GAUSSIAN KERNELIZED SELF-ATTENTION FOR LONG SEQUENCE DATA AND ITS APPLICATION TO CTC-BASED SPEECH RECOGNITION

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ABSTRACT

Self-attention (SA) based models have recently achieved significant performance improvements in hybrid and end-to-end automatic speech recognition (ASR) systems owing to their flexible context modeling capability. However, it is also known that the accuracy degrades when applying SA to long sequence data. This is mainly due to the length mismatch between the inference and training data because the training data are usually divided into short segments for efficient training. To mitigate this mismatch, we propose a new architecture, which is a variant of the Gaussian kernel, which itself is a shift-invariant kernel. First, we mathematically demonstrate that self-attention with shared weight parameters for queries and keys is equivalent to a normalized kernel function. By replacing this kernel function with the proposed Gaussian kernel, the architecture becomes completely shift-invariant with the relative position information embedded using a frame indexing technique. The proposed Gaussian kernelized SA was applied to connectionist temporal classification (CTC) based ASR. An experimental evaluation with the Corpus of Spontaneous Japanese (CSJ) and TEDLIUM 3 benchmarks shows that the proposed SA achieves a significant improvement in accuracy (e.g., from 24.0% WER to 6.0% in CSJ) in long sequence data without any windowing techniques. 

Index Terms: speech recognition, end-to-end, self-attention, long sequence data

1. INTRODUCTION

In recent years, automatic speech recognition (ASR) using self-attention (SA) [1] has attracted considerable attention. Both transformer-based speech recognition [2–6] and hybrid [7, 8] and connectionist temporal classification (CTC) [9, 10] models have shown a high recognition performance with SA. The SA network has a mathematically simple structure by fully using matrix-vector linear operation for parameters. However, SA is unsuitable for decoding long sequence data because it has a high computational complexity on the order of the square of the sequence length. In addition, the recognition accuracy degrades in long utterances owing to its excessive flexibility in context modeling. In this paper, we focus on the problems of the accuracy degradation in long sequence data. In general, self-attention requires dividing original long recordings into short segments during training for efficient GPU computing. This leads to a mismatch between the sequence lengths of the training and test data, resulting in a performance degradation.

To solve this problem, several studies have been proposed. Masking [11] limits the range of self-attention by using a Gaussian window, whereas relative positional encoding [12, 13] uses relative embedding in a self-attention architecture to eliminate the effect of the length mismatch. However, masking does not take into account the correlation between input features and relative distance. In addition, the relative positional encoding does not limit the attention to the neighborhood in a mathematical.

Inspired by the mathematical expression based on the shared-QK attention used in Transformer [14], in this paper, yet another self-attention reformulation based on a Gaussian kernel is proposed. First, we mathematically demonstrate that the linear layers and softmax functions in the shared-QK attention can be represented as normalized kernel functions, similarly to [15] and [16], interpreting bilinear pooling as a kernel function. These kernel functions are replaced with a Gaussian kernel and thus we call our model Gaussian kernelized self-attention. Gaussian kernel, known as a radial basis function kernel, has several useful features and has been widely used with a support vector machine (SVM) [17–21]. The Gaussian kernelization applied in our new formulation also provides a shift-invariance into the self-attention architecture. This shift-invariant property is a highly desirable property for controlling the relative position. To take advantage of this property, we propose concatenating the bare frame index to an input feature, which is called a frame indexing technique.

To compare the differences in SA structure, this paper applies the proposed Gaussian kernelized SA to CTC-based ASR because the decoder network of a CTC is rather simple compared with other end-to-end architectures, and we can purely evaluate the effectiveness between the proposed and conventional SA methods. An experimental evaluation shows that our proposed SA with frame indexing achieved a significant improvement in the long sequence data.

2. SELF-ATTENTION FOR LONG SEQUENCE DATA

2.1. Self-attention

Let \( X_i \) and \( X_j \) be \( D \)-dimensional input features of the self-attention network with time indexes \( i \) and \( j \) in a sequence, respectively. The scaled dot product attention [1] calculates the attention weight as follows:

\[
\text{Attn}(i, j) = \text{softmax} \left( \frac{(W^{(Q)} X_j)^\top (W^{(K)} X_i)}{\sqrt{d_k}} \right)
\]

where \( W^{(Q)} \) and \( W^{(K)} \) represent \( d_k \times D \) trainable matrices in the linear operation for \( X_i \) and \( X_j \), respectively. Note that the bias term is included in each matrix. Multi head attention, which individually calculates the above attention in multiple heads, is effectively used in every layer. For simplicity, we omit the head and layer indexes in our formulation.

2.2. Masking

Self-attention itself attends to the target frames without any positional limitations. This flexibility is an advantage over conventional neural networks. However, in typical speech recognition encoders,
local information is more important than global characteristics for representing phonetic features, particularly in long sequences. Therefore, several masking approaches are studied to control the attention and allow it to be more local.

Sperber et al. used a self-attention architecture with a weighting technique applying a hard or soft mask in acoustic modeling [11]. They limited the target frames to be calculated by adding a mask that has values within a range of $-\infty$ to zero to the attention before the softmax function. In [11], the authors reported that the soft mask itself does not limit the attention to the neighborhood of the frame. By contrast, masking is a reasonable approach for the encoder of the conventional shared-QK attention in Eq. (9). The proposed self-attention architecture requires the query and key matrices to be calculated using a shared linear transform and the corresponding value matrix $V^{(S)}$ is shift-invariant. In addition, because it is an exponential function, the attention value approaches zero as the difference between the shared-QK attention in Eq. (9) and $\Sigma$ in Eq. (7) is a positive semidefinite matrix, which can be regarded as the inverse of the full-covariance matrix.

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3.5. Relative positional information with frame indexing

The Gaussian kernel is a function that depends only on the $X_i - X_j$ term as in Eq. (10). However, the Gaussian kernel itself does not have the ability to obtain relative positional information. Therefore, we include the absolute positional information by simply appending the frame index $i$ to $X_i$. Owing to the shift-invariant nature of the Gaussian kernelized self-attention, the $X_i - X_j$ term is rewritten as follows:

$$
\hat{X}_i - \hat{X}_j = [(X_i - X_j)\top, (i - j)/\alpha]\top,
$$

where $\alpha$ is a scaling factor used to control the scales of the relative position and the input features, and is normalized through a layer normalization function. We set $\alpha$ to 100 in this paper.

By assigning Eq. (12) to Eq. (10), the frame indexing element becomes similar to Eq. (2). However, because $\Sigma^{-1}$ in Eq. (7) is trained by considering both $X_i$ and frame indexing, the standard deviation of the Gaussian window, which is proportional to $\Sigma$, is statistically adaptive to the input features. Thus, the proposed method properly embeds relative positional information to the model by concatenating the frame indexing to the input features. Note that the original self-attention has energy terms as in Eq. (9). When the frame indexes are concatenated to the input feature in the same way as the Gaussian kernel, these energy terms become dependent on the absolute indexes. Therefore, this indexing is ineffective unless the attention architecture is shift-invariant, as shown in the experiments below.

4. EXPERIMENTAL EVALUATION

4.1. Experimental setup

The Gaussian kernelized self-attention was evaluated using the CSJ dataset [22] and TED-LIUM 3 dataset [23]. We compared the Gaussian kernelized self-attention with an RNN, self-attention (Sec. 2.1), masking (Sec. 2.2), relative encoding (Sec. 2.3), and shared-QK attention (Sec. 2.4). The CTC [24] model based on self-attention [9] was used as our baseline architecture to purely compare the difference between the proposed and other self-attention methods because CTC has a simple decoder architecture compared with other end-to-end models. The methods other than an RNN were implemented under the same conditions except for the structure corresponding to the self-attention. The baseline model consisted of convolutional layers and a subsequent 12-layer self-attention blocks. In each self-attention block, the number of dimensions $d_h$ in Eq. (4) was 256 and the number of heads was 4. A middle linear layer followed each self-attention network and a position-wise feedforward network expanded the dimension of the middle layer to 2,048. The input features were 80-dimensional Mel filter banks and pitch features. The SpecAugment [25] technique was applied to the data. In addition, the features were subsampled to reduce their number by a factor of 4 in the convolutional layers. A positional encoding was added to the input feature just before the first self-attention block. The RNN based encoder consisted of 4 RNN layers with 1,204 units. All methods were evaluated using greedy decoding without any external language model to purely evaluate the performance of the proposed self-attention network.

For CSJ data, the training and development set consisted of 413,408 and 4,000 utterances, respectively. The tokens consisted of 3,262 Japanese characters, including a blank label. For the evaluation data, we prepared standard evaluation sets, eval1, eval2, and eval3, which were split into short segment units (short eval (1, 2, 3)). To investigate the recognition performance in long sequence data, we also used the original long data without splitting into segments as an additional evaluation set (long eval (1, 2, 3)). The average sequence length was approximately 4.7 sec. for a short evaluation, and 772.6 sec. for long evaluation.

For TED-LIUM 3 data, the training and development sets consisted of 268,262 and 507 utterances respectively. The tokens consisted of 654 English tokens which were encoded using the unigram language model [26], including a blank label. For the evaluation data, a longer dataset was prepared in addition to the standard set as in CSJ. The average sequence length was 8.2 sec. and 1,004.1 sec., respectively. Note that the longest single talk (1,772 sec.) was extremely long, and was evaluated by splitting it in half to avoid a memory shortage.

4.2. Results

Table 1 shows the performance of different model architectures in the CSJ data. In our experiments, the self-attention and shared-QK
attention achieved similarly lower error rates in the short dataset. However, in the long dataset, the accuracy of these methods decreased. As reason for this, the structure of the self-attention itself could not limit the attention to its neighborhood. By contrast, masking was effective and the performance difference between short and long sequence data was small. However, the recognition performance for short utterances was worse than that of a simple self-attention because the flexibility of the attention was suppressed by the fixed-length window. As with self-attention, Gaussian kernelization achieved low error rates in short sequence data, but its performance degraded significantly in long sequence data. By using the frame indexing to take into account the relative positional information along with the input features, the Gaussian kernelized attention significantly improved the recognition performance in long sequence data. However, when the frame indexing was used for self-attention, the recognition accuracy significantly degraded in both short and long utterances. This was because the energy term of the self-attention became dependent on the absolute positional information, which greatly reduced its generalization ability.

Unfortunately, we could not decode the long data using the relative positional encoding. Because the second term of Eq. (1) required the same amount of memory as the self-attention, relative positional encoding required more than twice as much memory, at over 700 GB.

Therefore, we further investigated the speech recognition performance per utterance length including the relative positional encoding within a decodable range. We sampled 100 segments each from the CSJ eval1 set to create subsets such that the average utterance length of each subset became 10 seconds, 20 seconds, and so on. Figure 2 visualizes the attention weights obtained by a standard self-attention network based on $\text{Attn}(i, j)$ in Eq. (4) (Figure 2 (a) and (d)), the Gaussian kernelized self-attention $\text{Attn}^{\text{Gk}}(i, j)$ in Eq. (10) (Figure 2 (b) and (e)), and the Gaussian kernelized self-attention with the frame indexing in Eq. (12) (Figure 2(c) and (f)). Self-attention was flexible in short utterances as indicated in Figure 2(a). However, when there was a length mismatch between the training and testing data, attention was dispersed and the attention weights became smaller, as shown in Figure 2(d). In the case of the Gaussian kernel, the diagonal components mathematically became peaky as in Figure 2(b). However, the attention was dispersed in long sequence data as in the case of self-attention shown in Figure 2(e). By contrast, using frame indexing, the components around the diagonal location were correctly attended even in the long speech, as indicated in Figure 2(f).

Table 2 shows the performance for the TED-LIUM 3 data. In this case, masking maintained the recognition performance even for short utterances. The performance of the self-attention with frame indexing was significantly worse than that of CSJ data. This may be because the average length of the evaluation data was longer than that of CSJ. By contrast, the Gaussian kernelized self-attention with frame indexing can achieve a low token error rate similar to masking for both short and long data.

### 5. CONCLUSION

In this paper, we proposed a new SA architecture called Gaussian kernelized SA. This structure was a natural combination of conventional masking with the kernel structure of SA. With frame indexing, the attention can statistically adapt depending on both the input features and their relative positions. We applied this novel structure to the encoder of the CTC-based ASR model to improve the recognition performance in long sequence data, which showed length mismatches between the training and testing data. In the experiments using CSJ and TED-LIUM 3 data, the Gaussian kernelized SA with frame indexing achieved a performance close to that of conventional SA in short sequence data. In addition, our model achieved a significant accuracy improvement (e.g., from 24.0% WER to 6.0% in the Corpus of Spontaneous Japanese (CSJ) benchmark) in long sequence data. In the future, we will attempt to apply the Gaussian kernelized self-attention to RNN-T. In addition, we will expand the Gaussian kernel to include asymmetric attention and source-target attention and use our architecture in a transformer-based ASR.

### Table 1: Comparison of the recognition performance (character error rate) for short and long data in CSJ data. The relative encoding in long sequence data was skipped due to the huge memory requirements over 700GB (-).

| average length (sec.) | short data | long data |
|-----------------------|------------|-----------|
| eval1 | eval2 | eval3 | avg. | eval1 | eval2 | eval3 | avg. |
| RNN | 7.9 | 5.8 | 6.3 | 6.7 | 9.7 | 6.5 | 7.4 | 7.9 |
| self-attention | 6.5 | 4.7 | 5.3 | 5.5 | 25.4 | 23.6 | 23.1 | 24.0 |
| + soft mask | 7.8 | 5.5 | 6.4 | 6.6 | 9.1 | 6.2 | 7.0 | 7.4 |
| + frame indexing | 20.4 | 26.4 | 18.9 | 21.9 | 80.1 | 78.5 | 75.2 | 77.9 |
| + relative encoding | 9.5 | 7.9 | 10.1 | 9.2 | - | - | - | - |
| + shared-QK | 6.3 | 4.9 | 5.7 | 5.6 | 82.1 | 81.4 | 77.4 | 80.3 |
| + Gaussian kernel | 6.7 | 4.7 | 5.6 | 5.7 | 79.9 | 79.1 | 79.0 | 79.3 |
| + frame indexing | 6.5 | 4.5 | 5.4 | 5.5 | 7.5 | 5.0 | 5.6 | 6.0 |

### Table 2: Comparison of the recognition performance (token error rate) for short and long data in TED-LIUM 3 data.

| average length (sec.) | short data | long data |
|-----------------------|------------|-----------|
| dev | test | dev | test |
| RNN | 21.7 | 25.6 | 22.4 | 30.8 |
| self-attention | 15.2 | 17.3 | 82.8 | 84.6 |
| + soft mask | 14.7 | 17.4 | 15.0 | 22.0 |
| + Gaussian kernel | 21.9 | 20.1 | 99.0 | 98.5 |
| + frame indexing | 15.0 | 17.2 | 114.9 | 21.0 |
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