BERT-LID: Leveraging BERT to Improve Spoken Language Identification

Yuting Nie†, Junhong Zhao†, Wei-Qiang Zhang∗, Jinfeng Bai†

†Beijing National Research Center for Information Science and Technology
Department of Electronic Engineering, Tsinghua University, Beijing 100084, China
‡Computational Media Innovation Centre, Victoria University of Wellington, New Zealand
§TAL Education, 18 Zhongguancun Avenue, Beijing 100080, China

nyt19@mails.tsinghua.edu.cn, junhong.jennifer@gmail.com, wqzhang@tsinghua.edu.cn, baijinfengl@tal.com

Abstract

Language identification is the task of automatically determining the identity of a language conveyed by a spoken segment. It has a profound impact on the multilingual interoperability of an intelligent speech system. Despite language identification attaining high accuracy on medium or long utterances (>3s), the performance on short utterances (<=1s) is still far from satisfactory. We propose a BERT-based language identification system (BERT-LID) to improve language identification performance, especially on short-duration speech segments. We extend the original BERT model by taking the phonetic posteriorgrams (PPG) derived from the front-end phone recognizer as input. Then we deployed the optimal deep classifier followed by it for language identification. Our BERT-LID model can improve the baseline accuracy by about 6.5% on long-segment identification and 19.9% on short-segment identification, demonstrating our BERT-LID’s effectiveness to language identification.

Index Terms: BERT, language identification (LID), short-segment

1. Introduction

Language identification technology has been widely used to facilitate a variety of speech applications, such as multilingual speech identification [1, 2], spoken language translation [3, 4], and pronunciation assessment. It enables these speech systems to tackle hybrid-language speech by providing language identities. Considering the case of multilingual speech recognition, a state-of-the-art multilingual speech recognition system is often composed of sub-systems operating in parallel, where each system focuses on a specific language. Language identity can help determine which language model should be triggered to perform the recognition process [5, 6]. For the code-switching speech recognition where more than one language is present in one utterance, since there is intra-sentential shifting between language varieties [7], additional language-specific information (e.g., language switching timestamp) is required by the recognition process to guarantee the accuracy [8, 9, 10]. Previous studies have revealed that advances in language identification can contribute to the performance of the speech recognition system [11, 12]. Recent years have witnessed significant improvement in language identifications. Although state-of-the-art solutions achieve high accuracy on medium- and long-length utterances, they remain unsatisfactory for short-length utterances. By short length, we mean less than one second. However, in spontaneous conversation in real life, multilingual code-switching speech occurs quite frequently and often comes up with short-length fragments of a language, as the example shown in Figure 1. The transience characteristic makes it challenging to capture sufficient features and develop effective models. It motivates us to search for more powerful methods to promote the performance of short or even long-segment language identification.

Languages contain a phonotactic system that dictates how alphabets are used to form words and morphemes, as well as a syntactic system regulating how sentences are constructed with words and morphemes. Every language has its own phonotactic and syntactic systems, which make it distinct from other languages [13, 14]. In this paper, we introduce BERT to improve phonotactic and syntactic modeling for language identification, by taking advantage of the enormous capability of BERT on language representation. We investigate how to adapt BERT to model language differentiations. We also explore various BERT combinations with other networks, including CNN, DPCNN, LSTM, and RCNN, for language classification. The performance is evaluated on different datasets in terms of accuracy and F-score. Results indicate that BERT-RCNN is the best-performing model. For both long and short segment language identification, it outperforms the baselines (x-vector [15] and n-gram-SVM [16]) by a large margin on accuracy and F-score, with the most improvement on the short-segment language identification task.

Figure 1: An example of an intra-sentential multilingual utterance, where the Chinese-English language interweaved in one speech segment. The total duration of the utterance is 1.9s, with the first Chinese part last 1s and the second English part last only 0.9s.
2. Related Work

2.1. Language identification

The language identification problem has been extensively investigated in the speech domain. There are acoustic model methods and phonotactic methods that constitute mainstream techniques [2, 17, 18]. The acoustic model methods concentrate on modeling acoustic spectral features. The phonotactic method, however, often starts by using single/multiple phone recognizer to decode speech sequences into one/multiple phone sequences, then goes on to model phono- or syntactic relationships from there. For acoustic model approaches, the i-vector based system has led the way for a long time [19], and then the x-vector based system followed [15]. Both systems have two main components, acoustic feature embedding extractor, and back-end classifier. X-vector innovates i-vector system with a discriminative feature embedding extractor including deep neural network and its counterparts [2, 17]. For phonotactic approaches, major efforts have been taken on language model improvement, beginning with the seminal work of the n-gram lexicon model, to vector space model (VSM) [20, 21, 22] and recent work on RNN [23, 24] and transformer-based language models [25].

BERT-LID will follow the phonotactic research track. Unlike prior works, it will incorporate not only phonotactic but also syntactic-level language discriminations to improve long- and particularly short-segment language identification.

2.2. BERT

BERT is a powerful transformer-based encoder pre-trained using masked language modeling and the next sentence predicting objectives to effectively model long contextual dependencies of the input text [26]. Originally, BERT was meant to work with text-based representations. However, we will swap out the BERT’s input to suit speech-based applications.

2.3. BERT in language identification

The prior work [18] applied the BERT-style pertaining concept to improve language identification. However, it mainly focuses on acoustic-based methods, to partially improve the acoustic features extraction of the x-vector system by training with time and frequency-wisely masking objectives. In contrast, BERT-LID positions the BERT as a phonotactic-syntactic feature extractor (language model), capable of modeling phoneme and higher level information.

3. System Description

The proposed work aims to improve the language identification performance on both long and short-length speech segments, mainly focusing on exploring advanced phonotactic and syntactic modeling methods. As a means of achieving this goal, we take advantage of BERT’s capabilities for language representation and explore its benefit for language identification. Our proposed BERT-LID system is illustrated in Figure 2. It includes a phone recognizer, a customized BERT module, and a deep classifier.

3.1. Phone recognizer

Following the general phonotactic-based language identification approaches, our pipeline begins with a phone recognizer, developed by using the bottleneck NN network trained with block softmax output layer [28]. It takes Fbank features and outputs the phonetic recognition results. Rather than directly using recognized phonetic transcriptions for the following language modeling, we rely on the Phonetic Posterior Grams (PPG), which has been widely used in a broad spectrum of application [29, 30, 28]. For each frame of the running speech, it gives the posterior probability belonging to each phone or phone-like unit. The phone recognizer will remain fixed once it has been built.

3.2. BERT adaption and token embedding methods

Following the phone recognizer is the customized BERT module. The inputs of the original BERT model are the aggregation of the token (word/subword), position, and segment embeddings. In this work, we study how to adapt BERT to the phone-level task at a low cost. We chose to maintain the same triplet aggregation scheme as the original BERT but change primarily the token and position embeddings from token-level to frame-level, depending on the front-end phone recognition output. We explore different embedding methods, including:

(1) Frame-level PPGs and position embeddings (denoted as \( \text{PPG}_{\text{frame}} \)), in which we use the PPG vectors of each frame as the frame embedding vectors. Position embeddings are derived from frame positions spread throughout the whole segment.

(2) Text-based phone and position embeddings (denoted as \( \text{Phone}_{\text{emb}}, \text{emb} \)), in which we obtain first the phone recognition results from the front-end phone recognizer, and then use the transcription to extract the phone embeddings based on a lookup table, as in the original BERT algorithm [26]. The phone positions arranged within the whole segment are used to extract the position embeddings.

(3) The phone-wise averaged PPGs and position embeddings (denoted as \( \text{AvPPG} \)), where the phone embeddings are obtained by averaging the PPGs based on the time boundary extracted from the phone recognizer. As (2), the position embedding is derived based on the phone positions along with the entire segment.

3.3. Deep classifier variants

We investigate several variants of the classifier that follow the BERT module for language identification. The representative networks from the sequence processing domain are taken into account, including:

CNN [31]. The CNN classifier we used include one 1-D convolutional layer with the kernel size of 200, followed by a max-pooling and a linear layer.

LSTM [32]. The LSTM classifier we utilized include two bidirectional hidden layers with 300 hidden nodes, followed by a max-pooling and a linear layer.

DPCNN (Deep Pyramid Convolutional Neural Networks) [33]. Following Johnson et al. [33], the DPCNN network we use has a region embedding extractor followed by repeating convolution blocks, each of which includes one 1/2 pooling layer and two equal-width convolution layers coupled with skip connections (15 weight layers in all).

RCNN (Recurrent Convolutional Neural Networks) [27]. The RCNN we use contains a bidirectional LSTM followed by a max-pooling layer. From the bidirectional LSTM, left and right context vectors are concatenated to represent the current frame in its context.

A softmax layer was added to each classifier as the penultimate layer for classification. The classifier is initialized with random initialization method and is trained with a cross-entropy loss.
## 4. Experiments

We evaluate BERT-LID on long- and short-segment language identification tasks, including natural short-segment code-switching speech. Considering the binary classification tasks on such code-switching data, we use not only traditional EER but also accuracy and F1-score as evaluation metrics.

### 4.1. Baseline systems

We compared the BERT-LID system with one phonotactic-based baseline n-gram-SVM and the state-of-the-art acoustic-based baseline, x-vector. The phonotactic-based baseline starts with a phone recognizer, followed by a bag-of-n-grams model to capture the phonotactic features and an SVM as a classifier. For acoustic-based method comparison, we follow the prior work [34] to set up the x-vector baseline system.

### 4.2. Datasets

We use three datasets in our experiments for training and evaluation. OLR20 is a multilingual dataset containing six languages. The average segment length of this dataset is 5.45s. T&T is a Chinese-English mixture dataset combining THCHS-30 (Chinese) [35] and TIMIT (English) [36]. We made it a short-length dataset by chopping all sentences (non-silent part) into one-second speech fragments. TAL-ASR is a dataset collected under a scenario of English classes taught by Chinese. It contains many code-switching speeches with Chinese and English intertwined.

### 4.3. Implementation detail

To train models, we use the BertAdam optimizer with learning rate of $5 \times 10^{-5}$, $\beta_1 = 0.9$, $\beta_2 = 0.99$. The training epochs range between [150, 400], and gradient accumulation steps range between [1, 4]. They will be chosen case by case based on the performance on the development dataset. We will forcefully terminate the training when the loss in the development dataset successively increases by 50 times. For more implementation details of our experiments, we encourage readers to refer to our code.

## 5. Results

### 5.1. Phone recognition impact

We use the open-source tool BUT [28] to develop the phone recognizer and extract PPGs. It provides numerous models trained on different datasets, including monolingual Fisher-English model and multilingual Babel-17 (17 languages) model. We experiment with both models on BERT-CNN and BERT-RCNN pipelines to validate the contributions of the phone recognizer for the final performance.

The results are shown in Table 2. It’s observed that different phone recognizers will impact the final performance on both accuracy and F1-score, although the significance varies across different system setups. The Babel-17 model showed adequate robustness. As such, we will use it for PPG extractions in the following experiments.

### 5.2. Token embedding impact

We evaluate the performance of different token embedding methods on the final language identification results. As shown in Table 3, the network performs better when the token embedding changed from frame-level (PPG$_{frm}$, 2nd column) to phone-level (Phone$_{emb}$ and AvPPG, 3rd and 4th column). The phone-wise averaged PPGs achieve the best performance in most cases. One possible underlying reason is that phone-level input has a reduced mismatch with the BERT pre-trained model trained on word- or sub-word language tasks compared to frame-level input. It’s noteworthy that for Phone$_{emb}$ case, it needs to keep the phoneme set used by the phone recognizer to be consistent with the language dictionary used by BERT pre-training.
Table 3: Accuracy of different token embedding methods for BERT module on OLR20 and T&T dataset

| Database | Model | PPG \(_{f/rm}\) | Phone\(_{emb}\) | AvPPG |
|----------|-------|----------------|----------------|--------|
| OLR20    | CNN   | 0.9792         | 0.9734         | 0.9821 |
|          | LSTM  | 0.9204         | 0.9290         | 0.9349 |
|          | DPCNN | 0.9634         | 0.9669         | 0.9736 |
|          | RCNN  | 0.9871         | 0.9835         | 0.9921 |
| T&T      | CNN   | 0.9198         | 0.9277         | 0.9306 |
|          | LSTM  | 0.9327         | 0.9408         | 0.9484 |
|          | DPCNN | 0.9302         | 0.9482         | 0.9524 |
|          | RCNN  | 0.9623         | 0.9771         | 0.9751 |

5.3. Ablation study

We combined BERT modules with the deep classifier to improve language identification. To understand the contribution of each module, we show how our network performs with either just a BERT (denoted as BERT) or a deep classifier (denoted as LiD). In BERT case, one output layer was added to the BERT pre-trained model and fine-tuned for language classification. In LiD case, the PPGs are directly fed into the deep classifier. With the frame-level PPGs as the input, we evaluated different networks on the OLR20 and T&T datasets. The accuracy is shown in Table 4.

Table 4: Accuracy of different models in ablation studies on OLR20 and T&T dataset.

| Database | Model | BERT-LID | LiD | BERT |
|----------|-------|----------|-----|------|
| OLR20    | CNN   | 0.9792   | 0.9412 | 0.9183 |
|          | LSTM  | 0.9204   | 0.9318 |     |
|          | DPCNN | 0.9634   | 0.9572 |     |
|          | RCNN  | 0.9871   | 0.9619 |     |
| T&T      | CNN   | 0.9198   | 0.8295 |     |
|          | LSTM  | 0.9327   | 0.8705 |     |
|          | DPCNN | 0.9302   | 0.8616 |     |
|          | RCNN  | 0.9623   | 0.8738 |     |

We found that using BERT representations can consistently improve performance compared with directly feeding frame-level PPGs into the back-end classifier. On OLR20, BERT-RCNN increases the identification accuracy from 96.19% to 98.71%. More improvements were achieved on short-length data of T&T. Results demonstrate that BERT is compatible with phone- or frame-level PPGs and can generate the language representation reliably for language identification.

5.4. Comparisons

From the above experiments, we found that the BERT-RCNN model with phone-wise averaged PPGs shows the best performance in both long and short-duration conditions. So in our comparisons, we choose this system and compare it with the baseline systems.

OLR20. From Table 5 we can see that BERT-RCNN systems outperform both baseline systems by a large margin on OLR20 dataset. It yields a 0.08 EER, 6.5% accuracy and 6.9% F-score improvements compared with n-gram-SVM baseline, and 0.15 EER, 13% accuracy and F-score improvement compared with the x-vector baseline. The x-vector system shows no advantage over other systems, obtaining the lowest accuracy and F-score values.

**T&T.** The evaluation on T&T dataset is to explore the BERT-LID performance on short-segment language identification tasks. As we can observe, there is a significant performance degradation across all systems on this dataset compared with OLR20 results. Among them, the x-vector system has the largest drops. Such a result is predictable since the one-second constraints are rather restrictive for sufficient feature extraction and decision-making. Although this, the BERT-LID model can still improve the baseline systems significantly, giving a 11.8% improvement on both metrics (from 85.72% on n-gram-SVM to 97.51% on BERT-RCNN). It reflects our assumption that improving phonological and syntactic representations that BERT-LID mainly contributes to will benefit short-segment language identification.

**TAL.** We also evaluate the BERT-RCNN system on the bilingual code-switching dataset TAL ASR. As shown in Table 5, the intra-sentential multilingual recognition task present in TAL ASR is the most challenging task and got the lowest performance compared with OLR20 and T&T. However, the BERT-RCNN system showed the most significant improvement over the n-gram-SVM baseline, by a margin of 19.9% on both accuracy and F1-score, and 0.21 on EER. Those findings indicate that BERT-RCNN has the most excellent generalizability and can highly benefit language identification of short-segment speech from real-life scenarios.

6. Conclusion

We proposed a BERT-powered language identification system that can extract better phonological and syntactic features beneficial to language identification. We achieved this by deploying a pipeline that includes a phone recognizer, a customized BERT with phone embedding input, and an RCNN classifier. The results show that the proposed BERT-LID system significantly improves language identification performance, especially on the short-segment and code-switching tasks. Further work can consider investigating more optimized network structures and loss functions.

7. Acknowledgement

This work was supported by the National Key R&D Program of China under Grant No. 2020AAA0104500, and the National Natural Science Foundation of China under Grant No. U1836219 and No. 62276153.
8. References

[1] M. A. A. Albadr, S. Tiun, M. Ayob, and F. T. Al-Dhief, “Spoken language identification based on optimised genetic algorithm—extreme learning machine approach,” International Journal of Speech Technology, vol. 22, no. 3, pp. 711–727, 2019.

[2] D. Snyder, D. Garcia-Romero, A. McCroe, G. Sell, D. Povey, and S. Khudanpur, “Spoken language recognition using x-vectors.” in Odyssey, 2018, pp. 105–111.

[3] A. Waibel and C. Fugen, “Spoken language translation,” IEEE Signal Processing Magazine, vol. 25, no. 3, pp. 70–79, 2008.

[4] M. A. Di Gangi, M. Negri, and M. Turchi, “Adapting transformer to end-to-end spoken language translation,” in Proc. INTERSPEECH 2019. ISCA, 2019, pp. 1133–1137.

[5] H. Soltan, H. Liao, and H. Sak, “Neural speech recognizer: Acoustic-to-word lstm model for large vocabulary speech recognition,” arXiv preprint arXiv:1610.09975, 2016.

[6] E. Battenberg, J. Chen, R. Child, A. Coates, Y. G. Y. Li, H. Liu, S. Satheesh, A. Siriram, and Z. Zhu, “Exploring neural transducers for end-to-end speech recognition,” in Proc. ASRU 2017. IEEE, 2017, pp. 206–213.

[7] D.-C. Lyu, T.-P. Tan, E.-S. Chng, and H. Li, “Mandarin–english code-switching speech corpus in south-east asia: Seame,” Language Resources and Evaluation, vol. 49, no. 3, pp. 581–600, 2015.

[8] C. Nilep, “code switching” in sociocultural linguistics,” Colorado Research in Linguistics, vol. 19, pp. 1–22, 2006.

[9] J. Y. Chan, P. Ching, T. Lee, and H. Cao, “Automatic speech recognition of Cantonese-English code-mixing utterances,” in Proc. ICSPS, 2006.

[10] K. Li, J. Li, G. Ye, R. Zhao, and Y. Gong, “Towards code-switching ASR for end-to-end CTC models,” in Proc. ICASSP 2019. IEEE, 2019, pp. 6076–6080.

[11] R. Durosoile, M. Sahisullah, D. Jouvet, and I. Illina, “Modeling and training strategies for language recognition systems,” in Proc. INTERSPEECH 2021, 2021.

[12] D. Liu, J. Xu, P. Zhang, and Y. Yan, “A unified system for multilingual speech recognition and language identification,” Speech Communication, vol. 127, pp. 17–28, 2021.

[13] S. Yu, S. Hu, S. Zang, and B. Xu, “Chinese-english bilingual speech recognition,” in Proc. International Conference on Natural Language Processing and Knowledge Engineering. IEEE, 2003, pp. 603–609.

[14] D.-C. Lyu and R.-Y. Lyn, “Language identification on code-switching utterances using multiple cues,” in Proc. INTERSPEECH, 2008.

[15] D. Snyder, D. Garcia-Romero, G. Sell, D. Povey, and S. Khudanpur, “X-vectors: Robust dnn embeddings for speaker recognition,” in Proc. ICASSP 2018. IEEE, 2018, pp. 5329–5333.

[16] L. Wang, E. Ambikairajah, and E. H. Choi, “Multi-lingual phoneme recognition and language identification using phonotactic information,” in Proc. ICPR’06, vol. 4. IEEE, 2006, pp. 243–248.

[17] Y. Song, X. Hong, B. Jiang, R. Cui, I. McLaughlin, and L.-R. Dai, “Deep bottleneck network based i-vector representation for language identification,” in Proc. INTERSPEECH, 2015.

[18] Q. Zhan, X. Xie, C. Hu, and H. Cheng, “A self-supervised model for language identification integrating phonological knowledge,” Electronics, vol. 10, no. 18, p. 2259, 2021.

[19] N. Dehak, P. J. Kenny, R. Dehak, P. Dumouchel, and P. Ouellet, “Front-end factor analysis for speaker verification,” IEEE Transactions on Audio, Speech, and Language Processing, vol. 19, no. 4, pp. 788–798, 2010.

[20] H. Li, B. Ma, and C.-H. Lee, “A vector space modeling approach to spoken language identification,” IEEE Transactions on Audio, Speech, and Language Processing, vol. 15, no. 1, pp. 271–284, 2006.

[21] W.-Q. Zhang, W.-W. Liu, Z.-Y. Li, Y.-Z. Shi, and J. Liu, “Spoken language recognition based on gap-weighted subsequence kernels,” Speech Communication, vol. 60, pp. 1–12, 2014.

[22] H.-S. Lee, Y. Tsao, S.-K. Jeng, and H.-M. Wang, “Subspace-based representation and learning for phonotactic spoken language recognition,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 28, pp. 3065–3079, 2020.

[23] C. R. Salamea Palacios, L. F. D’Haro Enríquez, R. d. Cordoba Herralde, and R. San Segundo Hernández, “On the use of phone-gram units in recurrent neural networks for language identification,” in Proc. Odyssey, 2016, pp. 117–123.

[24] C. R. Salamea, L. D’Haro, and R. Cordoba, “Language recognition using neural phone embeddings and rnmlms,” IEEE Latin America Transactions, vol. 16, no. 7, pp. 2033–2039, 2018.

[25] D. Romero, L. F. D’Haro, and C. Salamea, “Exploring transformer-based language recognition using phonotactic information,” Proc. IberSPEECH, pp. 250–254, 2021.

[26] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, “Bert: Pre-training of deep bidirectional transformers for language understanding,” arXiv preprint arXiv:1810.04805, 2018.

[27] S. Lai, L. Xu, K. Liu, and J. Zhao, “Recurrent convolutional neural networks for text classification,” in Proc. Twenty-ninth AAAI conference on artificial intelligence, 2015.

[28] R. Fer, P. Matiška, F. Gréoli, O. Plichot, K. Veselý, and J. H. Cernocký, “Multilingually trained bottleneck features in spoken language recognition,” Computer Speech & Language, vol. 46, pp. 252–267, 2017.

[29] T. J. Hazen, W. Shen, and C. White, “Query-by-example spoken term detection using phonetic posteriogram templates,” in Proc. ASRU. IEEE, 2009, pp. 421–426.

[30] G. S. Srivaram and H. Hermansky, “Multilayer perceptron with sparse hidden outputs for phoneme recognition,” in Proc. ICASSP 2011. IEEE, 2011, pp. 5336–5339.

[31] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet classification with deep convolutional neural networks,” Advances in Neural Information Processing Systems, vol. 25, 2012.

[32] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” Neural computation, vol. 9, no. 8, pp. 1735–1780, 1997.

[33] R. Johnson and T. Zhang, “Deep pyramid convolutional neural networks for text categorization,” in Proc. 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), 2017, pp. 562–570.

[34] Z. Li, M. Zhao, Q. Hong, L. Li, Z. Tang, D. Wang, L. Song, and C. Yang, “Ap20-olr challenge: Three tasks and their baselines,” in Proc. APSIPA ASC 2020. IEEE, 2020, pp. 550–555.

[35] D. Wang and X. Zhang, “Thchs-30: A free chinese speech corpus,” arXiv preprint arXiv:1512.01882, 2015.

[36] J. S. Garofolo, L. F. Lamel, W. M. Fisher, J. G. Fiscus, and D. S. Deng, “The DARPA TIMIT acoustic-phonetic continuous speech corpus cd-rom. nist speech disc 1-1.,” NASA STI/Recon Technical Report N, vol. 93, p. 27403, 1993.