A state of the art end-to-end speech recognition algorithm with a homogenous structure.

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Abstract

TODO(chanw.com) Revise the abstract. This paper proposes a new end-to-end speech recognition system referred to as Recurrent neural network Sequence Classification (RSC). Recently, end-to-end speech recognition systems have been gaining more attention from researchers and several different structures have been proposed. Typical examples include Connectionist Temporal Classification (CTC), Recurrent Neural Network Transducer (RNN-T), and Sequence-to-Sequence Modeling using the attention mechanism. The CTC-based approaches are using the CTC loss assuming the conditional independence property. Although the structure of CTC is simpler than other end-to-end systems, the performance is worse due to this conditional independence assumption. RNN-T and attention-based approaches have distinct components such as the prediction network and encoder in RNN-T, and the encoder, the decoder, and the attention layer in the attention-based model. Compared to these models, FSC has a homogeneous structure from the bottom to the top layer. LSTM and max-pooling layer are repeated followed by the top softmax layer. The embedded softmax output is fed back as input of each RNN layer. The training starts with flat initialization and alignment is made after every epoch. The loss is the Cross Entropy (CE) loss using this alignment result. In our experimental results, FSC algorithm has shown better performance than more complicated attention-based end-to-end speech recognition system. Another major advantage is training is significantly faster.

1 Introduction

Recently, there has been tremendous improvements in speech recognition systems fueled by advances in deep neural networks [8, 12, 15, 18, 19, 21].

TODO(chanw.com) Talk about the AI speakers.

TODO(chanw.com) Talk about the advancements of the end-to-end systems.

Recently, it has been frequently observed that if sequence-to-sequence end-to-end ASR systems are trained on sufficiently large amounts of acoustic training data, they can outperform conventional HMM-DNN/RNN hybrid systems [6, 1].

Recently, we observed that training with large-scale noisy data generated by a *Room Simulator* [5] improves speech recognition accuracy dramatically. This system has been successfully employed for training acoustic models for Google Home or Google voice search [5].

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2 Review on sequence-to-sequence speech recognition algorithms

In this section, we review well-known *sequence-to-sequence* algorithms used in speech recognition. [7, 9, 11, 16]. A *sequence-to-sequence* speech recognizers maps a sequence of input acoustic features into a sequence of graphemes [7, 4] or words [16]. We denote a sequence of input acoustic feature vectors by $\mathcal{X}_0^{M-1}$ and a sequence of target labels in *one-hot vector* representation by $\mathcal{Y}_0^{L-1}$ as shown below:

$$\mathcal{X}_0^{M-1} = \left\{ \vec{x}[m] \middle| 0 \leq m \leq M-1,\ \vec{x}[m] \in \mathbb{R}^d \right\}, \tag{1a}$$

$$\mathcal{Y}_0^{L-1} = \left\{ \vec{y_l} \middle| 0 \leq l \leq L-1,\ \vec{y_l} \in \mathbb{V} \right\}, \tag{1b}$$

where M is the number of frames in the input feature sequence, d in (1a) is the dimension of the input feature. L is the number of labels in the output target sequence, and $\mathbb{V}$ in (1b) is the set of output labels, which may be graphemes [7, 4], subword units [23, 6], and words [20]. Note that the sequence index in (1a) is a frame index, whereas the sequence index in (1b) is label index. Depending on whether the neural network generates the inference output for every frame or not, there are following categories:

- **Label-synchronous inference** In this category, the neural network generates the inference output $\widehat{\vec{y_l}}$ only when a new label is expected. The loss function $\mathbb{L}\left(\mathcal{X}_0^{M-1}, \mathcal{Y}_0^{L-1}\right)$ is defined as follows:

$$\mathbb{L}\left(\mathcal{X}_0^{M-1}, \mathcal{Y}_0^{L-1}\right) = \sum_{l=0}^{L-1} y_l \odot \log\left(\circ\, \widehat{\vec{y_l}}\right) \tag{2}$$

  where $\odot$ and $\log(\circ)$ denote element-wise product (a.k.a *Hadamard product*) and element-wise log, respectively.

- **Frame-synchronous inference** In this category, from the original target label in (1b), we either explicitly or implicitly obtain the label boundaries. In the framewise Cross Entropy (CE) training [13, 5, 3], *Viterbi alignment* [14, 17] is usually employed. Using these alignment algorithms, we obtain corresponding *frame-synchronous* label sequences $\vec{z}[m] \in \mathbb{V}$ for each frame index m. This latent label sequences are often called a *path*.

$$\mathcal{Z}_0^{M-1} = \left\{ \vec{z}[m] \middle| 0 \leq m \leq M-1,\ \vec{z}[m] \in \mathbb{V} \right\}, \tag{3}$$

  Fig. 2 shows one such example. Such an alignment is usually called a *path*.

$$l = \sum_{l=0}^{l=L-1} y_l \log\left(\hat{y}_l\right) \tag{4}$$

Moreover, in almost all the large speech training database, the temporal boundray of each label is not marked. In the attention-based model described in Sec. 2.3 and shown in Fig. 1c, lack of the temporal alignment information in the training database is not a problem, since the *decoder* portion of the attention-model directly generates the output label sequences. The loss function is also defined for each labels.

2.1 Connectionist Temporal Classification

Fig. 1a shows the entire structure of the Connectionist Temporal Classification (CTC) [10]. In CTC, we use the following CTC loss [10, 11]:

$$P\left(\mathcal{Y}_0^{L-1} | \mathcal{X}_0^{M-1}\right) = \sum_{\mathcal{Z}_0^{M-1} \in \mathcal{A}_{CTC}\left(\mathcal{X}_0^{M-1}, \mathcal{Y}_0^{L-1}\right)} \Pi_{m=0}^{M-1} P\left(\vec{z}[m] | \mathcal{X}_0^{M-1}\right), \tag{5}$$

where $\mathcal{A}_{CTC}\left(\mathcal{X}_0^{M-1}, \mathcal{Y}_0^{L-1}\right)$ correspond to frame-level alignments of length M such that removing blanks and repeated symbols from $\mathcal{Z}_0^{M-1}$ yields $\mathcal{Y}_0^{L-1}$.

2.2 RNN-Transducer

Fig. 1b shows the entire structure of the RNN-T structure. The loss function used in RNN-T is given as follows:

$$P\left(\mathcal{Y}_0^{L-1}|\mathcal{X}_0^{M-1}\right) = \sum_{\mathcal{Z}_0^{M-1} \in \mathcal{A}_{CTC}\left(\mathcal{X}_0^{M-1}, \mathcal{Y}_0^{L-1}\right)} \Pi_{m=0}^{M-1} P\left(\vec{z}[m]|\mathcal{X}_0^{M-1}\right), \tag{6}$$

2.3 Attention-based model

3 Feedback Sequence Classifier

3.1 Neural Network Structure

Fig. 1d shows the entire structure of the FSC. As shown in this figure, LSTM layers and max-pool layers are interleaved from the bottom layer up to the third max-pool layer.

In Fig. 1d, speech features $\vec{x}[m]$ are sampled at every 10 *ms*, which is the usual frame period in speech recognition [14, 2], Using three two-to-one max-pool layers, $\vec{z}[p]$ has a frame period of 80 *ms*. The relationship between the temporal index p in $\vec{z}[p]$ and m in $\vec{x}[m]$ is given by:

$$p = \lceil m/8 \rceil \tag{7}$$

$$\mathcal{Z}_0^{M-1} = \left\{ \vec{z}[m] \middle| 0 \leq m \leq M-1,\ \vec{z}[m] \in \mathbb{V} \right\}, \tag{8}$$

The reason for using the one dimensional max-pool layer is to make the neural network output have a similar rate to the that of each *phone* in utterances. Note that a *phone* is any distinct speech sound serving as a phonetic unit.

It has been observed that the average phone duration is between 50 *ms* ~100 *ms* [22, 24].

3.2 Training of the Feedback Sequence Classifier

In this section, we describe how to train FSC. As mentioned in Sec. , the FSC operates in the frame -synchronous way. Since we do not have the alignment information

The first step is making an alignment using the N-best alignment. The second step is updating the neural network parameters using the Cross Entropy (CE) criterion.

3.3 Training procedure

The first step is finding the optimal frame-synchronous sequence $\mathcal{Z}_0^{M-1}$.

$\mathcal{Z} = A(\mathcal{X}|\Theta)$

Updates the model.

3.4 Viterbi alignment and N-best alignment

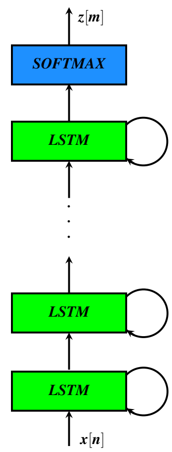
In CTC in Sec. 2.1 and in RNN-T in Sec. 2.2, the forward-backward algorithm is employed to update parameters. TODO(chanw.com) cite HMM tutorial paper.

For example in CTC, the forward algorithm is given by the following equation:

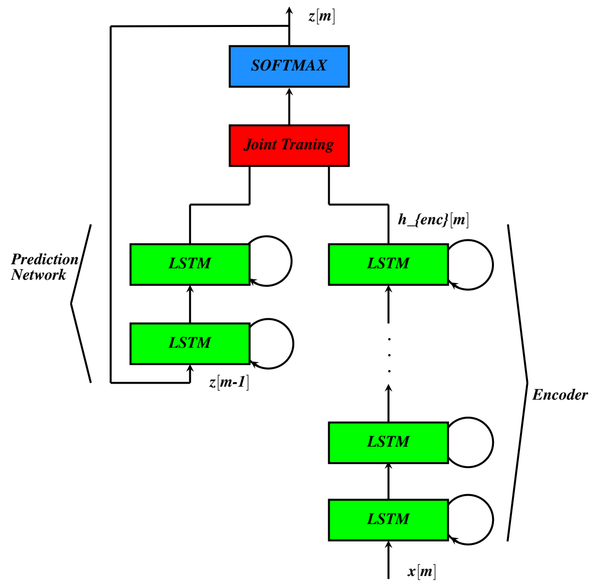
In conventional frame-wise CE-training, Viterbi alignment (a.k.a forced alignment) has been performed to obtain the frame-level acoustic unit boundaries TODO(chanwcom). Even though the Viterbi algorithm has advantages in simplicity and efficiency, it is based on the conditional independence assumption.

In TFSC, we propose the following N-best alignment approach rather than the Viterbi alignment algorithm to find the alignment information.

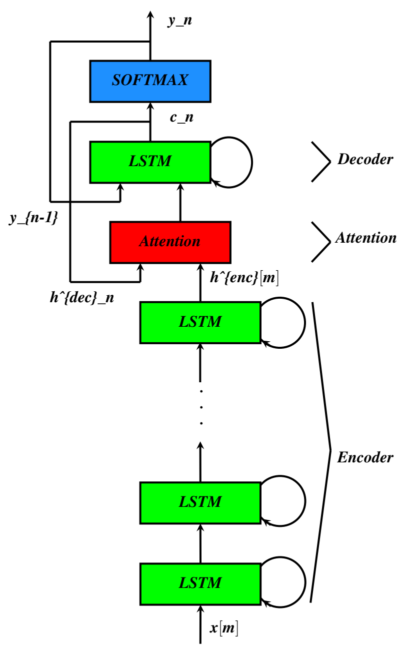
for $m = 0, ..., M-1$ **do**
    for $l = 0, ..., N_b - 1$ **do**



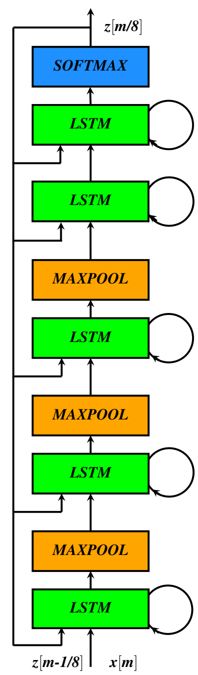
(a) Connectionist Temporal Classification (CTC) Model.



(b) RNN-T Model.



(c) Attention-based Model.



(d) Feedback Sequence Classifier (FSC) Model.

Figure 1: Comparison of block diagrams of different sequence-to-sequence speech recognition approaches. The proposed Feedback Sequence Classifier (FSC) is shown in Fig. 1d.

```
            π^(l)[m]
        end for
    end for
    if i ≥ maxval then
        i ← 0
    else
        if i + k ≤ maxval then
            i ← i + k
```

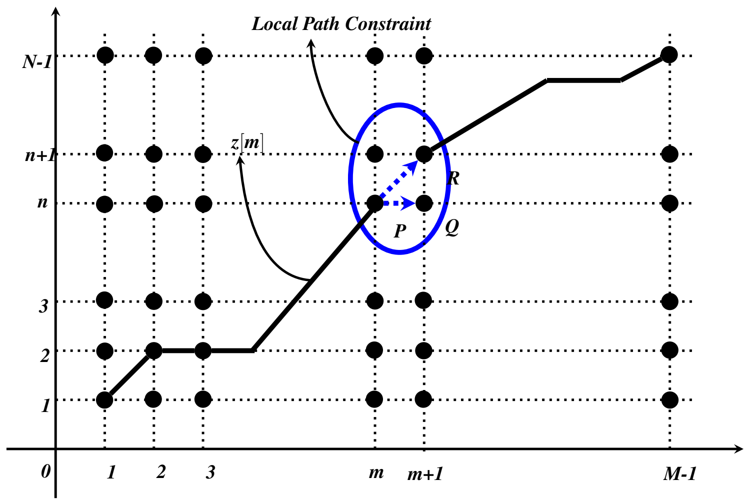


Figure 2: An example of a path $\mathcal{Z}_0^{M-1}$ and the path movement constraint shown by TODO(chanw.com)[Check the latex arrow symbol] $P->Q$ and $P->R$.

end if

end if

4 Experimental Results

Acknowledgments

References

References follow the acknowledgments. Use unnumbered first-level heading for the references. Any choice of citation style is acceptable as long as you are consistent. It is permissible to reduce the font size to `small` (9 point) when listing the references. **Remember that you can go over 8 pages as long as the subsequent ones contain *only* cited references.**

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