IMPROVING GENERALIZATION OF TRANSFORMER FOR SPEECH RECOGNITION WITH PARALLEL SCHEDULE SAMPLING AND RELATIVE POSITIONAL EMBEDDING

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ABSTRACT

Transformer showed promising results in many sequence to sequence transformation tasks recently. It utilizes a number of feedforward self-attention layers in the encoder and decoder to replace recurrent neural networks (RNN) in attention-based encoder decoder (AED). Self-attention layer learns temporal dependence by incorporating sinusoidal positional embedding of tokens in sequences for parallel computing. Quicker iteration speed in training than sequential operation of RNN can be obtained. The deeper layer of transformer also makes it perform better than RNN-based AED. However, this parallelization makes it hard to apply schedule sampling training. Self-attention with sinusoidal positional embedding may also cause performance degradations for longer sequence that has similar acoustic or semantic information at different positions. To address these problems, we propose to use parallel schedule sampling (PSS) and relative positional embedding (RPE) to help transformer generalize to unseen data. Our proposed methods achieve 7% relative improvement for short utterances and 30% absolute gains for long utterances on a 10,000-hour ASR task.

Index Terms— speech recognition, transformer, parallel schedule sampling, relative positional embedding

1. INTRODUCTION

Conventional hybrid DNN-HMM based ASR systems require independently optimization of acoustic model (AM), pronunciation model (PM) and language model (LM). The end-to-end (E2E) methods aim to simplify ASR system by jointly learning these models within one single neural network and has achieved promising results. Connectionist Temporal Classification (CTC) \textsuperscript{1}\textsuperscript{2}, Recurrent Neural Network Transducer (RNN-T) \textsuperscript{3}\textsuperscript{4}\textsuperscript{5}, Recurrent Neural Aligner \textsuperscript{6}\textsuperscript{7} and Segment Neural Transduction \textsuperscript{8} and Attention-based encoder decoder (AED) models \textsuperscript{9}\textsuperscript{10}\textsuperscript{11} are such E2E models that are well explored in the literature.

AED model \textsuperscript{9}\textsuperscript{10} was examined on many speech tasks. AED consists of a encoder, a decoder and a attention which extract relevant feature from encoder output for the decoder to decide which token needs to be output. The encoder uses RNNs to capture temporal characteristics of speech and outputs higher level features from raw input spectral features. The decoder generates output tokens sequentially conditioned on the context tokens and the encoder output. While ground truth labels are used as context tokens in training, the predicted tokens are used as context tokens for decoder input. Schedule sampling (SS) \textsuperscript{12} is often adopted to compensate the discrepancy between training and inference. Sequential iterations of RNN are also suitable for SS to be integrated at each token level without sacrificing training efficiency. However, this sequential feature of RNN makes training time-consuming.

The state-of-the-art architecture for AED is self-attention layer proposed in transformer \textsuperscript{13} for neural machine translation (NMT). The self-attention architecture learns temporal and contextual dependency inside the input sequence by employing temporal attention on the input feature itself and this can replace the RNN in LAS. Transformer has been applied to E2E speech recognition systems \textsuperscript{14}\textsuperscript{15}\textsuperscript{16} and has achieved promising results. The transformer-based E2E ASR system relies on feedforward self-attention components, thus it can be trained faster with more parallelization than RNN based AED. With deeper structures, transformer obtains better performance than RNN-AED. However, the non-recurrent parallel forward process of decoder in transformer also lead it difficult to utilize schedule sampling in training stage. Moreover, time order of speech, which can be represented by recurrent process of input features, is an important distinction. Although absolute positional embedding (APE) can be added to input features for transformer to make use of the order of sequence, performance degradation of long sentences of AED, as mentioned in \textsuperscript{17}, becomes more serious for transformer. Compare to RNN-based AED, we indeed found transformer is more sensitive to sentences longer than the training set.

In this paper, we propose to use parallel schedule sampling for speech-transformer. More precisely, greedy search is used to get the model prediction with label as input. Then we mix the ground truth label and the generated output to form a new input to the decoder. We also use recognition results from a chain model as the text sequence to be mixed with label sequence. Experimental results show that we could get similar results with this two methods, which is about 7% relative gain compare to teacher forcing training.

We also found transformer makes a lot of deletion errors for long utterances. Characters that appears further than max length of training set are likely to be deleted. We call this deletion as tail deletion (TD). Other deletion appears between similar acoustic or semantic segments and we call such deletion as internal deletion (ID). We argue self-attention and source attention accessing the whole sentence make the model confused for focusing on unseen long sentences. Naturally, we want to restrict the attention position range to avoid model from this confusion. Relative position embedding is proposed to help model generalize to unseen longer sentences and 30% absolute gain is obtained on test set longer than 40 Chinese characters.
The rest of paper is organized as follows. Section 2 briefly reviews transformer used in ASR tasks. The proposed methods are described in details in Section 3. Experimental setup and results are presented in Section 4 and the paper is concluded with our findings described in details in Section 5.

2. TRANSFORMER BASED E2E ASR

The AED used in ASR is common to other sequence to sequence tasks presented in Section 4 and the paper is concluded with our findings described in details in Section 3. Experimental setup and results are presented in Section 4 and the paper is concluded with our findings described in details in Section 5.

2.1. Encoder and decoder architecture

The encoder is composed of a stack of N identical blocks. Each block has two sub-layers. The first is a multi-head self-attention layer (MHA), and the second is a position-wise fully connected feed-forward network (FFN). Each of the two sub-layers contains a skip connection followed by layer normalization. Similar to the encoder, decoder is also composed of a stack of M identical blocks. Besides the two sub-layers and residual connections as in encoder block, a third sub-layer is added to decoder block between the MHA and FFN sub-layer, which performs multi-head source attention over the output representations of the encoder stack.

2.2. Multi-head attention

The attention layer used in transformer takes the “scaled dot-product attention” with the following form:

$$\text{Attn}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V, \quad (1)$$

where $Q$ and $K$ are queries and keys of dimension $d_k$, $V$ are values of dimension $d_v$. In order to allow the model to pay attention to different representation subspace, [13] proposed to use multi-head attention to perform parallel attention:

$$\text{MHA}(Q, K, V) = \text{Concat}([H_1, H_2, \ldots, H_m])W^O, \quad (2)$$

$$H_i = \text{Attn}(QW^Q_i, KW^K_i, VW^V_i), \quad (3)$$

where $W^Q \in \mathbb{R}^{d_m \times d_k}, W^K \in \mathbb{R}^{d_m \times d_k}, W^V \in \mathbb{R}^{d_m \times d_v}$ and $W^O \in \mathbb{R}^{kd_v \times d_m}$ are learnable weight matrices, $h$ is the total number of attention heads, $H_i$ is the output of the $i$-th attention head, $d_k$ is the individual dimension for each attention head, $d_m$ is the model feature dimension.

For encoder and self-attention layers in decoder, all of the keys, values and queries, $K, V, Q$ come form the output features of previous layer. In the source attention layers, queries come from the previous decoder layer, and the keys and values come from the final output of encoder.

2.3. Absolute positional embedding

Transformer contains no recurrence and no convolution, in order for the model to make use of the order of the sequence, input representations are added with absolute positional encoding before feeding to the encoder and decoder stacks.

$$PE_{pos,i} = \begin{cases} \sin(pos/10000^{i/d_m}), & i \text{ is even,} \\ \cos(pos/10000^{(i-1)/d_m}), & i \text{ is odd.} \end{cases} \quad (4)$$

where $pos$ represents the absolute position in sequence, $i$ represents the $i$-th dimension of input feature. Since raw speech spectral features often contains several hundreds of frames, it is beneficial to use a network before the APE operation to compute the down-sampled features. For more details please refer to [13][14].

3. PROPOSED METHODS FOR IMPROVING GENERALIZATION OF TRANSFORMER

3.1. Parallel scheduled sampling

Scheduled sampling is a training strategy to bridge the gap between training and inference. Previous work has showed that it can improve the performance of speech transformer with castrated SS which only several step of samples are considered [19]. However, vanilla transformer, when applied with scheduled sampling, is instead inferior to LAS due to the destructed parallelism and duplicated calculations. In order to alleviate the problem, we hope to acquire the whole input token series of decoder in advance by simulating the error distribution of inference to form a parallel scheduled sampling. We will describe our two methods of parallel scheduled sampling as follows. Unlike several step of samples in [19], our methods considers to sample from model at each step without losing efficiency.

3.1.1. PSS with hybrid model result

In this method, we achieve PSS with the decoding results of chain model. First, for each utterance, we obtain its hypothesized text $\hat{y} = (\hat{y}_1, \ldots, \hat{y}_u)$ from chain model, which simulates the decoding result of transformer. Then, $\hat{y}$ is mixed with ground truth $y = (y_1, \ldots, y_u)$ according to a teacher force rate. The teacher force rate represents the possibility to use the token in $y$ as final decoder input and is scheduled by the following piece-wise linear function:

$$P(i) = \max(min(1, 1 - (1 - P_{min} \times \frac{i - N_{st}}{N_{ed} - N_{st}}), P_{min}) \quad (5)$$

where $P_{min}$ is the minimum teacher force probability, which is usually not zero to prevent under-fitting over training set. $i$ is the training step and $N_{st}$ and $N_{ed}$ represent the starting step and the ending step in the schedule respectively. The step to be “epoch” and “batch” are both explored in our experiments and “batch” is slightly better. At last, we acquire the whole token series $\bar{y} = (\bar{y}_1, \ldots, \bar{y}_m)$ as decoder input to achieve parallelism. The increased time cost compared to teacher force training exists in obtaining the hybrid system result of each utterance. This is supposed to be much faster than the simple application of AED scheduled sampling on transformer.

Furthermore, we investigate mixing at "token" and "sentence" level and "token" performs slightly better. For token level mixing, it can be formulated as:

$$\bar{y}_j = \begin{cases} y_j & \text{with } P(i) \\ \hat{y}_j & \text{with } 1 - P(i) \text{ and } j \leq q \\ \text{PAD} & \text{with } 1 - P(i) \text{ and } j > q \end{cases} \quad (6)$$

where $j = 1, 2, \ldots, u$ and PAD is the padding token to fill up short sentences in a batch. For sentence level, the whole $\bar{y}$ or $y$ is selected for the input according to $P(i)$. 

Our method is related to [20] which adopts back-translation to get source text with errors to be used for training. SS aims to make AED robust to several decoding errors. Although there is no evidence that the error distributions of hybrid system have any relation to that of AED, hybrid system results, containing several errors, can be viewed as a special kind of data augmentation technique. So it should help the model to generalize.

3.1.2. PSS with self-decoding result

The second method we describe here is to mix \( y \) with hypothesized result decoded by transformer itself. One simple way is to generate hypothesized text with teacher forcing trained model as an offline mode like decoding from chain model. On the contrary, we generate hypothesized result and update the model iteratively in an online training process. Therefore, to simply the online training process, we obtain hypothesized result with ground truth as decoder input by greedy search decoding. Then, the same scheduled strategies in the last subsection is used.

Inspired by the work [21] which is proposed for machine translation, we find that our work of this method is a special case in [21] when \( K = 1 \), where \( K \) is the number of times to do above operations. Besides, we further reveal that teacher forcing training is the special case when \( K = 0 \). To associate them with conventional scheduled sampling, we can make the following reasoning process. When \( K = 1 \), only the first generated character \( \mathbf{y}^{(1)} \) is sampled from decoding. If \( \mathbf{y}^{(t)} \) is fed to decoder and repeat the above operation, both \( \mathbf{y}^{(t)} \) and \( \mathbf{y}^{(t-1)} \) are sampled reasonably. Therefore, repeating above process for \( K >= u \) times, PSS with self-decoding result is equivalent to the original scheduled sampling. The time cost will also be approximately the same as conventional SS.

3.2. Relative positional embedding

We observe a large amount of deletion errors, TD and ID, for long utterances. TD is because transformer didn’t seen such long sentences at training stage and tends to finish decoding when output length approaching the max length of training set. ID of transformer may due to the the attention jumping between similar acoustic and semantic segments.

Many works attempted to solve this long sequence generation problem by increasing training data length. In this direction, their main work focus on memory controlling by sparse attention mechanism or segmental transformer [22][23][24]. The original APE proposed for NMT may not be suitable for speech applications. APE may make model attend to wrong positions for long utterance since it is never trained on such long sentences. Inspired by [25], we introduce RPE to speech transformer to alleviate long sentence generalization problem other than just adding long data. Our main purpose is to restrict the position range and strengthen the relative position relationship within the range. TD may be alleviated by RPE since model already learned how to pay attention to relative context. Furthermore, fewer similar segments may appear in restricted position range, thus ID may also be solved.

Suppose the input of a self-attention layer is \( z = (z_1, ..., z_T) \), we define the relative position between each \( z_i \) and \( z_j \) as \( a_{ij} \). To restrict the position range, we consider a maximum absolute value of relative position \( k \) and acquire \( 2 \times k + 1 \) embeddings, denoted as \( w = (w_{-k}, ..., w_k) \). Then, any relative positional embedding between two inputs can be formulated as:

\[
a_{ij} = w_{\max}(-k, \min(k, j-i))
\]  

Next, the relative position embedding \( a_{ij} \) is incorporated to the similarity computation (softmax input) in Eq. (1) as follows:

\[
e_{ij} = \frac{z_i W^Q(z_j W^K + a_{ij})^T}{\sqrt{d_k}}
\]  

Here, query and key are the same with \( z \). We share the RPE across different attention heads. Other calculation is the same as original transformer.

Eq. (8) can be modified by applying distributional law of matrix to apart it into two terms for efficient training:

\[
e_{ij} = \frac{z_i W^Q(z_j W^K)^T + z_i W^Q(a_{ij})^T}{\sqrt{d_k}}
\]  

The first term is equivalent to the original similarity computation. The second term can be calculated with tensor reshaping, which means a matrix with size \( bhT \times d_k \) multiply a matrix with size \( d_k \times T \). And then it is reshaped to fit with the first term.

4. EXPERIMENT

4.1. experimental setup

Our experiments are conducted on a 10,000 hour Sogou Chinese speech dictation data, which contains about 12 million sentences. Only about 1,000 utterances in training set contains more than 40 Chinese characters (about 10 seconds). Sentence longer than 10 seconds or has more than 40 characters is discarded. The main test sets we used include \(~33K\) short utterances (SU) less than 40 characters long and \(~3.6K\) long utterances (LU) greater than 40 characters. 71 dimension fbanks are extracted every 10 mini-seconds within 25 mini-second window using the conventional ASR front end. Every four consecutive frames are stacked to form a 284-dimensional feature vector and we jump 4 frames to get shorter input feature sequence for transformer models.

6812 characters is used as modeling unit, including 26 English characters, 6784 Chinese characters, start of sequence (SOS), end of sequence (EOS) and unknown character (UNK). All models are trained by optimizing the cross entropy between label sequence and predicted sequence via adam optimizer. Label smoothing (LS) are set to 0.1 during training to improve performance. We also apply 10% dropout rate to the output of each sub-layer, before it is added to the sub-layer input and normalized. The total training epoch is fix to 12. We train our model from random initialization with an initial learning rate of 0.0002 and halve it from epoch 7. Five-hypotheses-width Beam search is used without an external language model to evaluate our model on test sets.

4.2. Improve by PSS

The base transformer model contains 5 MHA-FFN blocks and 3 MHA-MHA-FFN blocks. The model dimension \( d_{n} \) is 768 and the inner-layer dimension of FFN is 2,048. We employ \( h = 16 \) attention heads. For each of these heads we use \( d_k = d_v = d_{m} / h = 48 \). A two layer feed forward network with 2048 and 768 nodes maps the raw 284-dimensional feature to 768 dimension. We also train an LAS, constituting of 4-layer BLSTM encoder and 1 LSTM decoder with the same base settings in [25], for comparison. The CER of our base models are presented in the first block of Table [1]. Compare with B0 and B1, it is interesting to find that transformer performs better than LAS on SU but degrades a lot on LU. We leave the LU set degradation to subsection [5] and focus on improving SU with schedule sampling here.
Due to lack of space, we only report experiments with "token" and "batch" style as mentioned in section 4.2. Using the model in B1 as a start point, we perform several SS experiments. First we perform SS with decoded text results from TDNN-LSTM chain model (CM) trained with 50,000 hours of data, numbered as E1. CER of this CM is 6.65 and 5.32 for SU and LU respectively. With final $P_{\text{ SS}}=0.8$, we obtain a 8.93 CER on SU. One may argue that this gain may come from the larger training data of the TDNN-LSTM. So we conducted E2 with hypothesized text generated by beam search decoding training set with $K=10$. E2 achieve a similar result with E1. Then in E3, we generate hypothesized text during training stage in an online fashion with label as decoder input to be more closer to real schedule sampling process. We reach 8.88 CER on SU with $K=1$ and $P_{\text{ SS}}=0.5$, about 7.2% relative reduction. Better results achieved by E3 show decoding as training proceeds is a better choice for parallel schedule sampling.

### 4.3. Improve by RPE

As mentioned above, LAS generalize better on LU than transformer because the iteratively process of sequence make the LAS learn order information better than transformer. It reveals that order information learned by self-attention layers with APE generalize poorly to sequences not seen in training set. Lots of deletion errors due to TD or jumping attention from where it suppose to be another position are illustrated in Fig. 1.

Experiment results are summarized in Table 2. Without PE, although LU improves, SU drops a not. In E6, we replace the fixed APE with a learnable token ID APE, just like the token embedding in the decoder. Token ID embedding is worse on LU than sin/cos APE but similar on SU. Then we try to introduce RPE in encoder (E7) and decoder (E8). When RPE is added to MHA layer in encoder, LU improves from 42.41 to 33.56. It further improves to 29.87 without APE and set $k=10$, which represents to attend to about 2 Chinese character on both sides. The CER continues to decrease to 12.73 as we utilize a 2-character-range RPE to the decoder MHA. With RPE, even long sentence presents, the local attention relationship has already been learned. Besides, the possibility of similar segments appearing in the near context becomes smaller which makes the model has little burden to distinguish among them. Thus RPE helps to decrease TD and ID. This also indicates local and relative position is more suitable for speech recognition. Overall, with relative position embedding, we lower CER of LU set from 42.41 to 12.73, an absolute 30% gains.

### 4.4. Combine PSS and RPE

Finally, we report results of model trained with PSS and RPE in Table 3. E9 is the combination of PSS and RPE with settings in second row of E3 and first row of E8, respectively. We assume the little improvement of PSS on LU is because we only perform the mixing process with $K=1$. B2 is TDNN-LSTM chain model trained with lattice free MMI on the same training set. Examining Fig. [1] and Table 3 without integrating external language model, our proposed methods surpass hybrid model on SU and not too far behind chain model on LU. Compared to the base transformer, there is a 7.0% relative improvement of CER on SU and about 30% absolute gain for LU, which again confirms the effectiveness of our methods.

### 5. CONCLUSIONS AND FUTURE WORK

In this work, we apply PSS and RPE to successfully improve the generalization ability of transformer. PSS mixes the chain model result or the self-decoding result with ground truth to approach the real sampling process of scheduled sampling. RPE endues transformer the ability to distinguish similar acoustic and semantic segments. Experiments show 7% relative improvement for short utterances and 30% absolute gains for long utterance are achieved. The RPE can be only applied to self-attention computation in encoder and decoder. To further improve the generalization of transformer in speech, attention restriction in source attention is our next direction.
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