USING MULTI-TASK LEARNING TO IMPROVE THE PERFORMANCE OF ACOUSTIC-TO-WORD AND CONVENTIONAL HYBRID MODELS

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ABSTRACT

Acoustic-to-word (A2W) models that allow direct mapping from acoustic signals to word sequences are an appealing approach to end-to-end automatic speech recognition due to their simplicity. However, prior works have shown that modelling A2W typically encounters issues of data sparsity that prevent training such a model directly. So far, pre-training initialization is the only approach proposed to deal with this issue. In this work, we propose to build a shared neural network and optimize A2W and conventional hybrid models in a multi-task manner. Our results show that training an A2W model is much more stable with our multi-task model without pre-training initialization, and results in a significant improvement compared to a baseline model. Experiments also reveal that the performance of a hybrid acoustic model can be further improved when jointly training with a sequence-level optimization criterion such as acoustic-to-word.

Index Terms — Multi-task, CTC, Acoustic-to-word, Frame-wise, Cross-Entropy

1. INTRODUCTION

The recent trend of automatic speech recognition (ASR) research is to simplify the recognition process by using a single neural network to approximate the direct mapping from acoustic signals to textual transcription. The introduction of connectionist temporal classification (CTC) [1, 2] is appealing thanks to the ability to directly model the alignment between acoustic observations and the labels. It is notable that the traditional phoneme-based systems which are built-up using pronunciation lexicons, frame-wise alignment or Hidden Markov Model (HMM) topology are not mandatory in end-to-end approaches [3, 4, 5] using simple character sequences as labels. This level of granularity is even lower in other works with an acoustic-to-word setup [6]. In such cases, neither language models nor beam search decoders are necessary.

The aforementioned works have shown the potential of the CTC framework to be able to jointly learn to predict the labels and to align between inputs and outputs. However, the disadvantage of CTC is training complexity, i.e., the convergence is not guaranteed or optimization gets stuck in local optima [7, 8]. Data sparsity is also known to be a hindrance to train CTC models effectively, as can be seen from the work of [9] reporting that without a pre-training initialization, an A2W model is much harder to converge on the well-known Switchboard training data set.

Our work is motivated by the findings in our previous study [10], in which the correlation between the phone probabilities estimated by CTC models and the hard labels produced by traditional frame-wise alignment models was found. This evidence indicates the correlation between two training schemes: sequence-wise prediction with CTC and frame-wise classification typically using a cross-entropy (CE) optimization criterion. To the best of our knowledge, the idea of combining these two training criteria CTC and CE, so that the models can employ both sequence-level and frame level properties, has not been successfully explored.

In this work, we propose a novel architecture in which a shared neural network is used to train acoustic models with both CTC and framewise CE, that we treat with a multi-task learning perspective. Our experiments show that both tasks can benefit from each other. First we showed that training an acoustic-to-word model is much more stable with our model without pre-training initialization, and results in a significant improvement compared to a plain model. Second, we reveal that the performance of the framewise CE acoustic model can be further improved when jointly training with a sequence-level optimization criterion such as CTC acoustic-to-word.

2. MULTI-TASK LEARNING OF CTC & FRAMWISE CE

In this section we review two popular optimization criteria CTC (Section 2.1) and framewise CE (Section 2.2) frequently used in training neural network-based acoustic models. Then our proposed network architecture and training methods for combining these criteria is described in section 2.3.

2.1. CTC Task

Given an audio utterance $x$ and the corresponding transcript $z$ (a sequence of labels), the CTC framework estimates alignments between the utterance and the transcript as a latent variable, dubbed the CTC path. Let us denote $y_{\pi}^{t}$ as the posterior probability that the neural network assigns to the corresponding label of $\pi$ at time $t$, then the CTC loss function is defined...
as the sum of the negative log likelihoods of the alignments for each utterance:

$$L_{CTC} = - \sum_{\pi} p(\pi|x) = - \sum_{\pi} \prod_t y^\pi_t$$

In order to optimize towards the CTC criterion, [1, 2] proposed to use the forward-backward algorithm which efficiently computes the gradient with respect to the activation of neural networks for every input frame.

CTC loss is typically computed on entire training utterances so that the model can effectively learn the prediction for the labels and their corresponding alignments at the same time. So far, the bidirectional Long-Short Term Memory (BLSTM) networks which are capable of capturing long-term context dependencies are the most popular architecture to learn the representation which is then trained via the CTC loss function.

### 2.2. Framewise CE Task

Assuming that HMM-based speech recognition uses Viterbi forced alignment to obtain a state label (i.e., context-dependent phoneme) \( l \) from the ground-truth transcript \( w \) for each input frame of a training utterance \( x \), a neural network model is trained by optimizing the CE loss function, to model this state distribution:

$$L_{CE} = \sum_{t=1}^{|x|} \sum_l \delta(l, l_t) \log y^l_t$$

where \( \delta(l, l_t) \) is the Kronecker delta and \( y^l_t \) is the network output for the state \( l \) at the frame \( t \). According to the HMM assumptions, a neural network model, which minimizes the CE loss, approximately maximizes the likelihood of the input \( p(x|w) \).

The framewise CE loss does not consider each utterance in its entirety, but instead it is defined over individual samples of acoustic frames and state labels. To build an acoustic model for the speech recognition task, successful hybrid Feed-Forward networks (FFNN) models are typically trained on random batches of all training samples.

Recently, the BLSTM has outperformed FFNN and become the state-of-the-art for acoustic modeling with framewise CE criterion. BLSTM is known to be better at modeling the dependencies between a long sequence of acoustic frames and its corresponding states. Different from the optimization of the CTC criterion, several works [11][12][13] have adopted an approach in which training utterances are divided into subsequences of fixed-sized chunks (e.g., 50 frames) when training BLSTM acoustic models with CE loss.

### 2.3. Multi-task Learning

The network models trained with CTC and framewise CE criterion provide very different label distributions even when the used label sets are identical, because they learn the mapping function at different scales. However, as in our previous work [10], the models resulting from training with either CTC or the framewise CE criterion end up sharing similar traits in representations, which motivates us to use those loss functions jointly. Here we consider each of them as a task, in which the model is assigned to learn features at either local or global levels. The aim of our work is to establish the shared underlying neural network model to efficiently learn from both tasks in parallel.

Figure 1 illustrates our proposed network architecture combining the two training criteria. Basically, the entire LSTM architecture used for encoding input sequences is shared, only two output layers are separated to perform the specific tasks. This structure allows gradients to be propagated back to the encoding network as early as possible. We further added a small projection layer (i.e. 200 neurons) into the shared network, on top of the LSTM layers. The projection layer was found to speed up training and improve convergence [11]. In this case, it significantly reduces the number of parameters in the task-specific layers, so that it pushes the shared layers to learn their needed representations.

In practice, the optimal setup for optimizing CE loss is found when dividing training utterances into subsequences of frames which is different from the setup for CTC loss. To obtain optimal performance for both tasks, it is efficient to combine the loss functions at utterance level while keeping the attention for synchronizing between complete utterances and their subsequences. However, such a synchronization implementation is usually less memory efficient or has a largely increased training time.

In our experiments we found that training a BLSTM model with CE loss on entire utterances also gives performance comparable to the use of subsequences even though the training time increases due to less parallelization optimization. So we propose to compute and combine CE loss and CTC loss over entire utterances. The combined loss function is then the weighted sum of CTC and CE losses with a hyper-parameter \( 0 \leq \lambda \leq 1 \):

$$L_{MLT} = (1 - \lambda)L_{CTC} + \lambda L_{CE}$$
3. EXPERIMENTAL SETUP

Our experiments were conducted on the Switchboard-1 Release 2 training corpus which contains 300 hours of speech. The Hub5’00 evaluation data was used as test set. We used a deep BLSTM with 5 layers of 320 units (big models with 500 units). All the models were trained on 40 log mel filter-bank features which are normalized per conversation. We adopted a new-bob training schedule in which an initial learning rate is fixed for 12 epochs, then exponentially decays with a factor of 0.8 if the cross validation error degraded. For training the multi-task models and plain CTC models, we used stochastic gradient descent in which the loss is averaged over the number of utterances in each mini-batch. For the framewise CE training with sub-sequences, we normalized the loss per frame.

We used the PyTorch toolkit to build and train the BLSTMs. The character and phoneme CTC systems were decoded using Eesen [4] while for the hybrid systems, we used Janus [14]. A 4-gram language model is used in all decodings (except for the word models), which is trained on the transcripts of the training dataset and English Fisher corpus.

4. RESULTS

4.1. CTC Baseline Model

First of all, we are interested in how the multi-task network improves the performance on CTC task. We experimented with the CTC task on three popular label types including phonemes, graphemes and word labels.

In Table 1, we summarize the results from recent studies which reported their CTC systems and training optimization on the Switchboard 300 hours training set. So far, the effective training optimization typically includes the usage of a pre-trained model or the order selection of training utterances. For fair comparisons, the selected phoneme and grapheme systems use 45 English phones and 46 characters as the label sets while the decoding was performed with n-gram language models. The word models were trained with 10k label units and only greedy decoding is applied.

The convergence of the models optimized with CTC is not stable [7]. Several works have adopted a curriculum learning strategy in which training utterances are sorted in ascending order of frame length to improve the stability and the accuracy of model training. [3] proposed to use curriculum learning only in the first epoch and then a random order for the rest.

When switching to word labels, CTC training convergence is even poorer due to data sparsity. [9] has presented that on the Switchboard training set, model initialization through pre-training is critical and a random initialization of model parameters usually fails to converge. [9] [15] [16] used a pre-trained phone model and GloVe word embeddings [17] to initialize their word models.

Note that the presented systems employ slightly different network models and input features. [3] and [16] added two and three CNN layers in front of the LSTM layers, while [9] [15] used i-vectors and deltas as additional input features.

| AM     | Pre-training | Train. Order | SWB | CH |
|--------|--------------|--------------|-----|----|
| Phone  | N            | Ascending    | 14.1 | 25.7 |
| Phone  | N            | Descending   | 14.5 | 25.1 |
| Char   | N            | Ascending    | 17.3 | 31.0 |
| Char   | N            | Random       | 20.0 | 31.8 |
| A2W    | Phone+GloVe  | Descending   | 20.8 | 30.4 |
| A2W    | Phone+GloVe  | Ascending    | 14.9 | 23.8 |
| A2W    | Phone+GloVe  | Ascending    | 14.8 | 25.8 |
| A2W+CE | Phone+GloVe  | Ascending    | 14.3 | 25.0 |

Table 1. Baseline systems trained with CTC task using phoneme, grapheme and word labels on Hub5’00 test set.

4.2. Performance of the CTC Task

We trained several models using the multi-task learning structure proposed in Section 2.3. The CTC task is performed on different label sets mentioned in Section 4.1 while the framewise CE task of classifying 8,000 phone states was kept the same. We observed that when $\lambda$ is set to about $[0.9 \pm 0.05]$, both token error rate (TER) and phone error rate (PER) measured on the CTC and framewise CE task decrease faster than in the training of the plain models. This indicates an optimal value of $\lambda$ in which the learning of the shared network can maximally benefit. Our training optimization then includes two steps. We first train the multi-task models with $\lambda = 0.9$ until the combined loss converges. Then, we perform fine-tuning on the individual tasks.

Table 2 presents the results of the CTC systems trained with the proposed multi-task learning. We also provide the results of our plain CTC training with the same label sets. The performance of our plain models on phonemes and characters are at par with [4]. We tried to randomly initialize word models, but it was not effective. However, when using the LSTM layers from the pre-trained phone model, the word model training converged successfully.

[7] [8] used parameters initialized from a framewise CE model to stabilize phone-based CTC training. We found that learning an A2W model jointly with framewise CE solved the problem of data sparsity. Without any pre-trained initialization, our word models converged as well as phone or character models. In our setup, learning a shared network also leads to better accuracy for the CTC task, as the performance of the multi-task models are improved over the plain models for all different label sets.

Curriculum learning is usually effective due to the training of CTC models not being stable. However, since the framewise CE task stabilizes the training of our multi-task models, we can apply different optimizations. In this study, we propose to use a random order of training utterances together with dropout [18] on LSTM layers. These techniques improve generalization and have shown effectiveness for framewise CE training [13]. With this optimization, we achieved a


| AM      | Train. Order | TER  | PER  | SWB  | CH  |
|---------|--------------|------|------|------|-----|
| Char    | Ascending    | 15.0 | 17.2 | 29.6 |
| Phone   | Ascending    | 15.1 | 14.5 | 25.9 |
| A2W(p-pretrain) | Ascending | 23.6 | 18.8 | 29.1 |
| A2W(p-pretrain) | Random      | 25.1 | 20.8 | 31.1 |
| Char+CE | Ascending    | 15.0 | 29.8 | 29.3 |
| Phone+CE| Ascending    | 14.3 | 29.6 | 23.5 |
| A2W+CE  | Ascending    | 22.5 | 29.2 | 18.0 |
| Char+CE | Random       | 14.1 | 28.3 | 15.1 |
| Phone+CE| Random       | 13.5 | 27.5 | 13.4 |
| A2W+CE  | Random       | 20.4 | 26.7 | 16.5 |
| A2W(m-pretrain-3) | Random     | 22.6 | 17.9 | 29.0 |
| A2W(m-pretrain-10) | Random    | 20.5 | 16.6 | 27.0 |
| A2W(m-pretrain-∞)  | Random      | 20.3 | 16.3 | 26.9 |

Table 2. The performance of our plain CTC models and multi-task CTC models on Hub5’00 test set.

| AM      | Hours | Words | Occurrence | OOV  | SWB  | CH  |
|---------|-------|-------|------------|------|------|-----|
| A2W     | 300   | 4k    | ≥ 20       | 23k  | 17.3 | 27.7|
| A2W     | 300   | 7k    | ≥ 10       | 21k  | 16.6 | 27.7|
| A2W     | 300   | 10k   | ≥ 5        | 17k  | 16.5 | 27.0|
| A2W     | 300   | 14k   | ≥ 3        | 13k  | 16.2 | 26.7|
| A2W     | 100   | 9k    | ≥ 3        | 9k   | 23.1 | 34.2|
| A2W(big) | 14k   | ≥ 3   | 13k         | 15.8 | 26.2 |

Table 3. The performance of multi-task CTC models with different label set sizes.

13.2% rel. WER improvement on the SWB sub-set for both character and word models compared to the plain models.

We also experimented with optimizing plain A2W models initialized with the parameters of the multi-task models from different training epochs (labeled as m-pretrain-epoch). We were able to train the plain A2W models with the new optimization, although it was hard to gain further improvement. This indicates that the framewise CE does not only stabilize the training but also leads to the learning of a shared representation which is effective for the CTC criterion.

In Table 3, we experimented with the training of word models with different label sizes. OOV means number of rare words mapped to unknown while the number of appearances of a word in the training set is marked as occurrences. The multi-task models can be trained stably even when there is a large number of rare words (some modeled words are only seen 3 times in whole training set). Our setup also allows to train a word model on a sub-set of 100 hours. When using a bigger model, we achieved slightly better improvements.

### 4.3. Performance of Framewise CE Task

As shown in Table 2, the framewise CE task of the multi-task models converged at different phone error rates depending on the label sets used for the CTC task. Interestingly, jointly training with A2W can supplement and boost the performance of the hybrid model over the plain training. This is shown in Table 4 where we compared several hybrid systems trained with and without multi-task training. All the models use dropout regularization.

With and without multi-task learning. We also compared the LSTM acoustic models when using entire utterances or sub-sequences as input. Our setup for constructing subsequences is similar to the optimal setup found in [13], in which training utterances are divided into chunks of 50 frames while two consecutive chunks have 25 overlapping frames. We achieved a significant improvement (12% rel.) between the multi-task training and the plain training. The result of our multi-task model with bigger size is at par with the best model reported in [13], while this model employed more advanced input features.

### 5. RELATED WORK

We have presented an efficient approach for training encoder networks for modeling both word and context-dependent phone-state sequences concurrently. Our results suggest that such a proposed encoder network can be potentially shared among different training criteria. As future work, we will investigate the use of this encoding network in attention-based
speech recognition models.

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