LOW RESOURCE MULTI-MODAL DATA AUGMENTATION FOR END-TO-END ASR

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ABSTRACT

We explore training attention-based encoder-decoder ASR for low-resource languages and present techniques that result in a 50% relative improvement in character error rate compared to a standard baseline. The performance of encoder-decoder ASR systems depends on having sufficient target-side text to train the attention and decoder networks. The lack of such data in low-resource contexts results in severely degraded performance. In this paper we present a data augmentation scheme tailored for low-resource ASR in diverse languages. Across 3 test languages, our approach resulted in a 20% average relative improvement over a baseline text-based augmentation technique. We further compare the performance of our monolingual text-based data augmentation to speech-based data augmentation from nearby languages and find that this gives a further 20-30% relative reduction in character error rate.

Index Terms— Multi-modal data augmentation, multilingual ASR, encoder-decoder, low-resource

1. INTRODUCTION

Attention-based encoder-decoder networks have achieved state-of-the art performance in ASR when trained on over 12k hours of transcribed speech [1], but their performance lags behind conventional systems in more moderate resource conditions and has hardly been studied in low-resource conditions [2, 3]. An appealing approach to improving ASR performance without access to more within-language transcribed speech is to leverage linguistic resources from other languages and modalities. Bolstering the decoder with a language model (LM) trained on supplemental text data is one such method that improves end-to-end ASR performance [4]; however, more significant gains can be obtained by training on additional synthetically perturbed speech [5, 6, 7], or by multilingual training, which augments the training data with transcribed speech from other languages [8, 9, 10, 11, 12, 13].

Using an LM in decoding is appealing as it requires only text data, but it provides only modest improvements in performance. And while multilingual training often provides more significant improvements in performance, this approach also requires additional transcribed speech, preferably from similar languages [10]. Our aim is to achieve performance improvements similar to multilingual training, but obtained solely from text data.

As a starting point we consider multi-modal data augmentation (MMDA): a data augmentation scheme for encoder-decoder based ASR which only requires text data [14]. The approach involves using an additional augmenting encoder (in addition to the traditional acoustic encoder) which accepts a sequence of features derived from text as input and learns to predict the original text. Other work uses a text-to-speech system to generate the augmenting features, however, this requires more single speaker data than we have available in many low-resource situations [15].

We modify MMDA to work in low resource contexts. First we dramatically increase the amount of external text we expose to the network. We found that simply pre-training MMDA using only the augmenting data helps much more than other alternatives. MMDA’s usefulness for most low-resource ASR tasks is limited due to its reliance on frame-level phoneme alignments for training a phone duration model. [14] bypasses this problem by apply to each phoneme in a non-English language the duration model corresponding to a close English phone equivalent. In this work we propose a simple phoneme duration model that can work for any language.

Finally, due to the limited training data, the encoder may benefit from seeing the augmenting features more than in high-resource contexts. Hence, we propose a modified architecture that feeds the output of the augmenting encoder directly to the acoustic encoder. The augmenting data can then be viewed as pseudo-speech from some language that we add to our training data. We refer to this as pseudo-speech data augmentation (PSDA) as the augmenting encoder is implicitly tasked with learning representations of the augmenting data that resemble the original acoustic features.
Our architecture follows the encoder-decoder model which maximizes the log-likelihood:

$$ \mathcal{L}(\theta) = \log P(y | X; \theta_{\text{enc}}, \theta_{\text{att}}, \theta_{\text{dec}}) $$

(1)

$y$ denotes the desired output character sequence and $X \in \mathbb{R}^{L \times D}$ a tensor of speech frames of length $L$ and feature dimension $D$. We denote the entire set of network parameters by $\theta$, which is composed of acoustic encoder parameters $\theta_{\text{enc}}$, attention mechanism parameters $\theta_{\text{att}}$ and decoder parameters $\theta_{\text{dec}}$. The encoder consists of a projection-biLSTM with a pyramidal structure for the acoustic encoder [10], the decoder is a single-layer LSTM and location-aware attention completes the entire end-to-end network.

### 3.1. Multi-Modal Data Augmentation

The MMDA technique (fig. 1a) transforms the objective into a multi-task objective:

$$ \mathcal{L}(\theta) = \begin{cases} \log P(y | X; \theta_{\text{enc}}, \theta_{\text{att}}, \theta_{\text{dec}}) & \text{speech} \\ \log P(y | \hat{x}; \theta_{\text{DA}}, \theta_{\text{att}}, \theta_{\text{dec}}) & \text{text-based} \end{cases} $$

(2)

When the inputs are acoustic features, $X$, MMDA uses the standard encoder-decoder network to maximize the original ASR objective and the primary task. When the inputs are text-based features, $X$, MMDA uses a data-augmenting encoder instead of the acoustic encoder and maximizes the probability of the output sequence paired with the text-based representation (secondary task). In Eq 2, $\theta_{\text{DA}}$ denotes the parameters of the data-augmenting encoder which is composed of an embeddings layer and a single-layer projection-biLSTM.

### 3.2. Pseudo-Speech Data Augmentation

We propose a variation of MMDA which changes the architecture during the secondary task (fig. 1b). In this setup, we cascade the data-augmenting and acoustic encoders and force the data-augmenting encoder’s output to match the dimensionality of acoustic frames (which are the input in the primary task). Thus, in PSDA the entire encoder-decoder network is part of the computation graph in both tasks.

$$ \mathcal{L}(\theta) = \begin{cases} \log P(y | X; \theta_{\text{enc}}, \theta_{\text{att}}, \theta_{\text{dec}}) & \text{speech} \\ \log P(y | \hat{x}; \theta_{\text{DA}}, \theta_{\text{att}}, \theta_{\text{dec}}) & \text{text-based} \end{cases} $$

(3)

PSDA can be viewed as a proxy multilingual training method, where the pseudo-speech generated by the data-augmenting encoder (which is fed into the acoustic encoder) is a cheap approximation of real acoustic features of some new, but related language. We use the same structure for the data-augmenting encoder as in the MMDA case.

### 3.3. Multi-task Training & Pre-training

[14] propose training the MMDA network by alternating between audio-data and augmenting-data minibatches. We allow for more flexibility in the multi-task training by using a hyper-parameter $\rho \in (0, 1)$ that decides if the model should be trained on speech data or text-based data. During training a random minibatch is selected by first generating a random number $u \in (0, 1)$. If $u < \rho$ an augmenting-data minibatch is selected and the secondary objective is used. If $u \geq \rho$ an audio-data minibatch is selected and the primary objective is used. Additionally, we explore pre-training the model with augmenting data in both MMDA and PSDA schemes and show that it significantly improves ASR performance.
4. EXPERIMENTS

We carried out experiments designed to determine the extent to which MMDA and our proposed variants help encoder-decoder ASR in low resource settings. We also examined the relative value of our pseudo-speech input to speech from other languages by comparing PSDA / MMDA with multilingual training on nearby languages. We restricted ourselves to multilingual training using languages whose written forms were close enough that the decoder network would still benefit from their inclusion and because related languages have been noted to help more than using unrelated languages [10, 13]. Finally we report performance when combining the best working techniques described.

We conducted experiments on 4 languages from the Voxforge corpus: Catalan, Portuguese, Italian, and French. We chose these languages because they are closely related to Spanish which we used in multilingual training (see 4.2). For Catalan, Portuguese, and Italian, we created 3 baseline systems on which the proposed augmentation schemes improve performance: A baseline monolingual encoder-decoder model, the same model decoded using shallow-fusion [17] with an RNNLM trained on augmenting data scraped from the web (see section 4.3), and a baseline MMDA system. We also used the two languages with the most data, Italian and French, to determine the extent to which our proposed approaches helped under different resource conditions.

4.1. Monolingual Systems

We trained monolingual systems for Catalan, Portuguese, and Italian. The training, development and evaluation sets are constructed by randomly sampling 80%, 10%, and 10% of the data for each set respectively, ensuring that no prompt in the development or test sets is duplicated in the training set. The Catalan and Portuguese systems were trained on the entire 30 min and 3 hour extracted training sets respectively. For Italian we trained only on a 4 hour subset of the full 16 hour training set in order to more closely mimic the training conditions of the two other languages. All systems were trained using ES-Pnet [18]. We trained encoder-decoder networks as described in [8] but without the augmenting encoder. We used the same configurations as in [10], except for we tuned the number of encoder layers used for each language use 5 instead of 4 encoder layers as this gave slightly better performance across our test languages.

4.2. Multilingual Systems

For Catalan and Portuguese we augmented the training data with all 30h of the Hub-4 Spanish Broadcast news corpus training set and all 16h of the Italian Voxforge training set. For Italian we only added the Hub-4 Spanish to training. All systems were trained using the same network configurations and training parameters as the monolingual systems. We followed [13] and use as output symbols the union of all graphemes seen in training such that the network was capable of outputting any of the languages seen in training.

4.3. MMDA & PSDA

We trained monolingual MMDA and PSDA systems as well as systems with pre-training (MMDA+P, PSDA+P) as described in section 3 using the same data splits as described in section 4.1. We also trained multilingual (ML) MMDA and PSDA systems which we compared to an ML baseline with RNNLM shallow fusion (ML+LM).

Augmenting Data: The augmenting data were generated by first scraping Wikipedia for text in the language of interest. We then filtered out tokens with characters that did not appear in the audio training data as well as long and short sentences. As in [14] we converted this text into sequences of phonemes. First, we created pronunciation lexicons for each language, by scraping Wiktionary for pronunciations of all words seen in the augmenting text data. For each language we then trained a grapheme-to-phoneme transducer using Phonetisaurus [19] on the corresponding scraped lexicons, which we then used to recover pronunciations for all words in the augmenting data absent from the lexicon.

We replaced the phone-duration model of [14] by model-

Table 1: Summary of monolingual experiments. We see that our proposed pre-training (indicated with +P) improves performance dramatically. Both MMDA+P and PSDA+P show strong and consistent improvement over Monolingual, LM and MMDA baselines, reducing CER by 20% to 26%.

| Task     | CA (0.5h) | PT (3h) | IT (4h) |
|----------|-----------|---------|---------|
|          | dev, eval | dev, eval | dev, eval |
| Monolingual | 85.2, 82.3 | 76.9, 80.1 | 31.2, 31.4 |
| LM       | 79.7, 76.9 | 77.6, 79.9 | 32.1, 32.1 |
| MMDA     | 79.1, 76.5 | 73.7, 72.3 | 27.9, 28.2 |
| PSDA     | 86.3, 81.4 | 80.0, 76.9 | 29.2, 29.4 |
| MMDA + P | 73.8, 75.3 | 55.4, 56.1 | 23.9, 24.1 |
| PSDA + P | 71.2, 72.2 | 47.4, 50.2 | 25.0, 26.0 |

Table 2: Summary of multilingual experiments. MMDA+P and PSDA+P yield performance gains beyond multilingual training and RNNLM fusion for both PT and IT.

| Task     | CA (0.5h) | PT (3h) | IT (4h) |
|----------|-----------|---------|---------|
|          | dev, eval | dev, eval | dev, eval |
| ML       | 33.1, 37.2 | 34.5, 38.4 | 20.1, 21.0 |
| ML+LM    | 31.1, 36.4 | 33.3, 37.7 | 18.7, 19.6 |
| MMDA+P+ML+LM | 34.2, 36.2 | 32.4, 35.9 | 17.2, 17.8 |
| PSDA+P+ML+LM | 34.9, 38.7 | 33.8, 35.3 | 17.1, 17.6 |
Fig. 2: CER of the baseline system, MMDA+P, and PSDA+P on the Voxforge Italian and French Corpora across varying training set sizes

Hyper-parameter Optimization: We randomly sampled hyper-parameters from the possible configurations of \# pre-training batches and augmenting ratio: \{2000, 5000, 8000\} \times \{0.1, 0.2, 0.5\}. We selected the parameters that performed best on the development set for each experiment. For the monolingual French and Italian experiments, however, we simply used 2000 pre-training batches and 0.1 and 0.5 augmenting ratios for PSDA and MMDA respectively as we found these values worked well for Portuguese and Catalan.

5. RESULTS

Tables 1, 2 show the performance (CER) of data augmentation across different languages with similar data sizes. We note that vanilla MMDA outperformed shallow fusion (LM) in all 3 languages. The pre-trained variants resulted in a further 20% relative improvement. PSDA+P outperformed pre-trained MMDA+P for both Catalan and Portuguese, which have extremely limited training sets, but MMDA+P was the best system on Italian. This corroborated our intuition that PSDA should help more when fewer data are available, though its utility may only be in extremely data constrained situations.

We also studied data augmentation on a single language across various amounts of training data. To this end we created 4 smaller Italian and French training sets by successively randomly removing half of the training examples from the original 16 and 30 hour training sets respectively. We then trained the baseline monolingual, MMDA+P, and PSDA+P systems on each resulting dataset using the same network and training parameters as before. We used the same hyperparameters as in the monolingual 4h Italian experiments. Both MMDA+P and PSDA+P performed similarly to each other across all training data sizes, except when training on just a few hours of speech (see fig.2). They both outperformed the baseline by a wide margin, with greater improvements when data were more scarce.

Finally, comparing the use of pseudo-speech features (PSDA+P) to multilingual training we see that PSDA+P gives about 50% of the improvement of multilingual training on extremely close languages. Furthermore, using either MMDA+P or PSDA+P along with Multilingual training and shallow fusion resulted in our best performing systems on the evaluation set in every language tested. In fact using these techniques in conjunction we are almost able to achieve with only 1/4 of the training data on Italian the performance attained when using all of the training data. If we rely solely on MMDA+P or PSDA+P, we can almost attain with half of the training data the performance of systems trained on the entirety of the training set for both French and Italian.

6. CONCLUSION & FUTURE WORK

We have demonstrated that a new data augmentation scheme, PSDA, and pre-training on augmenting data for both MMDA and PSDA outperforms the monolingual, vanilla MMDA and RNNLM baselines. We have shown that without using any additional transcribed speech in any language we can achieve performance improvements approaching those of multilingual training on related languages. Furthermore, our MMDA and PSDA variants improve upon multilingual systems for Portuguese and Italian. Future work should expand upon PSDA by attempting to more explicitly generate speech like features from text.
7. REFERENCES

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