STOCHASTIC ATTENTION HEAD REMOVAL: A SIMPLE AND EFFECTIVE METHOD FOR IMPROVING AUTOMATIC SPEECH RECOGNITION WITH TRANSFORMERS

Shucong Zhang, Erfan Loweimi, Peter Bell, Steve Renals
Centre for Speech Technology Research, University of Edinburgh, Edinburgh, UK

ABSTRACT
Recently, Transformers have shown competitive automatic speech recognition (ASR) results. One key factor to the success of these models is the multi-head attention mechanism. However, we observed in trained models, the diagonal attention matrices indicating the redundancy of the corresponding attention heads. Furthermore, we found some architectures with reduced numbers of attention heads have better performance. Since the search for the best structure is time prohibitive, we propose to randomly remove attention heads during training and keep all attention heads at test time, thus the final model can be viewed as an average of models with different architectures. This method gives consistent performance gains on the Wall Street Journal, AISHELL, Switchboard and AMI ASR tasks. On the AISHELL dev/test sets, the proposed method achieves state-of-the-art Transformer results with 5.8%/6.3% word error rates.

Source code: https://github.com/s1603602/attention_head_removal

Index Terms— speech recognition, end-to-end, self-attention, Transformer, attention head removal

1. INTRODUCTION
In self-attention based models such as Transformers [1], each self-attention layer uses multi-head attention to capture a set of different inputs representations, and have given competitive speech recognition results [2–9]. However, we observed that not all of the attention heads are useful. We found that in trained Transformer models, the attention matrices of some attention heads are close to the identity matrices, indicating that the attention mechanism only learns an identity mapping. Thus, such attention component is redundant, and the input sequence (after a linear transformation) can be directly used as the output of the corresponding attention head.

This observation leads to a question: if there are redundant attention heads in the trained Transformer models, then when we train a model from scratch, can we remove some attention heads without harming the model performance? In our experiments, we found some architectures with reduced numbers of attention heads have better performance, while some other structures give inferior results. However, searching for the best structure by enumeration is not time feasible. Inspired by dropout [10], we propose to randomly remove attention heads during training, and keep all the attention heads at test time (Figure 1). Through this method, the trained model is an ensemble of different architectures.

The proposed training method consistently gives significant performance gains on Wall Street Journal (WSJ) [11], AISHELL [12], Switchboard (SWBD) [13] and AMI [14] datasets. On AISHELL we achieved state-of-the-art results (5.8%/6.3% word error rate) without using external data or modifying the architecture of the original Transformer model.

2. SELF-ATTENTION
In this section we introduce self-attention [1]. The self-attention takes a 3-tuple of sequences as its input. Each self-attention layer has a multi-head attention (MHA) component and a feed-forward component. Each attention head \( A_i \) in the MHA uses a linear transformation to map the input sequences to a Query/Key/Value triplet, which is denoted as \((Q, K, V)\). Then, it uses the dot product to compute the similarity between each element of the \( K \) sequence and each element of the \( Q \) sequence. Using these similarities as weights, each element of the output sequence of the attention head is the weighted sum of the \( V \) sequence. Thus, an attention head \( A_i \) can be described as:

\[
A_i(X^Q, X^K, X^V) = \text{softmax}(\frac{Q_iK_i^T}{\sqrt{d_k}})V_i
\]

\[
(Q_i, K_i, V_i) = (X_i^QW_i^Q, X_i^KW_i^K, X_i^VW_i^V)
\]

where \( X^Q \in \mathbb{R}^{n \times d^Q}, X^K, X^V \in \mathbb{R}^{m \times d^Q} \) are inputs and \( m, n \) denote the lengths of the input sequences; \( W_i^Q, W_i^K \in \mathbb{R}^{d^Q \times d^Q} \) and \( W_i^K \in \mathbb{R}^{d^Q \times d^Q} \) are learnable parameters.

Fig. 1: During training each attention head is removed with probability \( p \). At test time all heads are present.
\|d^4 \times d^k\) and \(W_i^V \in \mathbb{R}^{d^k \times d^V}\) are trainable matrices.

The multi-head attention MHA is a linear combination of the outputs of the \(h\) attention heads \((A_1, A_2, \cdots, A_h)\), which can be described as:

\[
\text{MHA}(X^Q, X^K, X^V) = (A_1, A_2, \cdots, A_h) U^H,
\]

where \(U^H\) is a trainable matrix and \(U^H \in \mathbb{R}^{d^H \times d^M}, d^H = h \times d^V\). A residual connection links the output of the MHA and the query sequence \(X^Q\):

\[
X' = X^Q + \text{MHA}(X^Q, X^K, X^V)
\]

Finally, there is a feed-forward component upon the MHA:

\[
Y = X' + \text{ReLU}(X'S + b)Z + r
\]

where \(S \in \mathbb{R}^{d^M \times d^{FF}}\), \(Z \in \mathbb{R}^{d^{FF} \times d^M}\), \(b \in \mathbb{R}^{d^{FF}}\) and \(r \in \mathbb{R}^{d^M}\) are trainable matrices and vectors.

Transformer is a self-attention based model, which has a self-attention encoder to encode the input sequences and a self-attention decoder to decode the encoded sequences. For each self-attention layer in the encoder, \(X^Q = X^K = X^V\) and each sequence is the speech signal or its hidden representation from the previous layer. For each self-attention layer in the decoder, one MHA firstly attends the hidden representations of the previous output tokens. \(X^K_t = X^V_t\) are the hidden representations of the previous outputs. \(X^Q_t\) is the hidden representation of the current output token. Then, a second MHA looks at the encoded speech signal, \(X^K_s = X^V_s\) are the final hidden representations of the input speech sequence, and \(X^Q_s\) is the output of the previous MHA (with the residual connection). For both of these two MHAs, the residual connection is linked to the \(X^Q_t\).

### 3. STOCHASTIC ATTENTION HEAD REMOVAL

We introduce the stochastic attention head removal strategy in this section. We firstly train a baseline Transformer on WSJ (experimental setups are in Section 4). As shown in Figure 2, we observed that in the trained baseline model, the attention matrices of some attention heads are close to the identity matrices (denoted by \(I\)), which implies

\[
\text{softmax}(\frac{Q_i K^T}{\sqrt{d^k}}) \approx I, \quad \text{softmax}(\frac{Q_i K^T}{\sqrt{d^k}})V_i \approx V_i
\]

\[
A_i(X^Q, X^K, X^V) \approx X^VW^V_i = V_i.
\]

Thus, the attention head behaves like a linear layer and the attention mechanism is unnecessary.

Based on the observation that there are unnecessary attention mechanisms in the baseline model, we test if training Transformers with reduced numbers of attention heads from scratch will affect the performance. We tested the encoder architectures in Figure 3. The decoders are the same as the baseline. Table 1 shows with the same number of attention heads, while some encoder architectures lead to lower CERs, other structures result in worse performance. The inferior CERs of the 11-layer self-attention encoder indicate the performance gains from architecture (b) are not due to a reduced number of layers. Rather, the 12-layer architecture is beneficial, but there are redundant attention heads in these layers.

### Table 1: Character error rates (CERs) on WSJ for Transformers with encoder structures in Figure 3. # heads/# layers denote the number of heads/layers of the encoder.

| Model   | # Heads | # Layers | eval 92 | dev 93 |
|---------|---------|----------|---------|--------|
| a (baseline) | 48       | 12        | 3.5     | 4.6    |
| b       | 44       | 12        | 3.4     | 4.5    |
| c       | 44       | 12        | 3.7     | 4.6    |
| d       | 42       | 12        | 3.5     | 4.4    |
| e       | 42       | 11        | 3.6     | 4.8    |
| f       | 44       | 11        | 3.6     | 4.7    |

Fig. 2: A sample of attention vectors of the topmost encoder self-attention layer generated by the baseline Transformer. The sampled utterance is form WSJ eval92.

Fig. 3: The tested encoder architectures. Each blue square represents an attention head. Each white square denotes there is no attention head. When all the attention heads of a layer are removed (4 white squares), the feed-forward component of that layer is preserved. The orange square denotes there is no self-attention component/feed-forward component, and thus that layer is completely removed.
It is not time feasible to search for the best architecture through enumeration. To address this, we propose to randomly remove attention heads during training and keep all the attention heads at test time. The proposed method can be viewed as training different architectures and using the ensemble of these trained architectures as the final model at test time. In each training iteration, each attention head has a probability $p$ of being removed, where $p$ is set as a hyper-parameter. If the head is kept during training, then the output of that head is scaled by $\frac{1}{1-p}$:

$$A_i(X^Q, X^K, X^V) = \frac{1}{1-p} \times \text{softmax}\left( \frac{Q_iK_i^T}{\sqrt{d^K}} \right)V_i$$

At test time, the scale factor $\frac{1}{1-p}$ is removed and all the attention heads are always present. Thus, the expected output of the attention head is the same during training and testing. If at a training iteration all the attention heads of a layer are removed, that layer becomes a feed-forward layer. We tested removing encoder attention heads statically (Table 1). In the experiments of stochastic attention head removal, we apply the proposed strategy for both the encoder and the decoder.

4. EXPERIMENTS

4.1. Experimental setup

We experiment on datasets of a variety of scenarios. Table 2 describes these datasets.

| datasets   | language | hours | speech style       |
|------------|----------|-------|--------------------|
| WSJ        | EN       | 81    | read               |
| AISHELL    | ZH       | 170   | read               |
| SWBD       | EN       | 260   | telephone conversation |
| AMI        | EN       | 100   | meeting            |

We use Kaldi [15] for data preparation and feature extraction – 83-dim log-mel filterbank frames with pitch [16]. SpecAugment [17] is used on all datasets except WSJ. On all datasets, following the previous works [2, 4, 8], we employ the Transformers with 12-layer encoders and 6-layer decoders. The multi-head attention components of the self-attention layers have 4 attention heads and $d^K = 64$, $d^M = 256$. For the feed-forward module of the self-attention layers, $d^{FF} = 2048$. Dropout rate 0.1 is used. Below the encoder of the Transformer, there are two convolutional neural network layers with 256 channels, with a stride of 2 and a kernel size of 3, which map the dimension of the input sequence to $d^M$. Input sequences to the encoder and the decoder are concatenated with sinusoidal positional encoding [1]. Models are implemented using ESPnet [19] and PyTorch [20].

The training schedule follows [2]. For WSJ/SWBD the training lasts for 100 epochs and for AISHELL/AMI the training lasts for 50 epochs. The averaged parameters of the last 10 epochs are used as the parameters of the final model [2]. Adam [21] is used as the optimizer. The output units for WSJ/AISHELL/AMI are characters and the output tokens for SWBD experiments are tokenized at word-level using Byte Pair Encoding (BPE) [22]. The batch size is 32. Label smoothing with smoothing weight 0.1 is used. Besides the loss from the Transformer’s decoder $L^D$, a connectionist temporal classification (CTC) [23] loss $L^{CTC}$ is also applied to the Transformer encoder [24]. Following [4], the final loss $L$ for the model is:

$$L = (1 - \lambda) L^D + \lambda L^{CTC}.$$  (9)

where $\lambda = 0.2$ for SWBD and $\lambda = 0.3$ for other datasets.

Since the attention heads are removed randomly, to show the proposed method is stable, on WSJ, AMI, and SWBD, we run experiments three times with different random seeds. In the experiments of static attention heads removal (Table 1), encoder structure (b) which has 44 heads has given lower CERs and the baseline encoder has 48 heads in total. Thus, in the experiments of stochastic attention head removal, we test the removal probability from $1 - \frac{44}{48}$, and the proposed stochastic attention head removal strategy is applied to both the encoder and the decoder.

4.2. Experimental results

Table 3 summarises the experimental results on WSJ. The attention head removal probability $\frac{8}{48}$ consistently gives the best results on eval92, and it yields almost identical CERs on dev93 compared to the baseline. The removal probability $\frac{10}{48}$ has CERs which are never worse than the baseline. Furthermore, Table 1 shows only reducing the number of attention heads can lead to inferior performance. Thus, we conclude the proposed stochastic attention head removal strategy consistently improves the model’s performance.

| removal probability | seed 1 | seed 2 | seed 3 |
|---------------------|--------|--------|--------|
| 0 (baseline)        | 3.5/4.6| 3.6/4.5| 3.5/4.6|
| 4/44                | 3.6/4.5| 3.5/4.6| 3.5/4.4|
| 6/48                | 3.4/4.5| 3.5/4.6| 3.4/4.7|
| 8/48                | 3.4/4.6| 3.4/4.6| 3.4/4.6|
| 10/48               | 3.5/4.6| 3.5/4.5| 3.4/3.5|

On the AISHELL dataset, we run the experiments with three different random seeds. Then, we run a set of experiments with speed perturbation [25] at ratio 0.9/1.0/1.1 and decoding with a recurrent neural network language model (RNNLM) [26]. Table 4 shows all the tested probabilities are effective in the experiments without speed perturbation. In the experiments with speed perturbation and RNNLM decoding, we use probabilities 0.1 and 0.2 since the previously tested probabilities are approximately within this range. Due to speed perturbation, the training set has 510 hours of data in
total and the proposed method is still effective. Our training method achieves state-of-the-art CERs without using external data or modifying the original Transformer architecture.

Table 4: CERs on AISHELL of stochastic head removal.

| removal probability | seed 1 (CER%) | seed 2 (CER%) | seed 3 (CER%) |
|---------------------|---------------|---------------|---------------|
| 0 (baseline)        | 7.3/8.3       | 7.3/8.3       | 7.2/8.3       |
| 4/44                | 7.2/8.0       | -             | -             |
| 6/48                | 7.1/8.1       | 7.2/8.0       | 7.2/8.0       |
| 8/48                | 7.2/8.1       | -             | -             |
| 0 + speed perturbation + RNNLM | 6.0/6.5      |               |               |
| 1/10 + speed perturbation + RNNLM | 5.8/6.3      |               |               |
| 2/10 + speed perturbation + RNNLM | 5.8/6.3      |               |               |
| Previous works      |               |               |               |
| Transformer [4]     | 6.0/6.7       |               |               |
| Transformer + 5,000 hours pretrain data [6] | 6.26         |               |               |
| Memory equipped self-attention [27] | 5.74/6.46    |               |               |

Table 5 shows the experiment results on SWBD. For all tested probabilities, the proposed training method steadily gives lower word error rates (WERs). The probability $\frac{6}{10}$ results in significant performance gains and yields noticeably better results compared to the previous works on Transformers. This set of experiments shows our method is effective for telephone conversation, which is a more complicated speech recognition scenario than reading (WSJ/AISHELL).

Table 5: WERs on SWBD for stochastic head removal.

| SWBD/Callhome (WER%) | removal probability | seed 1 | seed 2 | seed 3 |
|----------------------|---------------------|--------|--------|--------|
| 0 (baseline)         | 9.0/18.1            | 9.1/18.2 | 9.1/17.9 |
| 4/44                 | 8.9/17.5            | 8.7/17.6 | -      |
| 6/48                 | 8.6/17.2            | 8.7/16.9 | 8.7/16.8 |
| 8/48                 | 8.8/17.6            | 8.9/17.2 | -      |
| Previous works       |                     |        |        |        |
| Transformer [4]       | 9.0/18.1            |        |        |        |
| Very deep self-attention [3] | 10.4/18.6   |        |        |        |
| Multi-stride self-attention [5] | 9.1/     |        |        |        |

We use AMI to test our method on a more difficult ASR task. We use the individual headset microphone (IHM) setup. The decoding is with an RNNLM. Table 6 summarizes the results. With the proposed training method, our model outperforms very strong conventional systems.

Table 6: WERs on AMI for stochastic head removal.

| removal probability | dev/test (WER %) |
|---------------------|------------------|
| 0 (baseline)        | 24.9/25.8        |
| 1/10                | **24.2/24.6**    |
| 2/10                | 24.3/24.8        |
| Previous works      |                  |
| 2D Conv [28]        | 24.9/24.6        |
| TDNN [28]           | 25.9/26.0        |
| OctCNN [29]         | 32.3/37.2        |

We found there are unnecessary attention heads in the trained Transformers. Based on this observation, we train models with reduced numbers of attention heads from scratch. We observed that for structures with the same number of attention heads, some architectures yield higher accuracies. We propose to randomly removing attention heads during training and keep all attention heads at test time. Thus, the trained model can be viewed as an ensemble of models with different numbers of heads while for dropout the final network can be viewed as an average of networks with reduced numbers of units.

Peng et al [33] proposed to train subsets that contain $h-1$ elements of the $h$ attention heads. During testing, the output is a linear combination of the outputs of these subsets. In our work, the attention heads are randomly removed. Therefore, in each training iteration, the number of trainable attention heads is not fixed.

6. CONCLUSION

We found there are unnecessary attention heads in the trained Transformers. Based on this observation, we train models with reduced numbers of attention heads from scratch. We observed that for structures with the same number of attention heads, some architectures yield higher accuracies. We propose to randomly removing attention heads during training and keep all attention heads at test time. Thus, the trained model can be viewed as an average of the structures with different numbers of attention heads. The proposed method consistently gives noticeable performance gains on datasets of a variety of ASR scenario. Since some structures with reduced numbers of attention heads give higher error rates, the performance gains of the proposed method are not due to the reduced numbers of attention heads during training. Rather, the benefit comes from the ensemble of different architectures.

The proposed method may bring even larger performance gains in training self-attention models which have very large numbers of attention heads in each layer since large numbers
of attention heads indicate massive collections of different structures during training. This is left as further work.

7. REFERENCES

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