveal one of the bottlenecks in CS ASR research: data insufficiency. Code-switching speech data is always scarce, only SEAME [13], a small set of 30 hours Mandarin-English speech data collected in Singapore and Malaysia is released to the public. Besides, in Mandarin-English CS ASR, there is no common testbed and open datasets for method validation and model comparison, especially in the area of fast development of data-hungry deep learning approaches. This challenge is especially designed for these reasons. Three speech datasets are released to participants, 740 hours in total, and 240 hours of them are Mandarin-English CS data [14]. A well-trained 3-gram CS language model in ARPA format is also provided. The participants are supposed to use the permitted data only to build CS ASR systems in three tracks: i) Traditional ASR system with identical official N-gram LM; ii) Traditional ASR system without LM limitation; iii) End-to-End ASR system. Totally 72 teams participated in the challenge. Participants have around 50 days to finish their system building and submit the recognition results.

The rest of this paper is organized as below: Section 2 describes detailed information of the datasets. In Section 3, rules, data using limitation of each track and results evaluation method are explained. Section 4 describes a overview of results submitted and advancing system building methods in all the tracks. Summary of the main findings in the challenge is in Section 5.

¹www.microsoft.com/en-us/research/event/workshop-on-speech-technologies-for-code-switching-2020

²Exploring www.datatang.com/competition for more detail about datasets and the challenge.
2. Open Source Datasets

Code-switching speech data is always scarce, which hinders the research of CS ASR seriously. For this challenge, DataTang released 3 ASR datasets to participants. The basic information of the datasets is as below.

Table 1: Basic information of the 3 released datasets

| Dataset  | Transcripts Type        | Dur/Hours |
|----------|-------------------------|-----------|
| TrainMan | Mandarin only           | 500       |
| TrainCS  | Intra-sen Mandarin-English CS | 200     |
| DevCS    | Intra-sen Mandarin-English CS | 40      |

All the data are collected by smart phones in quiet rooms from various Android phones and iPhones. The speakers were from 30 provinces in China. 70% of the speakers were under 30 years old, with no significant difference in the number of male and female.

The transcripts of data cover many common fields including entertainment, travel, daily life and social interaction. In TrainMan, each sentence has 10 Chinese characters in average. As for TrainCS and DevCS, each sentence has 8.6 Chinese characters and 1.6 English words in average. Most English words are nouns, personal names, song names and some adjectives. Besides, there are 6 kinds of symbols and tags for noise and English abbreviation in TrainCS and DevCS transcripts. Several examples from the dataset are shown in Table 2.

Table 2: Examples of CS transcription from the dataset

| CS transcription | EN translation                          |
|------------------|-----------------------------------------|
| "我今天要去买一个iPhone." | "I’ll buy an iPhone Today." |
| "Jeff是一个很sensitive的student." | "Jeff is such a sensitive student." |

3.3. Track3: End-to-End ASR

End-to-End ASR here refers to systems without frame-level forced-alignment, always modeling acoustic information and language information jointly. It is becoming an increasingly topical field and various of E2E ASR systems are proposed. Encoder-Decoder based system LAS [7] and transformer [6] use global attention and multi-head self-attention to generate implicit alignment. RNN-transducer combines two RNNs into a sequence transduction system [19,20].

Including the models above, any E2E ASR system is allowed in track 3, and CTC model is also regarded as an E2E rule. Rule 2-3 in track 1 are effective in track 3. Besides, as for systems need to model acoustic information and language information jointly, the text training data is limited to transcripts of permitted speech data.

3.4. Results Submission and Evaluation Plan

Competitors are supposed to submit their recognition results and system descriptions of each track they participated in. Recognition accuracy is the only target considered in the evaluation. Mixture error rate (MER) considers Mandarin characters and English words as the tokens in the edit distance calculation. Errors of Chinese and English will be counted separately according to the language of the reference token.

The error rate of the Chinese part and the English part in the final publicity result is only for reference, ranking is based on MER only.

4. Results and Discussion on Methods

4.1. Track1

35 teams submit their results of track 1, the top 10 best systems is listed in Table 3 along with the their key features. The following part introduces the main outcomes in three aspects.

4.1.1. Phone Sets

Building a traditional ASR system starts with building a phone set. Among the 20 teams that introduced their phone sets building methods, 11 teams use totally separate phone sets for Mandarin and English, 6 teams bind partial phones according to...
phonetics. 2 teams map all of the English phones to Chinese phones, above that, one team marked partial English words which appear frequently with Chinese phones.

Concatenating a Chinese lexicon and an English lexicon is the most simple and commonly used method, and the merged phone sets can be extracted from the lexicon directly. However, binding partial Chinese and English phonemes is proved to obtain improvement by teams with higher ranking. The last method ‘map partial English words’ refers to marking the high frequency English words with Chinese phonemes, with the rest part of the lexicon still using the first method. However, there is no detailed contrastive experiment results about phone sets reported.

4.1.2. Feature Extraction and Data Augmentation

Concatenating i-vectors feature to MFCC or PBank feature brings 5%-7% relative improvement. Librispeech data is abandoned by most teams as it raised error rate, even when using only a small part of it. This may because of the mismatch of native English speaker and Chinese speaker. Speed augmentation can enhance the robustness of the model modestly, while volume augmentation and reverberation simulation help little. This may because the training data and test data are collected in the environment with similar acoustic conditions. Spec-augment is a data augmentation method proposed by Google [21]. Several teams gain about 2% relative improvement using spec-augment layer in Kaldi Nnet3.

4.1.3. Network Structure

Kaldi chain model with lattice-free maximum mutual information (LF-MMI) [22] is used by all the teams, there are seldom differences among different systems. CNN or LSTM are used to combine with time-delay neural network (TDNN). The 1st team MobvoiASR used max-likelihood path to fix the original loss function and gain 3% relative improvement. The 2nd place team Qdreamer use LF-MMI-SMBR (State-level Minimum Bayes Risk) and gain 9% relative MER reduction comparing to original LF-MMI.

Table 4: The top 10 teams in track 2, along with their key method used, MER(%) stands for mixture error rate. MERR are calculated based on their results in track 1. A negative MERR indicates that participants achieved a better LM than the 3-gram released in track 1.

### Table 3: Top 10 of 35 submitted systems in track 1. The columns in the middle summarize the key features of systems, CER(%) for Chinese part error rate, WER(%) for English part error rate, and MER(%) for mixture. The right side of the table describe the error rate of Mandarin part, English part and total MER. Phone merging includes partial combining and totally binding of Chinese phones and English phones.

| Team         | NN Structure     | Phoneteme Merge | G2P for OOV | Data Augment | i-vector extract | Spec Augment | CH ER(%) | EN ER(%) | MER(%) |
|--------------|------------------|-----------------|-------------|--------------|-----------------|--------------|----------|----------|--------|
| MobvoiASR    | CNN-TDNN         | ✔               | ✔           | ✔            | ✔               | ✔            | 4.04     | 12.33    | 4.94   |
| Qdreamer     | CNN-LSTM-TDNN    | ✔               | ✔           | ✔            | ✔               | ✔            | 3.85     | 14.88    | 5.05   |
| XNZXYZ       | LSTM-TDNN        | ✔               | ✔           | ✔            | ✔               | ✔            | 4.05     | 15.43    | 5.28   |
| SZSXW        | TDNN             | ✔               | ✔           | ✔            | ✔               | ✔            | 4.61     | 14.44    | 5.66   |
| JRYY         | TDNN             | ✔               | ✔           | ✔            | ✔               | ✔            | 4.60     | 15.06    | 5.74   |
| VIVO ASR     | TDNN             | ✔               | ✔           | ✔            | ✔               | ✔            | 4.50     | 16.63    | 5.81   |
| I2R          | CNN-TDNN         | ✔               | ✔           | ✔            | ✔               | ✔            | 4.95     | 14.32    | 5.97   |
| Paopao       | TDNN             | ✔               | ✔           | ✔            | ✔               | ✔            | 5.22     | 14.14    | 6.19   |
| SCUT-ASR     | CNN-TDNN         | ✔               | ✔           | ✔            | ✔               | ✔            | 5.43     | 15.99    | 6.57   |
| Royalflush   | CNN-TDNN         | ✔               | ✔           | ✔            | ✔               | ✔            | 5.18     | 18.37    | 6.61   |

| Team         | Weight Tuning | Text Generation | Lattice Rescoring |
|--------------|---------------|-----------------|-------------------|
| MobvoiASR    | ✔             | ✔               | ✔                 |
| Qdreamer     | ✔             | ✔               | ✔                 |
| JingRong     | ✔             | ✔               | ✔                 |
| Royalflush   | ✔             | ✔               | ✔                 |
| VIVO ASR     | ✔             | ✔               | ✔                 |
| I2R          | ✔             | ✔               | ✔                 |
| Asig-xju     | ✔             | ✔               | ✔                 |
| Xmuspeech    | ✔             | ✔               | ✔                 |
| LKDMM        | ✔             | ✔               | ✔                 |
| MiniSpeech   | ✔             | ✔               | ✔                 |

4.2. Track2

The recognition results of the top 10 systems are shown in Table 4. The efforts teams made for track 2 are mainly about CS text generation, balancing Chinese and English text proportion, and RNN-LM rescoring.

Spontaneous code-switching text data for LM training is always scarce because of the randomness and casualness of CS...
phenomenon. Therefore, it’s necessary to expand the text data. The parallel language pair in machine translation is widely used in ASR to generate CS transcripts. Besides, text generation based on pointer generator [23] is used by team Royalflush, but this method is limited by the scale of CS text and only a small amount of available data is generated. As reported, a well-trained RNN-LM using external CS data can yield 2%-4% recognition improvement.

4.3. Track 3

In E2E track, 29 teams submit their results, the top 10 teams’ results and key features are described in Table 5. The outcomes of this track are mainly about modeling units, network structure, as well as taking language identification into consideration.

### 4.3.1. Modeling Units

The E2E ASR systems use sequence-to-sequence model to map the speech frames to the character sequence. In Chinese ASR, character is commonly used to be the modeling units directly as the amount of Chinese characters is around 6k. But modeling words in English directly is difficult because of the large amount and the sparsity of low frequency words. So in the challenge, Chinese character and English word piece [24] is mostly used. Its advantages mainly come from two aspects: balancing the granularity of Chinese and English modeling units and solving OOV problem with limited English training data. The number of English word pieces that teams used varied from 1k to 3k. Except for char + bpe, there are also teams using syllable for Chinese and letter for English.

### 4.3.2. Network and Language Modeling

The winner of track 3 went to a Transformer model [10] trained by ESPnet [25], using multi-task learning to guide the decoder to distinguish Chinese and English characters (as reported, the language distinguishing CE loss optimized at decoder outperformed it at encoder). Label smoothing, averaging checkpoints and spec-augment all yield recognition improvements. Data augmentation performs almost same as in track 1. Transfer learning in the table refers to all kinds of different languages pre-training and fine-tuning strategies.

#### 4.3.3. Language Modeling

As for language information modeling, 4 of the 10 teams in Table 5 use language model for rescoring or fusion with AM. Aisg-xju’s and Royalflush’s language models are RNN-LMs used for shallow fusion. UVoice’s language model is a 4-gram LM used in CTC prefix beam search. Qdreamer uses a 3-gram LM as first pass and an RNN-LM for rescoring.

### 5. Conclusions

In the ASRU 2019 code-switching automatic speech recognition challenge, participants used 500 hours Mandarin speech data and 200 hours intra-sentential CS data to build ASR systems with recognition ability for Mandarin and English within a single utterance. Most teams achieve 5% Chinese part error rate and English error rate under 20% with DNN-HMM based models. The E2E models haven’t outperformed the traditional model yet. It is clear that the systems tend to have higher recognition accuracy for Chinese part in the utterance, the reason may come from the imbalance of the data in two languages, which brings difficulty for LM training. The grammar of skipping between English words is completely invalid. According to the results of the three tracks aforementioned, traditional ASR trained by Kaldi chain model outperformed the E2E models, but the gap is quickly narrowing. The result has highlighted that the detail of pronunciation lexicon and neural network effect a lot. In track 2, text generation is proved to be the most effective way to augment the language model, both word substitution according to grammatical rules and generative neural network help in data expansion. It is worth noting that RNN-LM did not replace N-gram LM but complemented it. As to E2E models, it turns out that attention based models performed more competitive and language identification help the model distinguish languages. Besides, spec-augment is proved a robust method of data augmentation with obvious performance gain.

In this challenge, however, only recognition accuracy is considered in the evaluation. In the future, higher and more comprehensive requirements will be put forward, like streaming ASR system and ASR under complex acoustic environments.

| Team    | Model               | Char + BPE | Transfer Learning | Data Augment | Language Model | Spec Augment | LID Multitask | CH ER(%) | EN ER(%) | MER(%) |
|---------|---------------------|------------|------------------|--------------|----------------|--------------|---------------|----------|----------|--------|
| WYHZ    | Transformer         | ✔          | ✔                | ✔            | ✔              | ✔            |               | 4.33     | 18.95    | 5.91   |
| SJTU SL | Transformer         | ✔          | ✔                | ✔            | ✔              | ✔            |               | 6.93     | 24.35    | 8.82   |
| Royalflush | Transformer   | ✔          | ✔                | ✔            | ✔              | ✔            |               | 7.49     | 21.40    | 9.00   |
| Code-switcher | LAS           | ✔          | ✔                | ✔            | ✔              | ✔            |               | 7.38     | 25.69    | 9.37   |
| ZFZ     | Transformer         | ✔          | ✔                | ✔            | ✔              | ✔            |               | 8.49     | 24.56    | 10.24  |
| Qdreamer | CLDNN+CTC         | ✔          | ✔                | ✔            | ✔              | ✔            |               | 8.23     | 33.32    | 10.90  |
| VIVO ASR | Transformer       | ✔          | ✔                | ✔            | ✔              | ✔            |               | 9.05     | 32.21    | 11.57  |
| UVoice  | BLSTM+CTC          | ✔          | ✔                | ✔            | ✔              | ✔            |               | 8.94     | 41.46    | 12.48  |
| xmuspeech | Joint-CTC Attention | ✔          | ✔                | ✔            | ✔              | ✔            |               | 9.59     | 37.20    | 12.59  |
| Aisg-xju | Transformer       | ✔          | ✔                | ✔            | ✔              | ✔            |               | 10.44    | 31.60    | 12.74  |
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