DATA TECHNIQUES FOR ONLINE END-TO-END SPEECH RECOGNITION

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ABSTRACT

Practitioners often need to build ASR systems for new use cases in a short amount of time, given limited in-domain data. While recently developed end-to-end methods largely simplify the modeling pipelines, they still suffer from the data sparsity issue. In this work, we explore a few simple-to-implement techniques for building online ASR systems in an end-to-end fashion, with a small amount of transcoded data in the target domain. These techniques include data augmentation in the target domain, domain adaptation using models previously trained on a large source domain, and knowledge distillation on non-transcribed target domain data; they are applicable in real scenarios with different types of resources. Our experiments demonstrate that each technique is independently useful in the low-resource setting, and combining them yields significant improvement of the online ASR performance in the target domain.

Index Terms—online speech recognition, data augmentation, domain adaptation, knowledge distillation

1. INTRODUCTION

End-to-end speech recognition systems have gained increasing popularity, due to the simplicity of their modeling pipelines (without initial alignment for warm start), easiness of deployment (with more lightweight decoders), and comparable performance to the state-of-the-art. The two major classes of end-to-end models are variants of connectionist temporal classification (CTC) [1, 2, 3, 4], and attention-based sequence to sequence models [5, 6, 7, 8]. The advantages of end-to-end methods make them viable choices for developing ASR systems from scratch in a short amount of time. On the other hand, these models may suffer more from the data sparsity issue than traditional methods, as can be seen from their performance on standard benchmarks.

In this work, we are concerned with building end-to-end ASR systems for new use cases given limited in-domain data, which is a task frequently faced by practitioners in the early stage of the development. Furthermore, we are interested in deploying models with low latency, which rules out bi-directional architectures (despite that they give superior performance [9]). Since it is less trivial to deploy attention-based models in an online fashion [10, 11], and inspired by the success of ASR systems on mobile devices [12], we mainly consider unidirectional architecture and CTC-based models. More recent variants of CTC such as AutoSeg [3, 13] and RNN-transducer [14, 12] are left for future investigation.

Contributions We explore a few easy-to-implement techniques in this scenario, depending on the availability of different types of resources:

- data augmentation techniques in target domain [15, 16],
- domain adaptation from an initial model trained on a source domain with large amount of data [17, 18],
- teacher-student learning if non-transcribed data is available in the target domain [19, 20, 21, 22, 23, 24, 25].

We found each technique to be independently useful and we obtain significant accuracy improvement by combining them.

The common intuition behind our techniques is about data: augmenting target domain data, leveraging source domain data, and generating pseudo-labels so we have more (noisy) training data. This work shows how much we can gain by carefully manipulating data, even using relatively simple acoustic models. We believe our setting is quite common and our findings are useful to practitioners.

In the rest of this paper, we demonstrate the abovementioned techniques on the Wall Street Journal (WSJ) corpus [1], which yields about 50% relative improvement over a baseline, when trained on 15 hours of supervised in-domain data.

2. SETUP

We use the the WSJ corpus as our target domain. In particular, unless mentioned otherwise, we use the si84 partition (7040 utterances) as the transcribed target domain data, while the si284 partition (37.3K utterances) is used as unsupervised target domain data. We use the dev93 partition (503 utterances) as development set for hyper-parameter tuning, and the eval92 partition (333 utterances) as test set. We report both phone error rate (PER) and word error rate (WER) on

1Obtained from LDC under the catalog numbers LDC93S6B and LDC94S13B.
the evaluation sets. The units used by our CTC acoustic models are the 351 position-dependent phones together with the <blank> symbol. Acoustic model training is done with Tensorflow [29] and we use its beam search algorithm for phone-level decoding with a beam size of 20. For word-level decoding, we use the WFST-based framework [2] with the lexicon and trigram language model (with a 20K vocabulary size) provided by the kaldi s5 recipe [27], and run beam search with a beam size of 20 on per-frame log-likelihood produced by the acoustic model. The conversion from posterior (acoustic model output) to likelihood uses a uniform prior on non-blank symbols, and a different prior for <blank> which is tuned on the dev set [23]. <NOISE> and <UNK> are removed both from ground truth and decoding results for calculating WER.

Our source domain CTC acoustic models are trained on a 15000 hour subset of data used for training the Amazon Transcribe system [29]. We use two models trained on the source domain, one consisting of 5 uni-directional LSTM layers of 512 units for domain adaptation, and the other consisting of 5 bi-directional LSTM layers of 512 units in each direction, as the teacher model for knowledge distillation on non-transcribed target data. The source domain CTC models are trained with a different set of units than those used for the target domain. We use 5 LSTM layers instead of a shallower one because we find that, with careful tuning, the deeper architecture performs better even trained on si84 (e.g., a 3 uni-directional LSTM architecture gives 25.6% PER on dev93, versus the 23.71% obtained by 5 uni-directional LSTMs shown in Table 1).

For both source and target domains, 40 dimensional LF-BEs are extracted with a window size of 25ms and hop size of 10ms. We perform per-speaker mean normalization on the LF-BEs in the target domain. Furthermore, we stack every 3 consecutive frames to reduce input sequence length by three times to speeds up training and decoding, where the initial frame index for stacking is randomly selected from \{0, 1, 2\} during training and fixed to 0 during evaluation; this already provides a form of data augmentation [28].

For acoustic model training, we use the ADAM optimizer [31] with minibatches of 8 utterances, and an initial learning rate searched over the grid \{0.0002, 0.0005, 0.001, 0.002\} when the model is initialized randomly, and searched over the grid \{0.00002, 0.00005, 0.0001, 0.0002\} when adapting the source domain models (the smaller learning rates are important for domain adaptation). For all model training, we apply dropout [32] with rate tuned over \{0, 0.1, 0.2, 0.4\}, which is effective with small amount of training data. Each model is trained up to 50 epochs and the iteration which yields the best PER is selected for evaluation.

3. DATA AUGMENTATION

A natural approach for alleviating the data sparsity issue in the target domain is to augment the supervised training set with different perturbed versions [15][33][16]. Here we mainly explore speed perturbation and spectral masking.

3.1. Speed Perturbation

Speed perturbation is an augmentation technique that produces a warped time signal, and it is shown to improve performance on LVCSR [15]. The implementation we use is a mix of that of [15] and the time warping method of [16]: instead of perturbing the audio [15], we apply linear interpolation on the spectrogram via the function interpolate.inter2d from the scipy package to modify temporal resolution. In other words, we treat the spectrogram as an image and resize it in the time axis. The speed factors we use are \{0.9, 1.0, 1.1\} as suggested in [15]. We adopt this implementation because it is easy to implement and we can generate the perturbed versions on the fly, without the need of additional feature extraction from audio.

3.2. Spectral Masking

Recently, [16] proposed a set of data augmentation methods that operate on the spectrogram directly, including time warping, frequency masking, and time masking. They are shown to yield significant improvement for the attention-based model LAS [6], and we explore the two masking techniques here within the CTC framework. The masking method applies zero masks to randomly selected consecutive mel frequency channels and consecutive time steps on the spectrogram. The two main parameters are F and T, corresponding to the maximum length of frequency mask and time mask. We perform small grid search for them, and set F to 8 and T to 16 in all of our experiments. Instead of applying masks to input features and fixed it for training, the masks are generated and applied on the fly. We set the probability of applying masks to a given input utterance to 0.5, for the purpose of also exploiting clean data during training. Figure 1 gives an illustration of the abovementioned augmentation techniques. Augmentation is performed before stacking frames.
Table 1: Performance (measured by PER in %) of data augmentation techniques.

| Model                        | dev93 | eval92 |
|------------------------------|-------|--------|
| Train on target              | 23.71 | 18.32  |
| + Speed Perturbation         | 21.67 |        |
| + Spectral Masking           | 22.77 |        |
| + Both                       | 20.55 | 16.14  |

Table 1 shows the result of speed perturbation, spectral masking, and the combination of the two methods. Each technique helps to improve the performance independently and the gains from both are additive. Although it was suggested by [16] that time warping is not a major contributor to performance improvement, our observations on speed perturbation differ. We have not explored reverberation and adding noisy to the audio, as the WSJ data is relatively clean.

4. DOMAIN ADAPTATION

In speech, the domain differences come from the acoustic condition, speaker, and style of speech (conversational vs. read, etc.). In addition to the mismatch in the inputs, there might be a mismatch in the output labels (number of classes, phones vs. characters, etc.) between the source and target domains. In this section, we make use of an initial model that is well-trained on a large amount of source domain data (15000 hours of conversational speech, see Section 2) which is denoted as Pretrain, and try to transfer the modeling power to the target domain by finetuning from the pre-trained model which is denoted as Finetune. In our case, since the source domain model is trained with a different set of units, we replace the original softmax layer with a new randomly initialized one.

Apart from a good initialization, we could also insert an additional linear layer between the target domain input and the pre-trained model which is shared across all time steps, and only finetune this layer and the softmax in the early stage of training, so the smaller number of parameters in these adaptation layers are well trained with a small amount of labeled data. This method is known as linear input networks (LIN) [17, 18], and in this work we explore the method in the context of end-to-end ASR. This linear layer is initialized as an identity mapping for the purpose of fast convergence. For the first 10 epochs over our training data, we fix the weights of the 5 LSTM layers, and only update the LIN layer and the softmax layer.

Table 2 shows the results for domain adaptation, with or without LIN. Pretraining + finetuning alone improves the best performance from the previous section (training only on the target domain) by about 7% PER in absolute on the dev set, demonstrating that the modeling power is well transferred to the target domain. On top of that, LIN and data augmentation lead to consistent, further improvement.

Table 2: Performance (PER in %) of domain adaptation techniques. DataAug: Speed perturbation + Spectral masking. “Train on Target + DataAug” is taken from Table 1.

| Model                                | dev93 | eval92 |
|--------------------------------------|-------|--------|
| Train on Target + DataAug            | 20.55 | 16.14  |
| Pretrain + Finetune                  | 13.60 |        |
| + DataAug                            | 13.01 |        |
| Pretrain + Finetune + LIN            | 10.72 |        |
| + DataAug                            | 10.09 | 7.32   |

5. DISTILLATION

In practice, it is often the case that the speed of data collection is much faster than the speed of annotation. Therefore, in the early stage of the development, we would have a small amount of transcribed speech and at the same time a relatively large amount of non-transcribed data. In this section, we leverage the unsupervised data and generate pseudo-labels using a more powerful, bi-directional system. Note that the bi-directional system is not deployable in the online mode; they are used as teachers on the unsupervised data to provide guidance for the uni-directional student model.

Our bi-directional teacher is initially trained on the same source domain, and then adapted in the same manner described in the previous section. And as expected, it achieves much better performance—5.36% PER on dev93—than the best uni-directional model so far. We consider two approaches to generate pseudo-labels at the token (phone) level on unsupervised data. The first is to use phone level beam search decoding result (with a beam size of 20). The second approach is to first apply WFST-based word decoder to obtain the most probable word sequence, and then convert it back to the phone sequence using the lexicon. Here the language model used in word decoder is obtained from the source domain, to avoid using language model trained on si284. This decoding approach yields a dev PER of 3.68%. Clearly, incorporating language model can improve the quality of pseudo-labels.

The uni-directional student model is then trained on both supervised utterances with ground truth and unsupervised utterances with the pseudo-labels, using the CTC objective. A discount factor is applied to the pseudo-label loss term, which is tuned by grid search. It turns out a discount of 1.0 works best, perhaps because our pseudo-labels are relatively clean. For each gradient update, we use 8 supervised utterances and 32 unsupervised utterances. We provide in Table 2 the result of our trained student model, with the two types of pseudo-labels. To avoid cluttering, we only give the performance with adaptation and data augmentation; results without adaptation (not listed here) show similar behavior. We observe that knowledge distillation effectively explores the teacher’s modeling power, and yields significant PER reduction.

To see how much improvement comes from the use of
more (unsupervised) data versus the use of a more powerful teacher, we also perform semi-supervised learning with the self-training method of [34]. The uni-directional model produces pseudo-labels using greedy beam search decoding on the fly for an unlabeled utterance, and the pseudo-labels are used by the augmented version of the same utterance (with speed perturbation and spectral masking) for CTC training. We train the uni-directional model with a discount factor set to 1.0. We observe that while self-training does give sizable PER reduction, its performance is still inferior to that of the student guided by the bi-directional teacher.

We now connect our methodology to existing work. The pseudo-label approach is considered as sequence-level knowledge distillation by [22], in which the authors use a teacher model to generate top-k hypothesis on supervised data and use a weighted sum of CTC loss on the top-k hypothesis for training the student. In contrast, we explore sequence-level knowledge distillation on the unsupervised data, and incorporate a language model for label generation which leads to further improvement. In addition to sequence-level distillation, frame-level distillation has been explored [22, 23, 24, 25]. In general, frame level distillation from bi-directional teacher to uni-directional student with per-frame KL divergence loss seems to degrade the ASR performance [22, 25]. This phenomenon is attributed to the different timing behavior between posteriors produced by bi-directional systems and uni-directional systems, and thus [25] proposes to align the CTC spike timing between bi-directional model and uni-directional model with a pre-trained guiding CTC model. On the other hand, [24] perform distillation possibly on unsupervised data, where both the teacher and the student are uni-directional models (with different depths), and propose to use pseudo-labels computed with a forward-backward algorithm as frame targets. In comparison to these work, our sequence level distillation approach on unsupervised data is arguably simpler.

6. SUMMARY
In Table 4 we give the WER results of our methods on eval92, for the baseline and the best model from Section 5. To put our results in context, we also include in the table two CTC models from the literature [2, 35] under similar settings in terms of data and training objective. The recent work [35] which uses similar data partition for semi-supervised learning with attention model is also included. We also train our uni-directional architecture on si284 to obtain another baseline, which gives 11.98% WER on eval92. By combining the proposed techniques, we achieve more than 50% relative improvement over training only on the target domain (17.72% → 7.58%), and obtain an online system whose performance is better than that of a bi-directional system trained on the same unsupervised data (13.50% from [35]), and that of a uni-directional system trained on more supervised target domain data (11.98%).

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Table 3: Performance (measured by PER in %) of knowledge distillation using unsupervised data. “Pretrain + Finetune + LIN + DataAug” is taken from Table 2.

| Model | dev93 | eval92 |
|-------|-------|--------|
| Teacher (5 Bi-LSTM layers, Pretrain + Finetune + LIN + DataAug) | 5.36 | 3.68 |
| Pretrain + Finetune + LIN + DataAug | 10.09 | 7.32 |
| + Unsup KD (phone decode) | 8.37 | |
| + Unsup KD (word decode) | **8.25** | **6.04** |
| + Self-training | 9.50 | |

Table 4: ASR performance (measured by WER in %) of previous work and our methods on eval92, under similar settings.

| Model | WER |
|-------|-----|
| CTC (our uni-directional, train on si284) | 11.98 |
| This work (uni-directional, target si84) | 17.72 |
| Train on target (Sec. 3) | 7.58 |
| Adaptation + DataAug + KD on si284 (Sec. 5) | 7.58 |
