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End-to-end Continuous Speech Recognition using Attention-based Recurrent NN: First Results

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Abstract

We replace the Hidden Markov Model (HMM) which is traditionally used in continuous speech recognition with a bi-directional recurrent neural network encoder coupled to a recurrent neural network decoder that directly emits a stream of phonemes. The alignment between the input and output sequences is established using an attention mechanism: the decoder emits each symbol based on a context created with a subset of input symbols selected by the attention mechanism. We report initial results demonstrating that this new approach achieves phoneme error rates that are comparable to the state-of-the-art HMM-based decoders, on the TIMIT dataset.

1 Introduction

Speech recognition is challenging because it has to transform a long sequence of acoustic features into a shorter sequence of discrete symbols such as words or phonemes. Not only is the problem difficult because the two sequences are unequal in length, but also because the precise location of the output symbol in the input sequence is often not known in advance. Therefore, there is no straightforward way of building a classifier that predicts a target for each frame of the input signal. The speech recognition model must instead learn to both align the output sequence to the input sequence and to recognize the content of the utterance.

The model investigated in this work is a Recurrent Neural Network (RNN) that can be trained without an explicit alignment between the input and output sequences. When decoding, the model keeps track of its position in the input sequence through an attention mechanism. At each step of decoding, the model first scores all input frames against its hidden state to soft-select relevant input frames. Next, it summarizes the selection into a context vector and uses it to update the hidden state and generate the next output symbol.

This model achieves a phoneme error rate of 18.57% on the TIMIT dataset, which is comparable to the state-of-the-art DNN-HMM systems but slightly worse than the best reported error rates obtained using RNNs. However, it should be noted that this model is very easy to apply: it requires a narrow beam search, and we found that its accuracy deteriorates very slightly when greedy search (i.e. taking the most likely symbol at each time) is used for recognition. It is also easy to implement and tune (less than a month of work was enough to achieve these results).

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1.1 Background

It is possible to obtain the training target for each frame of the acoustic input by coupling a neural network to a Hidden Markov Model (HMM) (Bengio *et al.*, 1992; Bourlard and Morgan, 1994; Bengio, 1996). In this hybrid system the neural network acts as an acoustic model by predicting the state of the HMM from each corresponding input frame. Since a target is provided for each input frame, we can train the neural network in a usual way by minimizing the classification error. Once a per-frame classifier is trained, the whole system including the acoustic model and the HMM can be tuned jointly on full sentences to minimize the decoding error (LeCun *et al.*, 1998; He *et al.*, 2008; Vesel *et al.*, 2013). This hybrid approach has recently made important progress by adopting, as an acoustic model, deep neural networks such as fully-connected feedforward neural networks (A Mohamed *et al.*, 2009; Hinton *et al.*, 2012a), convolutional networks (Sainath *et al.*, 2014), and recurrent networks (RNN, Graves *et al.*, 2013a).

The hybrid architecture (NN-HMM) is, however, rather complicated and requires controlling the relative contribution from each part of the model to the decoding error. Moreover, training needs to be performed in multiple stages, beginning with a hybrid architecture having Gaussian Mixture Model (GMM) and HMM which is used to generate per-frame target states (forced-alignment). This is followed by iteratively training an acoustic model (neural network) and re-estimating the transition probabilities of the HMM. Furthermore, it has been reported by, for instance, Graves *et al.* (2013a) that the improvements in the per-frame classification do not necessarily translate to the decoding accuracy.

In contrast, some earlier works have proposed to minimize the final decoding error directly by optimizing the sum of costs along the paths in an alignment/decision graph (Bengio *et al.*, 1992; LeCun *et al.*, 1998). Along this line of research, Graves *et al.* (2006) proposed, more recently, an alternative approach called the Connectionist Temporal Classifier (CTC), which can be used without an explicit input-output alignment.

In the CTC-based model, each per-frame prediction is either one of the set of desired outputs (words, phones) or a special separator symbol. The final sequence is obtained by removing the separators and merging blocks of consecutive identical output symbols. A forward-backward algorithm is used to exactly compute the probability of a desired output sequence given the per-frame predictions.

As an extension of the CTC Graves (2012) proposed the RNN Transducer. Unlike the CTC, which can be seen as an acoustic-only model, the RNN Transducer has another RNN that acts as a language model. The transducer is composed of two parts: (1) a transcription network that produces for each frame of the input sequence either a target symbol or the separator and (2) a prediction network that generates the final sequence of outputs without separators and repeated symbols. These two components allow the RNN Transducer to model the probability of observing the next output symbol given its position in both the input and output sequences. Similarly to the CTC, the probability of observing an output sequence for a given input is computed using the forward-backward algorithm.

The RNN Transducer computes the score of each possible output token based on the position in the input and output sequences. Originally, the score was obtained by multiplying the separate scores from the transcription and prediction networks. Graves *et al.* (2013b), on the other hand, used a separate multi-layer perceptron (MLP) to combine the two scores from the transcription and prediction networks and achieved the state-of-the-art performance on the TIMIT dataset.

1.2 Attention Mechanism

The model we consider in this paper is closely related to the RNN Transducer, however, with an attention mechanism that decides which input frames be used to generate the next output element.

The attention mechanism in this respect was first used by Graves (2013) to build a neural network that generates convincing handwriting from a given text. At each step, the network predicts a (soft-)window over the input sequence that corresponds to the character being currently written.

A similar approach of attention was used more recently in a so-called “neural machine translation model” (Bahdanau *et al.*, 2014). In this case, for generating each target word, the network computes a score matching the hidden state of an output RNN to each location of the input sequence (Bahdanau

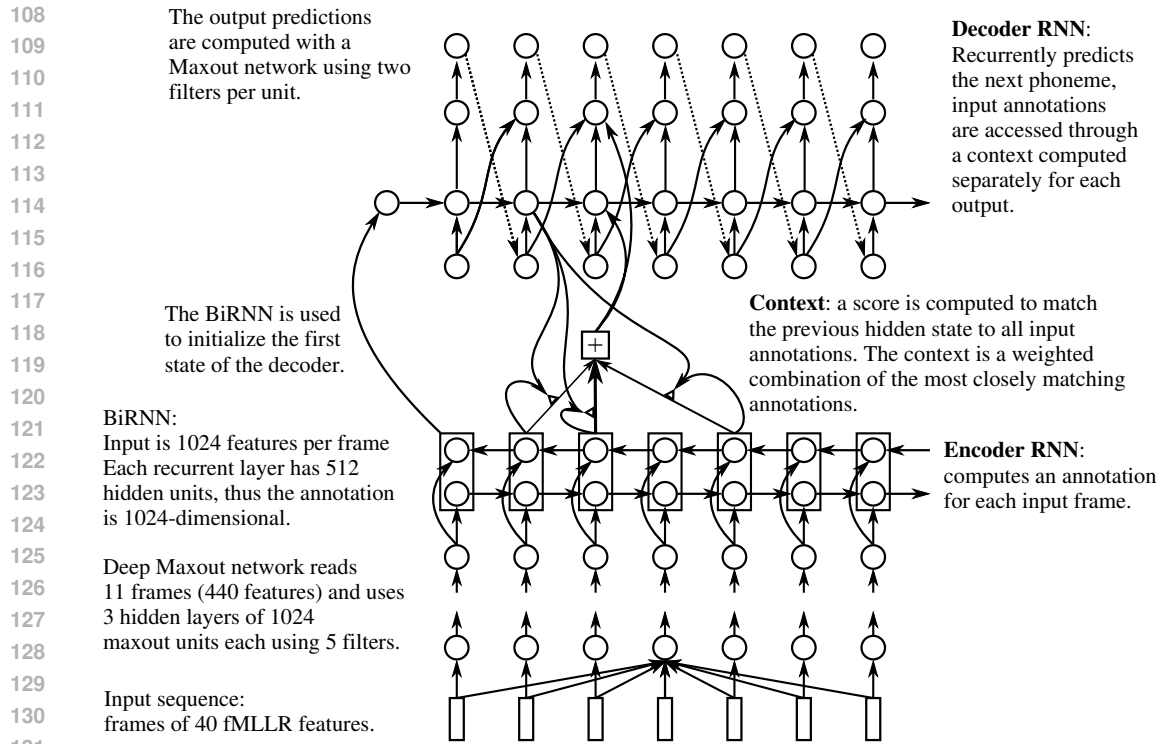


Figure 1: Proposed model architecture. The system contains three parts: an encoder that computes annotations of input frames (learned features that may depend on the whole sequence), an attention mechanism that decides where to look in the input sequence to provide a context for emitting the next output, and a generative output RNN which iteratively predicts the next phoneme conditioned on its state and the context. For visual simplicity we have shown only one context computation.

et al., 2014). The scores are normalized to sum to one over the input sequence and can be interpreted as a probability of each input location being aligned to the currently generated target word.

Unlike the handwriting generation network, the attention mechanism in the neural translation model may assign high scores to non-adjacent locations in the input sequence, which allows it to perform long-distance word reordering. In addition, it uses the features of the input sequence extracted by a bidirectional recurrent neural network, and not just the output RNN state, in order to predict these alignment probabilities.

In this paper, we propose a model, based on this neural translation model, that is more suited to speech recognition. We allow the learned soft alignment procedure to take the relative position into account and add a penalty helping the attention mechanism to choose a single, narrow mode and encourage that mode of attention to move forward. This helps the model to search nearby, potentially near-future, input frames given the current belief/state about which output symbols have been generated. The learned dependency on the relative position of successive points of attention can, further, be used to speed up decoding, as the final model has to consider only a tiny section of the input sequence when generating each output symbol.

2 Model architecture

The model consists of an *encoder* that maps the raw input sequence $\mathbf{x} = (x_i; i = 1, \dots, I)$ to a sequence of features $\mathbf{h} = (h_i; i = 1, \dots, I)$ (also called annotations), a *decoder* that generates the output sequence¹ $\mathbf{y} = (y_o; o = 1, \dots, O)$ and an *attention mechanism* that matches parts of the input

¹ The word “decoder” here is used in a sense that comes from the auto-encoder analogy, with the encoder producing the internal representation of the input sequence and the decoder mapping it to the output sequence distribution. This is different from the usual use of the word decoder in speech recognition systems to talk

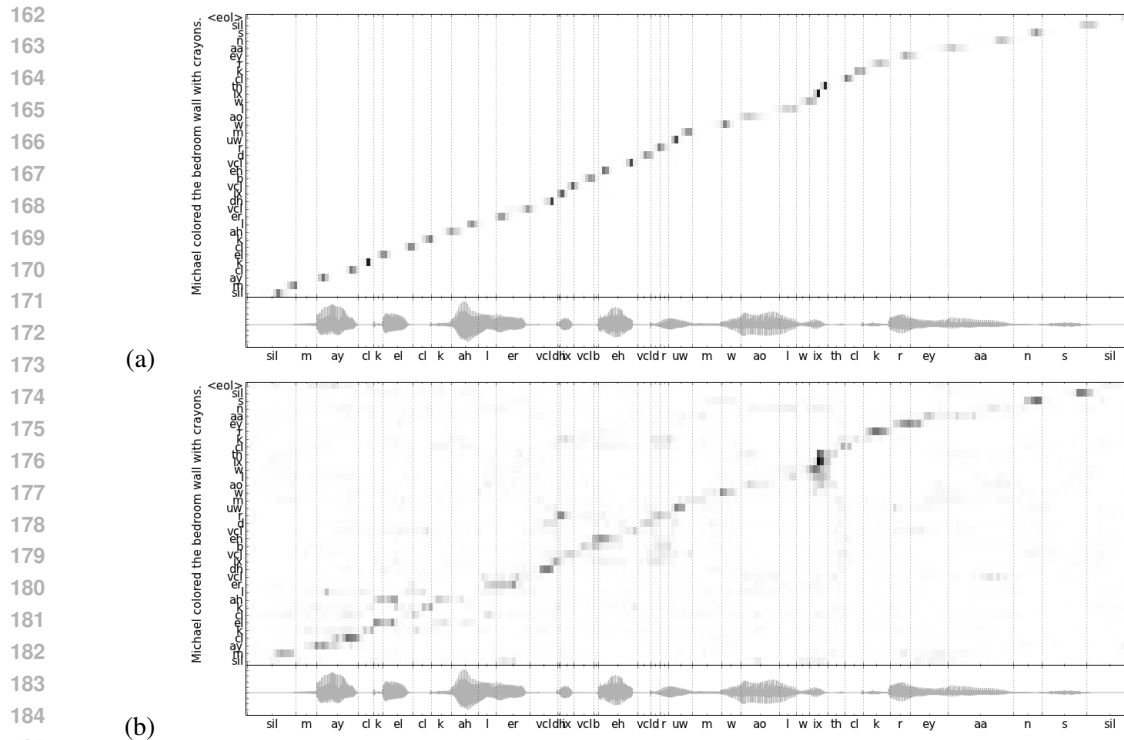


Figure 2: Alignments produced by the model: (a) when the alignment was successfully encouraged to be monotonic, and (b) when the model is free to select any frame in the input sequence. Each row in the plot contains the scores computed by the attention mechanism between the previous hidden state and all the input annotations. In (b), we observe how the absence of the learned preference for monotonicity makes the model confused by the repeated occurrence of the phonemes “cl k”, and to a lesser degree, by the repetition of “w”.

sequence with elements of the output sequence (Bahdanau *et al.*, 2014). A graphical illustration of the model is presented in Fig. 1.

2.1 Decoder

The decoder predicts the output sequence \mathbf{y} conditioned on the annotations \mathbf{h} of an input sequence \mathbf{x} by factorizing $p(\mathbf{y}|\mathbf{h})$ into ordered conditionals:

$$p(\mathbf{y}|\mathbf{h}) = \prod_{o=1}^O p(y_o|y_{o-1}, y_{o-2}, \dots, y_1, \mathbf{h})$$

The RNN decoder uses a subset of the input annotations summarized into a context c_o to compute both the update to its state and the prediction of the next output symbol:

$$s_o = f(s_{o-1}, y_{o-1}, c_o),$$

$$p(y_o|y_{o-1}, y_{o-2}, \dots, y_1, \mathbf{h}) = g(y_{o-1}, s_o, c_o),$$

where s_{o-1} and s_o are the previous and current state vectors, while y_o is the prediction of the next output. The recurrent state update (f) is computed using an affine layer with a reset-update gate used as the activation function (Cho *et al.*, 2014) to keep track of long-term dependencies. The next state prediction (g) is realized with an MLP composed of a Maxout (Goodfellow *et al.*, 2013a) and SoftMax layers.

about the search algorithm which approximately looks for the most probable configuration of latent and output variables (the output sequence), e.g., using beam-search. We also use an approximate search mechanism (with beam search) to look for the most probable output sequence, given the input sequence.

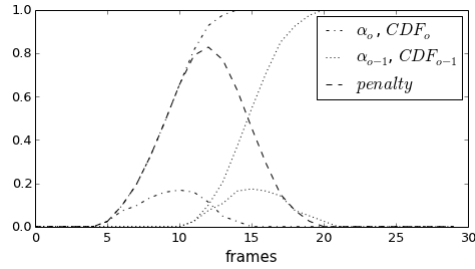
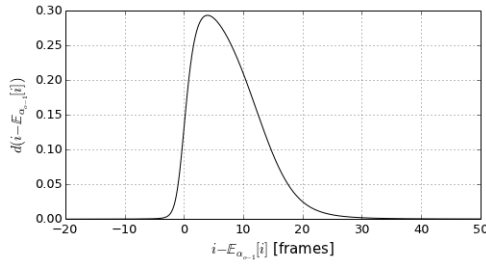


Figure 3: Learned gating function $d(\cdot)$ (Eq. 2). Figure 4: Illustration of the penalty in Eq. (3).

The context is a weighted sum of annotations:

$$c_o = \sum_{i=1}^I \alpha_{oi} h_i,$$

where α_{oi} is a normalized weight for each annotation h_i . This effectively means that the decoder selects each annotation h_i with a certainty α_{oi} .

The selection is performed in two steps. First, scores e_{oi} are computed to match the previous state of the decoder to all annotations. The scores are then penalized based on the relative position of the current and previous selection, and normalized:

$$e_{oi} = a(s_{o-1}, h_i), \quad (1)$$

$$\hat{e}_{oi} = d(i - \mathbb{E}_{\alpha_{o-1}}[i]) \exp(e_{oi}) = d\left(i - \sum_{k=1}^I \alpha_{o-1,k} k\right) \exp(e_{oi}), \quad (2)$$

$$\alpha_{oi} = \frac{\hat{e}_{oi}}{\sum_{k=1}^I \hat{e}_{ok}},$$

where the computation $a(\cdot, \cdot)$ is an MLP with one hidden layer and linear output, while $d(\cdot)$ is an MLP with a single hidden layer and logistic sigmoid output ($[0, 1]$).

The proposed addition of the gating procedure can be understood as follows. The attention mechanism searches through the input sequence to find frames that match the current state of the decoder. However, in an utterance there may be repeated phonemes that have very similar annotations, which consequently result in matching to all similarly sounding locations, as shown in Fig. 2 (b). The gating procedure prevents this behavior by confining the search to locations that are near the inputs relevant to the previously generated symbol.

It is, however, important to notice that the shape of the gating function d is not defined a priori, but learned. In Fig. 3, we show the shape of the learned gating function. $d(\Delta)$ directly encodes the preference of the input frames Δ steps away from the previously searched input location $E_{\alpha_{o-1}}[i]$. We clearly see that the model automatically learned to prefer approximately 4 frames in the future and strongly inhibit the selection of any past frames ($\Delta < 0$). Most of the mass is concentrated between $\Delta = 0$ and 12.

2.1.1 Learning to prefer monotonic alignments

We would like to constrain the selection of the frames for consecutive outputs to advance monotonically in time. To motivate the network to find monotonic alignments we design a penalty that is added to the optimization cost.

We penalize any alignment that maps to inputs which were already considered for output emission. Since the selection weights α_{oi} are normalized, their cumulative sum over the input sequence is monotonically increasing and bounded in the range $[0, 1]$. To encourage the monotonicity of the alignment over time, we add to the optimization cost the differences p_o between the cumulative

sums of the selection weights used to emit the current and previous phoneme:

$$p_o = \max \left(0, \sum_{i=1}^I \left(\sum_{k=1}^i \alpha_{ok} - \sum_{k=1}^i \alpha_{o-1,k} \right) \right) \quad (3)$$

An example of the penalty term is shown in Fig. 4. This figure shows the alignment weights and their CDFs computed for $o-1$ and o (represented by two dotted and dot-dashed curves), along with the penalty cost (long dashes). Intuitively, the proposed penalty encourages the attention mechanism to select nearby locations in the input sequence that are in the future, rather than in the past with respect to the previously selected location.

The effect of the proposed penalty term together with the gating procedure (see Eq. (2)) can clearly be observed in Fig. 2. In Fig. 2 (a) where both the gating procedure and the penalty term were used, the alignment at each time step is confined to a small subset of consecutive locations and is monotonic. On the other hand, the alignment without the proposed penalty shown in Fig. 2 (b) clearly does not show these properties.

Although this regularization term could have a hyper-parameter coefficient multiplying it, preliminary experiments suggested that a value of 1 worked well and we did not optimize it further.

2.2 Encoder

The encoder is implemented using a cascade of a multilayer Maxout network (Goodfellow *et al.*, 2013a) whose last layer is fed to a bi-directional RNN (BiRNN) (Schuster and Paliwal, 1997; Graves *et al.*, 2013a). We have chosen this hybrid architecture to combine the ability of the Maxout network to nonlinearly transform speech features with the efficient summarization of nearby preceding and following input frames provided by the BiRNN. The BiRNN uses the reset-update gate to account for long-term dependencies (Cho *et al.*, 2014).

3 Experiments

3.1 Problem setup

We evaluated the model on the TIMIT dataset. The baseline score was established using the recipe “s5” of the Kaldi toolkit (Povey *et al.*, 2011), using the “score_basic.sh” scoring script². All results are gathered in Table 1. All models were trained to recognize 48 phonemes, their predictions were converted to the 39 phoneme set before scoring. All SA sentences were removed from both training and testing sets. The models were evaluated on the 24 speaker core test set with an auxiliary 50 speaker development set used to select the best network. Similarly to the Kaldi’s DNN recipe we kept 10% of the training data for validation, which resulted in a final 4-way split of the data into testing, development, validation, and training sets³.

The networks were trained on speaker adapted fMLLR features obtained using the GMM-HMM built during stage “tri3” of the “s5” recipe provided by Kaldi. Each acoustic frame was described using 40 features, however the network had access to segments of 11 frames totaling in 440 features per frame. Furthermore we used the “tri3” triphone GMM-HMM model to force-align the data to obtain per-frame training targets.

The networks were implemented using the Theano (Bergstra *et al.*, 2010) and Pylearn2 (Goodfellow *et al.*, 2013b) libraries.

3.2 RNN training and evaluation

Due to slow convergence of the training process the experiment was limited to training a single network, with regularization and training hyper-parameters changed during the experiment run. The

²Two scoring scripts are provided (`basic` and `slite`), differing in the way errors in the silence phone are counted. The `basic` scoring script treats them as any other error, while the `slite` scorer can be configured to disregard errors related to recognizing silence phones.

³We have thus used the same data preprocessing as the Deep NN part of the TIMIT s5 recipe.

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Table 1: Phoneme error rates of evaluated models

Model	DEV	TEST
Kaldi TIMIT s5 recipe with basic scorer		
Speaker independent triphone GMM-HMM	23.15%	24.32%
Speaker adapted triphone GMM-HMM	20.56%	21.65%
DBN-HMM with SMBR training	17.55%	18.79%
DBN-HMM with SMBR training and greedy search	32.02%	33.00%
Proposed model with the basic scorer		
Maxout network with per-frame training	18.41%	19.68%
RNN model with frozen acoustic layer	17.53%	18.68%
RNN model trained end-to-end	16.88%	18.57%
RNN model trained end-to-end with greedy search	17.06%	18.61%
References		
Deep RNN Transducer (Graves <i>et al.</i> , 2013b)	N/A	17.7%

obtained results should thus be treated as a preliminary proof-of-concept validation of the proposed model, rather than a rigorous analysis of its performance.

To ease training of the network we decided to initialize the acoustic part of the RNN encoder with weights of a deep Maxout network trained with dropout regularization (Goodfellow *et al.*, 2013a; Hinton *et al.*, 2012b) to predict the states of the HMM. The network was trained purely discriminatively (no layer-wise initialization) to predict per-frame HMM states. The architecture of the network was mildly optimized, and coupled with an HMM decoder it reached 18.41% development set error and 19.68% test error.

Next we initialized the proposed RNN encoder-decoder. We removed the final affine transformation and softmax layer from the acoustic network and used it to initialize the acoustic part of the RNN encoder. Its parameters were then frozen until the RNN encoder-decoder reached good recognition performance. We initialized other weights randomly, however the weights in the recurrent connections were orthonormalized to ease training. For the first training iterations the network did not use the gating mechanism to disambiguate between matching input frames (2).

The RNN was trained with stochastic gradient descent using the AdaDelta learning rule (Zeiler, 2012) and an adaptive gradient clipping mechanism described in section 3.2.1. To save on computation time, mini-batches were composed of utterances of similar length (we re-shuffled the data on each epoch, divided it into groups of up to 32 utterances and sorted each group before forming the batches). We trained with a minibatch size 4. Each utterance was processed with the Maxout network, and then we appended a frame containing only zeros to indicate to the RNN where the utterance ends.

When the network started to generate good phoneme sequences we enabled the gating mechanism and added to the training cost the penalty for alignment non-monotonicity (c.f. sec. (3)). The gating MLP (d in eq. (2)) receives large inputs (up to the number of input frames), therefore its hidden layer was manually initialized: the weights were set to the constant 10^{-3} , while the corresponding biases were uniformly distributed in the $(-5, 5)$ range. At the same time we added a weight decay penalty of 10^{-3} applied to the weights of the MLP predicting the next phoneme and of $2 \cdot 10^{-4}$ to the weights in the network used to score input frames in Eq. (1). The best decoding error reached on the development set was 17.53% which corresponded to 18.68% on the test set.

Finally, we included into training the pre-initialized Maxout part of the encoder. However, we disabled dropout regularization as we found that it increased the decoding errors on the development set by a few percentage points and the network was very slow to recover. The training of the full network lowered the development set error to 16.88%, which corresponded to a test error of 18.57%.

In an auxiliary experiment we analyzed the importance of the beam-search width on decoding accuracy. We observed that a narrow beam width is required to reach optimal performance (decoding with beam width 10 is sufficient) and that the accuracy degraded very slightly if the beam search is replaced with a greedy search. To put this result into context we have used the HMM decoder with a beam search width limited to 1. We have tuned the weighting of the acoustic and language

378 model scores. Both development and test error rates increased to about 32%. This result shows is an
 379 important characteristic of the proposed model as it suggests that the RNN encoder-decoder really
 380 learns how to align the input and output sequences.
 381

3.2.1 Improving the Convergence of AdaDelta

382 In order to avoid the issue of exploding gradient, we rescaled the norm of the gradient, if it went over
 383 a predefined threshold (Pascanu *et al.*, 2013). However, with this gradient rescaling, we observed
 384 that AdaDelta failed to converge to a lower training error at the later stage of training. We addressed
 385 this problem by multiplying the gradient with a small scalar (typically, 10^{-2}) at the later stage of
 386 learning. As this procedure clearly affects the original gradient rescaling, we used the following
 387 algorithm to automatically adapt the gradient rescaling threshold:
 388

$$\begin{aligned}
 390 \quad \nabla_{\Theta} &= \text{gradient of the loss}, g = \nabla_{\Theta} \cdot \text{gradient scale}, ng = \sqrt{\sum g_i^2} \\
 391 \\
 392 \quad \text{Elog}_{ng} &= \min\left(\rho, \frac{\text{nsteps}}{\text{nsteps}+1}\right) \text{Elog}_{ng} + \left(1 - \min\left(\rho, \frac{\text{nsteps}}{\text{nsteps}+1}\right)\right) \log(ng) \\
 393 \\
 394 \quad \text{Elog2}_{ng} &= \rho \text{Elog2}_{ng} + (1 - \rho) \log^2(ng) \\
 395 \\
 396 \quad rg &= \begin{cases} g, & \text{if } ng \leq \exp\left(\text{Elog}_{ng} + \kappa * \sqrt{\max(0, \text{Elog2}_{ng} - \text{Elog}_{ng}^2)}\right) \\
 397 \quad g \frac{\exp(\text{Elog}_{ng})}{ng}, & \text{otherwise} \end{cases} \\
 398
 \end{aligned}$$

399 The rescaled gradient rg was then passed to the AdaDelta update procedure.

400 The accumulators Elog_{ng} and Elog2_{ng} were initialized to 0 at the beginning of the run. The algo-
 401 rithm uses a smaller decay constant to compute the moving average of the mean in the early stage
 402 to underestimate the standard deviation. This has the effect of having a threshold close to the mean
 403 value at the beginning and increasing the threshold only when the running averages are correctly
 404 tracking the norm of the gradient.
 405

4 Conclusions

406 We report preliminary results of phoneme recognition with an RNN model that does not require an
 407 explicit alignment and produces a desired output sequence directly, without resorting to intermediate
 408 per-frame predictions that have to be processed with a specialized decoding algorithm. The proposed
 409 model is an extension of the network used for neural machine translation (Bahdanau *et al.*, 2014) and
 410 is closely related to CTC and the RNN Transducer (Graves *et al.*, 2006, 2013b). Although closely
 411 related, our model differs from these models in multiple aspects.
 412

413 For instance, the proposed approach is related to the RNN Transducer in the sense that scores are
 414 computed for all pairs of positions in the input and output sentences. However, in the RNN Trans-
 415 ducer the scores define a distribution over a latent alignment, which is then marginalized out. The
 416 proposed model (a variant of RNN Encoder-Decoder (Cho *et al.*, 2014; Bahdanau *et al.*, 2014)) in-
 417 stead uses the scores as an explicit alignment which is used to compute a context vector. In addition
 418 the decoder state of our model contains information about previous alignment choices unlike the
 419 states of the generation network from the RNN Transducer.
 420

421 Accessing the input sequence through a context vector is related to the model that generates hand-
 422 written characters, proposed recently by Graves (2013). Their handwriting generation network,
 423 however, predicts the location of the inputs selected for the next step, while our model scans through
 424 all inputs looking for correctly matching patterns. This scanning of the whole sequence helps the
 425 model deal with irregularities in speech, such as long pauses. Nevertheless, our model learns an
 426 expected distance between inputs pertaining to subsequent output symbols to disambiguate between
 427 occurrences of similar input frames (see Fig. 3). This relation can be used to speed up the recogni-
 428 tion by confining the search for matching frames to the most probable locations only.

429 We observed that our model performs well even with a simple, narrow-beam search which is close to
 430 greedy search. This fact has its significance in extending the proposed approach to a large vocabulary
 431 speech recognition system. As the decoding of the phoneme stream is nearly deterministic, we may
 simply put on top of the phone sequence another RNN that models a sequence of words. In this case,

432 we will be able to directly search for the most probable sequence of words, instead of the phoneme
433 level or frame level (as is done by the HMM-based hybrid systems).
434

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