SEMI-SUPERVISED TRANSFER LEARNING FOR LANGUAGE EXPANSION OF END-TO-END SPEECH RECOGNITION MODELS TO LOW-RESOURCE LANGUAGES

Jiyeon Kim, Mehul Kumar, Dhananjaya Gowda, Abhinav Garg, Chanwoo Kim

Speech Processing Lab, AI Center, Samsung Research, South Korea
{jstacey7.kim, mehul3.kumar, d.gowda, abhinav.garg, chanw.com}@samsung.com

ABSTRACT
In this paper, we propose a three-stage training methodology to improve the speech recognition accuracy of low-resource languages. We explore and propose an effective combination of techniques such as transfer learning, encoder freezing, data augmentation using Text-To-Speech (TTS), and Semi-Supervised Learning (SSL). To improve the accuracy of a low-resource Italian ASR, we leverage a well-trained English model, unlabeled text corpus, and unlabeled audio corpus using transfer learning, TTS augmentation, and SSL respectively. In the first stage, we use transfer learning from a well-trained English model. This primarily helps in learning the acoustic information from a resource-rich language. This stage achieves around 24% relative Word Error Rate (WER) reduction over the baseline. In stage two, we utilize unlabeled text data via TTS data-augmentation to incorporate language information into the model. We also explore freezing the acoustic encoder at this stage. TTS data augmentation helps us further reduce the WER by $\sim 21\%$ relatively. Finally, in stage three we reduce the WER by another 4% relative by using SSL from unlabeled audio data. Overall, our two-pass speech recognition system with a Monotonic Chunkwise Attention (MoChA) in the first pass and a full-attention in the second pass achieves a WER reduction of $\sim 42\%$ relative to the baseline.

Index Terms— End-to-end speech recognition, Semi-supervised learning, Transfer learning, Encoder freezing, Low-resource language

1. INTRODUCTION
Recent advances in deep learning techniques have enabled the training of end-to-end (E2E) automatic speech recognition (ASR) systems consisting of a single neural network model. The E2E model architecture has a simpler training pipeline and better modeling capabilities compared to conventional architectures such as DNN-HMM systems. With these advantages, E2E speech models are widely used by state-of-the-art ASR systems for server-side and on-device applications [2, 3, 4, 5]. However, training E2E models from scratch for a new language requires a lot of data to achieve high accuracy [6, 7]. Obtaining valid and reliable transcriptions for speech data is costly, time-consuming, and refining both text and speech data is laborious work.

To overcome the requirement of a large amount of labeled data, there have been several efforts to train E2E models with a smaller amount of data. For example, [8, 9, 10, 11] explored transfer learning from a resource-rich language to a low-resource language. It has been also shown that using other language corpus and multi-lingual training, the performance for a low-resource language can be improved [12]. In other related works, [13] suggests a universal character set and creates a language-specific gating mechanism to increase the network’s modeling power. In [14], unsupervised pretraining is used to improve acoustic model training, and semi-supervised learning was used in [15] to leverage the lack of sufficient amounts of labeled data. Recent works like wav2vec 2.0 [16] particularly rely on self-supervision to train a task-agnostic encoder from the huge amount of unlabeled data before applying a task-oriented supervised training with limited data.

In this paper, we explore methods to improve the performance of an ASR model for an under-resourced language with the limited amount of labeled data. We split the training process into three stages, each using a different training paradigm to leverage either a model trained on resource-rich language or unlabeled text data or unlabeled audio data.

During each training stage, we use different training methodologies such as transfer learning from a resource-rich language, spectral augmentation, Text-To-Speech (TTS) augmentation, encoder freezing, and beam score filtering based semi-supervised learning. For our experiments, we use one of our recently proposed two-pass streaming architecture described in [4] with Monotonic Chunkwise Attention (MoChA) decoder in the first pass and a Bidirectional-encoder Full-Attention (BFA) decoder in the second pass.

To the best of our knowledge, this is one of the first works that explore leveraging a resource-rich language, unlabeled text data, and unlabeled audio data using transfer learning, TTS data augmentation, and semi-supervised techniques respectively, for training a streaming end-to-end MoChA attention-based model for a low-resource language.

As a case study, we use English and Italian as our high and low-resource languages. The English corpus has around 11K hours of transcribed data. The Italian corpus with around 4000 hours of labeled data is divided into two more subsets of around 400 hours and 40 hours each. The 40 hours subset represents the low-resource labeled speech corpus.

We show that there exists a huge difference in Word Error Rates (WER) when models are trained with different amounts of data from scratch using standard training practices used for E2E ASR models. We design a training methodology including a beam score filtering-based semi-supervised training method.

We show that transfer learning using a well-trained model from a resource-rich language helps achieve better accuracy compared to training models from scratch in a new language, especially when the amount of labeled data available is limited. TTS-generated audios are typical of sub-optimal quality as compared to real-world audios. To mitigate this effects of TTS audio, we propose freezing of encoder when applying TTS data augmentation. Using the proposed training methodology we reduce the performance gap of the model trained with 40 hours as compared to 400 hours and 4000 hours models by around 73% and 62%, respectively.
Transfer learning can be of two types, one that involves the transfer of soft knowledge, and the other that involves the transfer of hard knowledge [8, 9, 17]. Transfer of soft knowledge refers to teacher-student learning strategies that minimizing a cost function to reduce the output mismatch between teacher and the student. This strategy is more suited for applications like model compression or moving from a mono-lingual ASR to a bi-lingual or multi-lingual ASR where one may want to retain the performance of the teacher. Transfer of hard knowledge refers to borrowing the pretrained weights from a teacher model into a student model before continuing with independent training of the student. In this paper, we use hard transfer learning as a first step since we train the model independently for low-resource language by borrowing weights from a previously well-trained resource-rich language.

As the pool of acoustic sounds is universal with significant overlap across different language, we borrow the pretrained model weights from a high-resource language to a low-resource language.

However, the exact realization of these phonetic units may vary based on the regional or linguistic traits and may need some fine-tuning to the sounds of a target language. Also, the phonetic and linguistic grammar (combination or sequence of phones and words) are different between languages. Hence the encoders which encode the acoustic information in the audio signal should be more similar across languages as compared to decoders. To verify this hypothesis, we try to freeze the borrowed encoder before continuing with supervised training from the limited labeled data available for the target language.

3.2. Stage Two: Text-to-Speech data augmentation and Encoder freezing

Text data is more readily available for most languages as compared to audio data or transcribed audio-text pair. And can be easily obtained in large quantity using web-crawling, digital books, etc. Due to the abundance of text data, many methods have been explored to leverage it for building ASR models. First, an external language model can be built and used along with the ASR model using shallow fusion during inference [18]. Second, borrowing the weights of a pretrained language model to initialize the language modeling components of end-to-end models. This can be readily done for a recurrent neural network transducer (RNNT) architecture with a separate predictor block but would require a more careful integration into an Attention-based Encoder-Decoder (AED) model. The other option is to use a TTS engine for the target language to synthesize audio data from the text to train the ASR model. A variant to this approach is to use a Text-To-Encoder (TTE) approach wherein a parallel stack of the text-only encoder is used along with the standard encoder in an ASR that accepts audio-only inputs [19]. During the training stage, the text corresponding to the audio data is passed through the text-only encoder to produce a hidden text-encoder embedding that is forced to match the audio-encoder embeddings by minimizing the Kullback-Liebler divergence between the two. In this paper, we propose to use the TTS based data augmentation as it generally shows better performance compared to TTE based approach [19] except for the need of a TTS engine for the target low-resourced language. The Google Speech python library [20] can be readily used to read text using the Google Translate TTS APIs.

It has been observed that data augmentation with TTS performs better than the TTE approach [19]. However, this begs the question as to whether the single speaker, possible monotonous, and poor audio-quality TTS signals are good to update the encoder weights that learn to encode the acoustic information. Some of these limitations can be mitigated to a certain extent with the use of different perturbation techniques like speed, tempo, pitch, vocal tract length [21], and data augmentation techniques like spectral augmen-
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Table 3. Effect of using transfer learning from a well trained English model and supervised training with around 40 hours of data.

| Model                | ITA400h | ITA40th |
|----------------------|---------|---------|
| B1: Ita Baselines    | 15.79   | 37.56   |
| B0: Eng Model        | -       | 107.8   |
| M1: B0 + TL w/ Enc freezing | - | 30.69   |
| M2: B0 + Transfer learning | - | **28.50** |

Table 4. Effect of TTS based text data augmentation using around 360h of synthesized audio, with and without encoder freezing. The performance of different models is given in WERs (%).

| Model                  | ITA400h | ITA40th |
|------------------------|---------|---------|
| B1: Ita Baselines      | 15.79   | 37.56   |
| B2 (M2): Transfer learning | 15.33  | 28.50   |
| M3: B1 + TTS Aug       | -       | 34.30   |
| M4: B2 + TTS Aug       | -       | 23.50   |
| M5: B2 + TTS Aug w/ Enc freezing | - | **22.45** |

gives better performance as it allows both acoustic as well as linguistic fine-tuning.

4.3.2. Effect of TTS data augmentation

In stage two, we study the effect of TTS data augmentation for improving ASR performance. The impact of TTS data augmentation on models at different accuracy levels is shown in Table 4. By comparing the WERs of M3 and M4 we can easily conclude that using TTS augmentation provides larger improvements for a better model B2 as compared to B1. The improvements of model M3 and M4 over their baselines B1 and B2 are 3.26% and 5.0% absolute, or 8.6% and 17.5% relative, respectively. This shows that using transfer learning in stage one enhances the gains obtained from TTS augmentation.

As mentioned in Sec 3.2, the TTS audio may not be ideal for learning or updating the encoder weights which predominantly captures and encodes the acoustic information in a speech signal. Too much TTS audio may bias or overfit the model to TTS data, with a possible degradation in model performance. This can be seen from the experiments in Table 4 where the model M5 with a frozen encoder performs better than the M4 without encoder freeze by around 4.4% relative. Also, M5 gives an overall 21.2% relative improvement over the baseline model B2 after transfer learning, as against the 17.5% relative improvement obtained without freezing the encoder.

4.3.3. Effect of semi-supervised learning

As the final stage of training for language transfer for ASR models, we explore the use of the SSL from unlabeled audio data. While several methods have been proposed in the literature, we use the most straightforward approach of generating text labels for a corpus of unlabeled audio data using our best ASR model so far. It is well known that better-trained models tend to benefit more from audio-based SSL techniques as they can produce better hypotheses for the unlabeled data. Results for our experiments with SSL techniques can be seen in Table 5.

WERs for models M6 and M7 show that performance can degrade when all of the ASR-generated text labels are used indiscriminately for SSL. The adverse effect is more when the baseline accuracy of the ASR model is poorer. Comparing B3 and M7 shows that TTS augmentation as stage 2 is adequate as the WER increases in M7 without beam score-based filtering. Using a simple ASR hypothesis filtering by using the log posterior probability score of the top beam, it can be seen that the model improves by around 4.1% relative at stage 3.

Using a language model for generating text labels, different scores for filtering and iterative methods for SSL can help improve the gains further. To see the maximum gain possible with SSL if we were to use a better metric or score for filtering the hypotheses, we use the oracle ground truth labels to identify all correctly hypothesized data which amounts to around 60% of the total ~619K utterances (around 400 hours) available in the SSL unlabeled dataset. Using this oracle ground truth filtered data gives an improvement of around 8.9% relative as compared to around 4.1% relative when using a simple automated filtering mechanism. The performance of filtering by beam scores at different thresholds for filtering is shown in Table 6. It can be seen that with a harsher threshold we can expect lesser but more reliable transcripts and hence there is a progressive improvement in the gains achieved by SSL.

5. CONCLUSIONS

In this paper, we present a sequence of training strategies to develop and improve ASR models for a resource-constrained language. The training involved three stages: transfer learning from an ASR model in a resource-rich language, TTS text data augmentation with encoder freezing, and semi-supervised learning by filtering the automatically generated hypotheses for unlabeled data using beam scores. The proposed methodology improved the performance of the 40h model by around 42% relative to a model trained from scratch using the 40h data. It was seen that overall the proposed methodology reduces the gap in performance between the 40h and 400h models by around 73%, and for 40h and 4Kh models by around 62%. All the performances discussed so far in the paper are for the second pass BFA decoder. The first pass MoChA decoder of the final model (M8) gives a WER of 24.84%, an improvement by 43.9% relative, over the 40h baseline model (B1) with a WER of 44.35%.

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