MULTILINGUAL ADAPTATION OF RNN BASED ASR SYSTEMS

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ABSTRACT
A large amount of data is required for automatic speech recognition (ASR) systems achieving good performance. While such data is readily available for languages like English, there exists a long tail of languages with only limited language resources. By using data from additional source languages, this problem can be mitigated. In this work, we focus on multilingual systems based on recurrent neural networks (RNNs), trained using the Connectionist Temporal Classification (CTC) loss function. Using a multilingual set of acoustic units to train systems jointly on multiple languages poses difficulties: While the same phones share the same symbols across languages, they are pronounced slightly different because of, e.g., small shifts in tongue positions. To address this issue, we proposed Language Feature Vectors (LFVs) to train language adaptive multilingual systems. In this work, we extended this approach by introducing a novel technique which we call “modulation” to add LFVs. We evaluated our approach in multiple conditions, showing improvements in both full and low resource conditions as well as for grapheme and phone based systems.

Index Terms— Multilingual, automatic speech recognition, connectionist temporal classification, language feature vectors, low-resource

1. INTRODUCTION
Automatic speech recognition systems trained for well-resourced and -researched languages like English do achieve human-like performance on certain tasks [1]. But there exists a long tail of languages that suffer from data sparsity. A common method to address such situations is to incorporate data from supplementary source languages. In this work, we focus on multilingual systems, with a multilingual acoustic model trained to recognize speech from all languages seen during training. By using multilingual acoustic units, the problem arises that, although sharing the same symbols, the uttered sounds differ to some degree between languages. By applying multilingual adaptation techniques, we demonstrate that error rates can be lowered. Based on previous experiments, we now propose an improved approach to enhance the adaptation by not only adding language features to the input of the network, but also to the hidden layers. Similar to i-Vectors for speaker adaptation, we use language feature vectors (LFVs) [2]. Extracted using a neural network, they encode language properties. We demonstrate the effectiveness of our approach in a series of experiments. We show that the method presented here applies for both full- and low-resource conditions. In addition, we also omitted the pronunciation dictionary and built systems using graphemes only. In a multilingual scenario, this is particularly challenging as the network is required to learn pronunciations from multiple languages in parallel. To evaluate our systems, we use the token error rate (TER) as primary measure of the trained networks. But we also incorporate a recurrent neural network based language model for decoding to the determine the word error rate (WER).

This paper is organized as follows: In the next Section 2 we outline related work in the field, followed by a detailed description of the method proposed in Section 3. We describe the experimental setup in Section 4 followed by the results of our experiments (Section 5). This paper concludes in Section 6 where we also outline possible future work.

2. RELATED WORK

2.1. Multi- and Crosslingual Speech Recognition Systems
Building artificial neural network (ANN) based ASR systems is considered state of the art nowadays. Prior to this, systems were mainly built using a GMM/HMM based approach in the past. Methods for training/adapting such systems cross- and multilingually were proposed to handle data sparsity [3], [4]. These systems typically use context-dependent models. The process of clustering context-independent phones into context-dependent ones can also be adapted to account for cross- and multilinguality [5]. Due to their recurrent nature, RNNs are able to model temporal dependencies. This renders the need for context-dependent targets superfluous for certain ASR tasks. Using only context-independent targets has the advantage that no clustering is required.
2.2. Multilingual Bottleneck Features

Deep Neural Networks (DNNs) are prone to over fitting if trained on only a limited amount of data due to the number of parameters. Data from additional source languages can be utilized to mitigate this issue in a resource constraint scenario. DNNs are typically trained in two steps: Pre-training and fine-tuning. It has been shown that the pre-training step is language independent [6]. The fine-tuning can be modified in multiple ways to account for additional languages. One approach includes the use of shared hidden layers, with language dependent output layers [7]. Combining multiple output layers into one is also possible [8]. Training networks on multiple languages in parallel can be considered multi-task learning [9]. Each of these output layers is language dependent, having monolingual phone sets.

2.3. Neural Network Adaptation

Feeding additional input features into a neural network is a common way for adaptation. A popular approach for speaker adaptation is to supply i-Vectors [10], which encode speaker characteristics in a low-dimensional. Language adaptive neural networks can be trained this way [11]. Such low-dimensional codes can also be extracted using neural networks, called Bottleneck Speaker Vectors (BSVs) [12].

In the past, we proposed similar methods to adapt DNNs to multiple languages. We first introduced a method encoding the language identity using a one-hot encoding [13]. We enhanced this method in a similar way to BSVs, by extracting Language Feature Vectors (LFVs) [2]. These vectors have shown to encode language properties instead of the language identity alone, even for languages not seen during training.

2.4. RNN Based ASR Systems

RNN based ASR systems are becoming increasingly popular. One method to train them is the use of the Connectionist temporal classification (CTC) loss function [14], which does not require frame-level labels. It aligns a sequence of tokens automatically. As in traditional systems, phones, graphemes or both combined can be used as acoustic modeling units [15]. Given enough training data, even whole words can be used [16].

3. LANGUAGE ADAPTATION

In the past, we proposed methods for adapting (recurrent) neural networks to languages based on LFVs [2, 17]. We now propose a novel approach of adding LFVs to the network architecture. To extract vectors encoding language properties, we proposed a setup in [2]. Based on the combination of two neural networks, the first network is used to extract bottleneck features (BNFs) from acoustic input features. It was trained using a combination of log Mel and tonal features as input and context-dependent phone states as targets. The second network was trained for language identification using BNFs from the first network as input. As language information can be considered long term in nature, a larger context of frames was input into the second network. This network featured a bottleneck layer which was used to extract LFVs.

3.1. Modulating Layers

Appending LFVs to the input features has shown to improve the performance but might not be ideal as the first layers in a DNN typically learn to detect low level features. With every added layer, higher order features are being extracted. As LFVs do encode an abstract concept (language properties), integrating them at higher layers of the network should result in better classification performance. Based on the idea of Meta-PI [18], we modulated the output of hidden layers with LFVs.

3.2. Network Architecture

We use a network configuration as shown in Figure[1]. The architecture is based on Baidu’s Deepspeech2. It combines two TDNN/CNN layers with 4 bi-directional LSTM layers. The output layer is a feed-forward layer which maps the output of the last LSTM layer to the targets. We chose the number of LSTM cells in each layer to be a multiple of the dimensionality of the LFVs. This way, each coefficient of the LFVs gets to modulate the output of an equal amount of neurons by multiplying the output with the coefficient. Modulation can be seen as an intelligent from of dropout training, where, depending on the LFVs, the outputs of certain groups of neurons are being forced to learn features based on different language characteristics.
Two different configurations are shown in Figure[1]. Our first approach by appending the LFVs to the output of the CNN / TDNN layers, and the method proposed here, where we modulate the output of the second LSTM layer. In preliminary experiments, we determined modulating the output of the second layer to result in the best performance.

4. EXPERIMENTAL SETUP

We based our experiments on the Euronews corpus [20], which contains data from 10 languages. For each language, 70h of TV broadcast news recordings are available. For our experiments, we used a combination of 4 languages (English, French, German, Turkish), based on the availability of pronunciation dictionaries. We filtered utterances based on length, omitting very short ones (< 1s), and also removed ones having a transcript of more than 639 characters. Noises were only annotated in a very basic way with a single noise marker covering all different noise types, ranging from music, background and human noises. We therefore omitted utterances marked as noise. After applying all filtering, approx. 50h of data remained per language and was split into 45h of training and 5h of test data. For training, we created an additional subset containing only 8h out of the 45h training set to evaluate our approach in a low-resource condition.

4.1. Acoustic Units

As acoustic units, we used both phones and graphemes. To create the pronunciation dictionaries, we used MaryTTS [21]. For merging the monolingual dictionaries, we mapped the phone-symbols to a multilingual phone set using the definition of articulatory features in MaryTTS’ language description files. In addition to systems based on phones, we also trained networks using graphemes as acoustic units. To indicate word boundaries, an additional token was used.

4.2. Input Features

Log Mel and tonal features, extracted using a 32ms window with a 10ms frame-shift, were used. Based on these features, we trained a feed-forward network for the extraction of multilingual bottleneck features using data from 5 languages (French, German, Italian, Russian, Turkish). For training, we shared the hidden layers (including the bottleneck layer) between languages and used language dependent output layers with 6,000 context-dependent phone states each. The labels were obtained using traditional DNN/HMM ASR systems. The layers after the bottleneck were discarded after training and the output activations were taken as multilingual BNFs (ML-BNFs).

4.3. RNN/CTC Network Training

The RNN network was trained using stochastic gradient descent (SGD) and Nesterov momentum [22] with a factor of 0.9. Mini-batch updates with a batch size of 15 were used together with batch normalization. During the first epoch, the utterances were sorted ascending by length to stabilize the training, as shorter utterances are easier to align.

4.4. Evaluation

We evaluated our systems using two metrics. First, we used the token error rate (TER) as primary measure to determine the performance without the use of external (language) models. For decoding, we use the same procedure as in [14] and greedily search for the best path. In addition to the TER, we also determined the word error rate (WER). We used a recurrent neural network based language model, trained on characters as described in [23]. The model was trained on only a very limited set of sentences, consisting of the training utterances of the acoustic model only. While not being a strong language model, it should indicate whether the improvements observed as TER also result in a better word level speech recognition system.

5. RESULTS

We evaluated our proposed method varying two conditions: The availability of a pronunciation dictionary and the amount of data. ML-BNF input features were used throughout the experiments. A system without language adaptation is used as baseline. We present results for each language individually, as well as for all languages combined (“ML”).

5.1. Grapheme Based Systems

First, we evaluated the use of graphemes as acoustic modeling units. In general, the error rate of grapheme based systems is higher compared to ones based on phonemes, especially if the language at hand does not have a close relationship between letters and sounds, e.g., “though” (English) or “gâteau” (French). First, we used a network configuration with the RNN part having 420 LSTM cells per layer, trained using only 8h of data per language (see Table[1]). Adding LFVs after the TDNN / CNN layers (LFV add) does lower the TER, but applying the method presented here (LFV mod) lowers the TER even more. Similar gains can be observed using the full training set (Table[2]). Using more data does lower the TER, whereas the relative improvements are in the same order of magnitude. Training on more data also allows for larger networks. In an additional experiment, we increased the number of LSTM cells per layer to 840. As shown in Table[3] the TER decreases in absolute terms, but the difference between addition and modulation levels out. A possible explanation could be that the network is large enough to implicitly learn

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1Internal limitation within the implementation of CUDA/warp-ctc, see: https://github.com/baidu-research/warp-ctc, accessed 2017-10-27
to detect and adapt to the language and the difference in stimulation between addition and modulation does no longer have a big impact. Especially with French and Turkish having a subset of characters, it is easier for the network to observe language specific phenomena.

In the same notion as graphemes, we evaluated systems based on phonemes as acoustic modelling units. Starting with the limited data set (Table 4), improvements by the modulation (LFV mod) over the addition (LFV add) can be observed. Using all available training data and increasing the number of LSTM cells per layer to 840, similar improvements could be achieved (Table 5). In contrast to the grapheme based setup (Table 3), modulating the layers (LFV mod) improves the performance over the simple addition (LFV add). With the symbols (phones) being shared across languages representing the same acoustic events, the modulation enables the network to better adapt to language specific articulation of phones.

As final evaluation, we used the grapheme based setups and a character based language model to perform a greedy decoding for English. The results shown in Table 6 indicate that the improvements of TER are also observable w. r. t. WER after decoding with a language model.

We presented an improved method for language adaptation of recurrent neural networks in a multilingual setting. Similar to using i-Vectors for training speaker adaptive networks, LFVs can be used to adapt networks to languages. Modulating the output of a layer shows improvements over appending LFVs to input features.

Unlike speaker adaptation, where the collection of data covering hundreds of speakers is feasible, collecting data from that many languages is next to impossible. Optimizing the adaptation method is therefore key to maximize the performance in a multilingual scenario. Future work includes the development of methods to not only adapt network multibut also crosslingually to new languages.

### Table 1. TER of grapheme based system trained on 8h per language, 420 LSTM cells per layer

| Condition   | ML  | DE  | EN  | FR  | TR  |
|-------------|-----|-----|-----|-----|-----|
| ML Baseline | 31.2| 30.8| 38.0| 29.4| 30.9|
| LFV add     | 25.9| 22.9| 33.3| 27.3| 21.3|
| LFV mod     | 24.6| 20.7| 32.7| 25.4| 19.6|

### Table 2. TER of grapheme based system trained on 45h per language, 420 LSTM cells per layer

| Condition   | ML  | DE  | EN  | FR  | TR  |
|-------------|-----|-----|-----|-----|-----|
| ML Baseline | 14.4| 10.6| 18.2| 15.9| 9.1 |
| LFV add     | 13.0| 9.5 | 16.1| 14.3| 8.1 |
| LFV mod     | 12.4| 9.1 | 15.5| 13.6| 8.0 |

### Table 3. TER of grapheme based system trained on 45h per language, 840 LSTM cells per layer

| Condition   | ML  | DE  | EN  | FR  | TR  |
|-------------|-----|-----|-----|-----|-----|
| ML Baseline | 12.2| 8.9 | 15.0| 13.5| 7.9 |
| LFV add     | 10.8| 7.9 | 13.6| 11.8| 7.1 |
| LFV mod     | 10.7| 7.7 | 13.3| 11.7| 7.1 |

### Table 4. TER of phoneme based system trained on 8h per language, 420 LSTM cells per layer

| Condition   | ML  | DE  | EN  | FR  | TR  |
|-------------|-----|-----|-----|-----|-----|
| ML Baseline | 23.2| 21.7| 27.2| 23.9| 21.6|
| LFV add     | 21.9| 20.9| 26.4| 21.3| 19.5|
| LFV mod     | 20.6| 19.0| 25.6| 19.8| 17.6|

### Table 5. TER of phoneme based system trained on 45h per language, 840 LSTM cells per layer

| Condition   | ML  | DE  | EN  | FR  | TR  |
|-------------|-----|-----|-----|-----|-----|
| ML Baseline | 12.0| 9.6 | 14.6| 12.1| 8.5 |
| LFV add     | 11.0| 9.3 | 13.2| 10.8| 7.7 |
| LFV mod     | 10.5| 8.6 | 12.5| 10.2| 7.3 |

### Table 6. WER of English grapheme based systems, trained using 8h of data and 420 cells per LSTM layer (8h-420), or 45h and 840 cells per layer (45h-840)

| Setup     | BL  | LFV add | LFV mod |
|-----------|-----|---------|---------|
| 8h-420    | 32.4%| 30.6%   | 29.9%   |
| 45h-840   | 29.2%| 27.7%   | 27.3%   |

### 5.3. Language Model Results

As final evaluation, we used the grapheme based setups and a character based language model to perform a greedy decoding for English. The results shown in Table 6 indicate that the improvements of TER are also observable w. r. t. WER after decoding with a language model.

### 6. CONCLUSION

We presented an improved method for language adaptation of recurrent neural networks in a multilingual setting. Similar to using i-Vectors for training speaker adaptive networks, LFVs can be used to adapt networks to languages. Modulating the output of a layer shows improvements over appending LFVs to input features.

Unlike speaker adaptation, where the collection of data covering hundreds of speakers is feasible, collecting data from that many languages is next to impossible. Optimizing the adaptation method is therefore key to maximize the performance in a multilingual scenario. Future work includes the development of methods to not only adapt network multibut also crosslingually to new languages.

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