LEARNING MONOTONIC ALIGNMENTS WITH SOURCE-AWARE GMM ATTENTION

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ABSTRACT

Transformers with soft attention have been widely adopted to various sequence-to-sequence tasks. While the soft attention is effective for learning semantic similarities between queries and keys based on their contents, it does not explicitly model the order of elements in sequences which is crucial for monotonic sequence-to-sequence tasks. Learning monotonic alignments between input and output sequences could be beneficial for long-form and online inference applications that are still challenging problem for the conventional soft attention algorithm. In this paper, we focus on monotonic sequence-to-sequence tasks and propose Source-Aware Gaussian Mixture Model (SAGMM) attention in which the attention scores are monotonically calculated considering both the content and order of the source sequence. We show that the proposed attention mechanism improves the performance on the online and long-form speech recognition problems without performance degradation in offline in-distribution speech recognition through experiments.

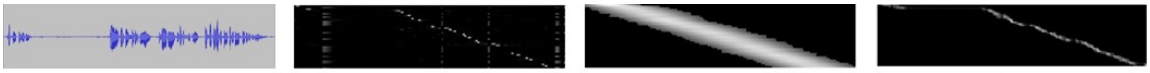
1 INTRODUCTION

For a recent few years, the transformer models with soft attention have been widely adopted to various sequence generation tasks (Raffel et al., 2019; Vaswani et al., 2017; Parmar et al., 2018; Karita et al., 2019). The soft attention does not explicitly model the order of elements in the sequence and attends all encoder outputs for each decoder step. However, the order of elements is crucial to understand monotonic sequence-to-sequence (Seq2Seq) tasks, e.g. automatic speech recognition (ASR), video analysis, and lip reading. Learning monotonic alignments helps model to attend to a subset of the encoder output without performance degradation in these tasks. In comparison, the soft attention is not suitable for streaming inference applications since the softmax operation needs to wait until all encoder outputs are produced. Figure 1 (b) shows the attention plot from soft-attention. The soft attention learns alignments between queries and keys based on their similarities while it requires all encoder tokens before attention score calculation. Furthermore, the soft attention has difficulty to decode long-form sequences which are not considered in training corpus.

The Gaussian Mixture Model (GMM) attention Graves (2013); Battenberg et al. (2020); Chiu et al. (2019) has been proposed to learn the monotonic mapping between encoder and decoder states for long-form sequence generation. The GMM attention is a pure location-aware algorithm in which the encoder contents are not considered during attention score calculation. However, each element in encoder output sequences has different amount of information and should be attended considering their contents. As shown in figure 1 (c), the GMM attention fails to learn detailed alignments and attends to many tokens simultaneously.

In this paper, we adopt the GMM attention mechanism to modern transformer structure and propose Source-Aware Gaussian Mixture Model (SAGMM) attention which considers both contents and orders of source sequences. Each component in SAGMM is multi-modal and discard non-informative tokens in attention

window. For online inference, we propose truncated SAGMM (SAGMM-tr) by discarding long-tail of the attention score in SAGMM. To the best of our knowledge, this is the first attempt to adopt the GMM-based attention to online sequence generation tasks. Learning accurate monotonic alignments helps SAGMM-tr to attend to a relevant subset of sequences for each decoder step and improves the performance of model in streaming and long-form sequence generation tasks. Figure 1 (d) shows the monotonic alignments learned by SAGMM-tr which enables online inference. The experiments on streaming and long-form ASR showed substantial performance improvements compared to conventional algorithms without performance degradation on offline in-distribution ASR. We also tested SAGMM-tr in machine translation task and showed the performance of proposed algorithm in non-monotonic tasks.



(a) (b) (c) (d)

Figure 1: The input speech waveform (a) and attention plots between speech waveform and transcription learned by (b) soft attention, (c) GMM attention, and (d) SAGMM-tr attention.

2 SOURCE-AWARE GMM ATTENTION

2.1 SOFT ATTENTION

In this paper, we abbreviate the head index h during attention score calculation for simplicity. In the dot-product multi-head soft attention Vaswani et al. (2017) without relative positional encoding , the attention score from soft attention α_{Soft} is derived from the query matrix $Q \in \mathbb{R}^{I \times d}$ and key matrix $K \in \mathbb{R}^{J \times d}$ as follows:

$$\alpha_{Soft} = \text{softmax}\left(QK^{\intercal}/\sqrt{d}\right) \tag{1}$$

where d, I, and J are feature dimension, decoder and encoder sequence length, respectively. The attention context matrix form h-th head H^h and the multi-head output M is given by

$$\mathrm{H}^h = \alpha^h_{Soft} V^h \tag{2}$$

$$\mathrm{M} = \text{concat}\left[\mathrm{H}^1; ...; \mathrm{H}^{n_h}\right] W_O \tag{3}$$

where α^h_{Soft} denotes α_{Soft} for h-th head, $V^h \in \mathbb{R}^{J \times d}$ is value matrix for h-th head, and n_h denotes the number of heads. In this paper, we adopt the relative positional encoding Shaw et al. (2018); Dai et al. (2019) for self-attention layers. The relative positional encoding gives a more strong baseline for the long-form sequence generation.

2.2 GMM ATTENTION

The previous studies on GMM attention Battenberg et al. (2020); Chiu et al. (2019) are based on early content-based attention (Cho et al., 2014). Li et al. (2020) adopt the GMM attention to the transformer framework, but they do not provide detailed descriptions. In this paper, we adopt v2 model in Battenberg et al. (2020) which improves the performance of attention mechanism proposed in Graves (2013).

We define the GMM attention as a variant of the multi-head attention by considering a Gaussian distribution component as an attention score of single-head in multi-head mechanism. Our GMM model is similar to Battenberg et al. (2020) when the value matrix is shared for all Gaussian components. The multi-head value matrices helps to attend to information from different representation subspaces (Vaswani et al., 2017).

Let us denote the i-th row of Q as $Q_i \in \mathbb{R}^{1 \times d}$. The normal distribution parameters for i-th step are given by

$$\Delta_i,\ \sigma_i,\ \phi_i = \zeta\left(Q_i W_\Delta\right),\ \ \zeta\left(Q_i W_\sigma\right),\ \ Q_i W_\phi \tag{4}$$

$$\mu_i = \Delta_i + \mu_{i-1} \tag{5}$$

where $\zeta(x)$ is a softplus function of x, and $W_\Delta \in \mathbb{R}^{d\times 1}$, $W_\sigma \in \mathbb{R}^{d\times 1}$, $W_\phi \in \mathbb{R}^{d\times 1}$. The softplus function is adopted similar to Battenberg et al. (2020) in which softplus activation showed better performance than exponential operation. A mixture component of the GMM attention, from i-th decoder step to j-th encoder token, is derived from the $\alpha_{GMM\|_{i,j}}$ is defined as follows:

$$N\left(j, \mu_i, \sigma_i\right) = \frac{1}{\sqrt{2\pi\sigma_i}} exp\left(-\frac{\left(j-\mu_i\right)^2}{2\sigma_i}\right) \tag{6}$$

$$\alpha_{GMM\|_{i,j}} = N\left(j, \mu_i, \sigma_i\right) \tag{7}$$

$$\mathrm{H}_i^h = \mathrm{softmax}_h\left(\phi_i^h\right) \sum_j \alpha^h_{GMM\|_{i,j}} V_j^h. \tag{8}$$

where $\mathrm{softmax}_h$ denotes softmax function over heads.

The conventional GMM attention mechanism is analogous to integral of source sequences with an uniform axis spacing as shown in Figure 2 (a). In this figure, each rectangle denotes the attention score with given Gaussian component parameters. The GMM attention assumes that each encoder output is equally important. However, this assumption is not satisfied for many input modalities, e.g. speech and videos from real environments. Moreover, the number of modes in GMM attention is limited by the number of mixture components. To learn robust alignments for monotonic Seq2Seq tasks, we propose SAGMM which considers both contents and locations during attention mechanism.

2.3 Source-aware GMM attention

Figure 2 (b) shows the scheme of proposed SAGMM attention. Compared to the GMM attention, the SAGMM is analogous to integral of normal distribution with non-uniform spacing based on encoder contents. In the figure 2 (b), the width of rectangle δ_j controls the model to selectively attend to the informative tokens during attention score calculation. This content-aware property of SAGMM helps the model learning stable monotonic alignments from the training corpus. Furthermore, SAGMM can easily discard non-informative tokens and aggregate information distributed over several remote tokens.

In SAGMM, the normal distribution parameter $\Delta_i, \sigma_i, \phi_i$, and μ_i are derived from the same equation with equation 4 and equation 5. To encode the contents of source sequences, the weight for each encoder output δ_j is given from the j-th row of the key matrix K as follows:

$$\delta_j = \mathrm{sigmoid}\left(K_j W_\delta\right). \tag{9}$$

where $W_\delta \in \mathbb{R}^{d\times 1}$ and the sigmoid function is introduced to smoothly bound the maximum weight δ_j similar to Dong & Xu (2020).

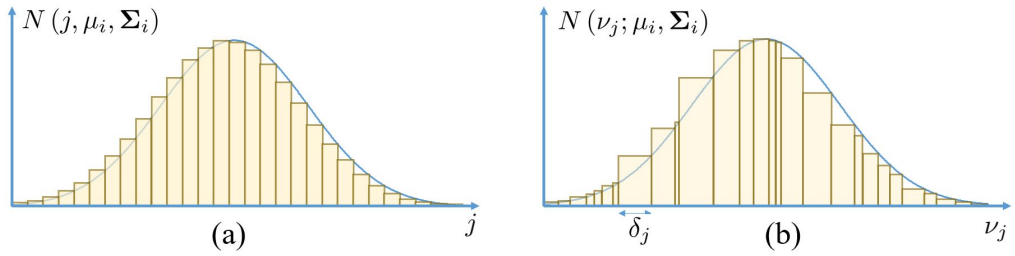


Figure 2: Scheme of (a) conventional GMM and (b) SAGMM attention score calculation which are analogous to integral of normal distribution on uniform and non-uniform axis spacing, respectively.

Then, the probability of normal distribution $N(\nu_j; \mu_i, \sigma_i)$ is calculated from its cumulative sum ν_j given by

$$\nu_j = \delta_j + \nu_{j-1} \tag{10}$$

$$N\left(\nu_j; \mu_i, \sigma_i\right) = \frac{1}{\sqrt{2\pi\sigma_i}} exp\left(-\frac{\left(\nu_j - \mu_i\right)^2}{2\sigma_i}\right) \tag{11}$$

Finally, the SAGMM attention score α_{SAGMM} is defined as follows:

$$\alpha_{SAGMM\|_{i,j}} = \delta_j \; N\left(\nu_j; \mu_i, \sigma_i\right) \tag{12}$$

where δ_j where δ_j is multiplied to describe uneven step size in summation.

In the early stage of training, we introduce length penalty loss to help learning alignments between μ and ν defined as

$$L_{length} = \lambda_{length} * \left(\left(\mu_I - \min\left(I, J\right)\right)^2 + \left(\nu_J - \min\left(I, J\right)\right)^2\right). \tag{13}$$

with $\lambda_{length} = 0.0005$ where I and J denote the length of decoder and encoder sequences, respectively. We turned off L_{length} after 200K training steps in experiments. Finally, we modify 5 as $\mu_i = \mu_{i-1} + \min(\max(\Delta_i, 0), 3)$ to scale the μ_i and ν_j similar to token indices. This modification helps the interpretability of μ and ν by scaling them.

The attention score for each encoder token in SAGMM is determined independently since they do not rely on softmax operation over encoder outputs. Note that $\sum_j \delta_j \; N\left(\nu_j; \mu_i, \sigma_i\right)$ approximates the integral of Gaussian distribution. Thus the sum of attention weights is close to 1, which helps numerical stability and learning without using softmax.

2.4 SAGMM-TR FOR ONLINE INFERENCE

Since the attention score in SAGMM is generated without softmax normalization over all encoder tokens, we can simply build the attention for streaming inference by cropping the long-tail of the Gaussian distribution. In SAGMM-tr, the normal distribution is truncated to limit past and future context as follows:

$$N_{tr}\left(\nu_j; \mu_i, \sigma_i\right) = \begin{cases} \frac{1}{\sqrt{2\pi\sigma_i}} exp\left(-\frac{(\nu_j - \mu_i)^2}{2\sigma_i}\right), & if \; \mu_i - 2\sqrt{\sigma_i} < \nu_j < \mu_i + 2\sqrt{\sigma_i} \\ 0, & else. \end{cases} \tag{14}$$

$$\alpha_{SAGMM\text{-}tr\|_{i,j}} = \delta_j \; N_{tr}\left(\nu_j; \mu_i, \sigma_i\right) \tag{15}$$

$$\mathrm{H}_i^h = \mathrm{softmax}_h\left(\phi_i^h\right) \sum_{j \in \mu_i - 2\sqrt{\sigma_i} < \nu_j < \mu_i + 2\sqrt{\sigma_i}} \alpha^h_{SAGMM-tr\|_{i,j}} V_j^h. \tag{16}$$

Discarding the tokens with threshold $2\sqrt{\sigma_i}$ removes about 5% percent of attention score. In online inference with SAGMM-tr, H_i^h can be calculated after ν_j becomes larger than $\mu_i + 2\sqrt{\sigma_i}$. Note that when $\nu_j \geq \mu_i + 2\sqrt{\sigma_i}$ satisfies in for a current token $j = \beta_i$, then the equation also satisfies for all $j > \beta_i$ and we can calculate H_i^h without waiting future contexts.

We initialize the parameters of SAGMM-tr attention with those from SAGMM model and fine-tuned them until the performance converges. We found that the models with SAGMM-tr showed slightly better performance than SAGMM and mainly reported the results with SAGMM-tr model.

For online speech recognition with SAGMM-tr, we randomly concatenate the **1**-vector after the end of source sequence with a probability p_{eos} in the training stage and trained to emit the end-of-sequence token EOS only with the utterances containing **1**-vector. The **1**-vector concatenation helps to suppress the EOS token

in a long silence part. Finally, we build the uni-directional encoder whose maximum latency is similar to Zhang et al. (2020); Dong et al. (2019) by adopting the block-wise mask on self-attention layers. The detailed explanation for the block-wise masking is given in Appendix. Algorithm 1 in appendix shows a pseudo code for the SAGMM-tr attention in inference stage.

The number of tokens we need to waits in equation 14 - 16 is given by model parameters. To strictly limit the maximum latency of model, we also trained and tested SAGMM-tr with fixed attention window width c in experiments. In this version, equation 14 - 16 are modified as follows:

$$\gamma_i = \underset{\gamma_{i-1} \leq j < J}{\arg\max}\, N\left(\nu_j; \mu_i, \sigma_i\right) \tag{17}$$

$$N_{tr}\left(\nu_j; \mu_i, \sigma_i\right) = \begin{cases} \frac{1}{\sqrt{2\pi\sigma_i}} exp\left(-\frac{(\nu_j-\mu_i)^2}{2\sigma_i}\right), & if\ \gamma - \frac{c}{2} < j < \gamma_i + \frac{c}{2} \\ 0, & else. \end{cases} \tag{18}$$

$$\alpha_{SAGMM\text{-}tr\|_{i,j}} = \delta_j\ N_{tr}\left(\nu_j; \mu_i, \sigma_i\right) \tag{19}$$

$$\mathrm{H}_i^h = \sum_{\gamma_i - \frac{c}{2} < j < \gamma_i + \frac{c}{2}} \alpha_{SAGMM\text{-}tr\|_{i,j}} V_j. \tag{20}$$

In equation 20, we wait $\frac{c}{2}$ additional tokens before producing output. We compared the performance of SAGMM-tr with adaptive and fixed window length in experiments.

3 Related works

Chiu & Raffel (2018) propose monotonic chunkwise attention (MoChA) based on hard monotonic sampling over attention window (Raffel et al., 2017). The monotonic multi-head attention Ma et al. (2019); Inaguma et al. (2020) and monotonic infinite lookback attention Arivazhagan et al. (2019) are based on the concept similar to (Chiu & Raffel, 2018). MoChA replaces hard sampling operation to probability distribution over memory in the training stage. In contrast, SAGMM uses the same operations for training and inference. Also, MoChA relies on numerically unstable cumulative product which requires additional efforts for training (Miao et al., 2019; Raffel et al., 2017). In contrast, SAGMM adopts the stable cumulative sum to describe monotonic alignments. Finally, MoCha is not effective for long-form speech recognition compared to GMM attention Chiu et al. (2019) while our model outperformed GMM in "test-long" set in experiments.

Dong & Xu (2020) introduce the encoder output weight for ASR task. Compared to their work, our attention mechanism considers the decoder content during attention score calculation. SAGMM also allows the overlap between successive attention windows which is helpful to generate semantics that span several decoder tokens. Lee et al. (2020) propose the online attention mechanism without softmax operation by aggregating the information of the encoded sequence with update gate. Similar to soft attention, their model does not learn monotonic alignment. Also, the update gate for online inference in Lee et al. (2020) is uni-modal.

The location-aware attention Chorowski et al. (2015); Watanabe et al. (2017); Moritz et al. (2019) is proposed to employ positional information to the content-based attention mechanism. The location-aware attention introduces attention score in the previous step as additional argument for the current step. However, it it not streamable attention.

The non-attentive neural network-based approaches which do not rely on encoder-decoder attention have been studied by Connectionist Temporal Classification (CTC) Graves et al. (2006); Liptchinsky et al. (2017); Li et al. (2019), and RNN-transducer (RNN-T) Graves (2012), Transformer-transducer (Transformer-T) Zhang et al. (2020); Yeh et al. (2019), and Imputer Chan et al. (2020). We focus on the Seq2Seq approach which do not require an assumption on sequence lengths and uses the simple beam search algorithm for inference. Finally, the block-wise inference has been widely studied with manually defined decoding blocks Jaitly et al. (2015); Tsunoo et al. (2020) or joint decoding with CTC model Moritz et al. (2020). We do not use the joint CTC decoding Kim et al. (2016) nor human supervision for the blocked inference.

4 EXPERIMENT

We conducted experiments in the speech command Warden (2018) and LibriSpeech Panayotov et al. (2015) datasets to compare the performance of our model in standard, online and long-form ASR tasks. We only compare the end-to-end speech recognition model without the external language model (LM) rescoring. We also performed preliminary experiments on the translation task to show the performance of the SAGMM-tr on non-monotonic tasks.

4.1 EXPERIMENTS ON CONCATENATED SPEECH COMMAND DATASET

First, we performed a speech recognition experiment with limited vocabulary to show that the common soft attention algorithm has difficulty to decode utterances with unseen sequence lengths. The speech command dataset consists of 1 second long speeches from various speakers saying single words from a vocabulary of 30 words. We built 100K utterances of training corpusWarden (2018) by concatenating randomly chosen 5-9 utterances in the training data. 500 test utterances were also built by concatenating $\{3, 7, 10, 15, 20\}$ randomly chosen words in the test set. We cropped both the start and end of chosen utterances randomly from 0.05s to 0.15s before concatenating them to prevent the SAGMM from finding a trivial solution.

We compared the word error rate (WER) of transformers with soft and SAGMM attentions on test sets. Detailed hyperparameters for the experiment are described in Appendix. In table 1, the soft attention mechanism tends to memorize the sequence length distribution from the training corpus and fails to decode correctly in the unseen sequence length. On the other hand, the proposed SAGMM algorithm was robust to sequence length mismatches. The decoded examples for soft attention and SAGMM are shown in Appendix.

Table 1: The word error rates (%) on the concatenated speech command dataset with various number of concatenated words.

	3	**7**	**10**	**15**	**20**
soft attention	40.00	**5.71**	13.20	39.80	56.05
SAGMM	**4.67**	6.29	**5.50**	**5.40**	**6.45**

4.2 EXPERIMENTS ON LIBRISPEECH DATASET

We conducted experiments on the LibriSpeech whose training dataset consists of 960 hours of read audio books (Panayotov et al., 2015). We validated the performance of models on dev sets and reported WERs in tests sets with the fixed beam width 4.

First, we compared the performance of SAGMM-tr with conventional algorithms in the offline speech recognition. We trained the multi-head transformers similar to the previous experiments. The encoder consisted of 10 layers of self-attention block with 768 hidden nodes and 3,072 filters. The decoder was constructed by stacking 4 self-attention blocks with the same node and filter sizes. The encoder and decoder self-attention employed soft-attention with relative positional encoding (Dai et al., 2019). We trained and tested models which employed the soft attention, GMM attention, and SAGMM-tr attention mechanisms as encoder-decoder attention. We adopt the auxiliary CTC loss on the encoder output with $\lambda_{ctc} = 0.1$ for fair comparison with the previous attention-based models Lee et al. (2020); Dong & Xu (2020); Kim et al. (2019). The SAGMM-tr model without CTC loss was 3.84% on test-clean dataset. The detail hyperparameters for the experiment and performance of SAGMM-tr without CTC loss are shown in Appendix.

Table 2 shows the performance of various non-streamable models. In non-streamable models, our baseline transformer showed similar performance with previous studies considering the number of parameters. We also compared the performance of GMM and SAGMM-tr models with the bi-directional encoder to other streamable encoder-decoder attention algorithms. The performance of SAGMM-tr attention matched our transformer model and showed better performance than other streamable Seq2Seq models. From the results,

Table 2: The word error rates (%) of offline speech recognition models without LM on LibriSpeech (with number of parameters when available).

		test-clean	**test-other**
Non-streamable	LAS (Zeyer et al., 2018)	4.70	15.20
	Location-aware attention Moritz et al. (2019)	6.1	20.0
	LAS (180M) (Park et al., 2019)	3.4	8.3
	LAS (361M) (Park et al., 2019)	**2.8**	**6.8**
	Transformer (270M) (Synnaeve et al., 2020)	2.89	6.98
Streamable decoders, bi-directional enc.	RNN-T (130M) (Zhang et al., 2020)	3.2	7.8
	Transformer-T (45.7M) (Yeh et al., 2019)	6.08	13.89
	Transformer-T (139M) (Zhang et al., 2020)	**2.4**	**5.6**
	DecGRC (Lee et al., 2020)	4.83	14.90
	Mocha (Lee et al., 2020)	4.95	15.32
	CIF (Dong & Xu, 2020)	3.41	12.62
Transformer(Ours)	Soft attention (121M)	**3.20**	**7.96**
	GMM (121M) (Ours)	3.71	8.52
	SAGMM-tr (121M) (Ours)	**3.21**	**7.99**

SAGMM-tr successfully described the monotonic alignments between speech and transcription without attending all encoder outputs.

Next, we tested the performance of SAGMM-tr in online ASR task. We trained the single-head and multi-head SAGMM-tr models with the block-wise masked encoder. The truncated GMM model was also tested. However, the model attended to the future context as shown in A.4 and failed to learn the correct alignments. In the multi-head SAGMM-tr, several heads in the first decoder layer were not trained and softmax(ϕ_i^h) went to zero. We simply pruned these heads after the performance on dev set converged and fine-tuned for additional 30K steps. We believe training with ϕ_i^h and head pruning helps to prevent over-fitting when the desired monotonic alignments do not require many heads especially in the first decoder layer.

Table 3 shows the performance of models with various online inference approaches. From the table, the single-head SAGMM-tr outperformed other CTC and attention-based algorithms. The multi-head mechanism further improved the performance of SAGMM-tr. Compared to the similar model with the bi-directional encoder, the block-wise mask on encoder self-attention layers increased the WER on test-clean set by 0.31%. Our model showed slightly worse performance than state-of-the-art algorithm with transformer-T (Zhang et al., 2020). Subword regularization Kudo (2018); Hannun et al. (2019) and sequence-level loss Sabour et al. (2019); Prabhavalkar et al. (2018) can help to match the performance of SAGMM-tr with the best transducer models. The SAGMM-tr can also be adopted to various monotonic Seq2Seq tasks easily since it can be inferred via simple beam search without probability marginalization in transducers and does not require assumption that the target should not be longer than the source.

Figure 3 shows the attention plots of the single-head SAGMM-tr which successfully captures alignments between speech and transcription for an utterance with a long silence. Figure 1 also shows the attention alignments from multi-head soft attention, truncated GMM attention and SAGMM-tr attentions. Detailed

Figure 3: Attention plots for single-head SAGMM-tr model with a speech utterance with a long silence. Each subfigure shows the alignment from each encoder-decoder attention layer in the decoder with four blocks.

Table 3: The word error rates (%) of online speech recognition models without LM on LibriSpeech (with number of parameters when available).

		test-clean	**test-other**
CTC variants	Gated ConvNet (Liptchinsky et al., 2017)	6.7	-
	CTC (Chan et al., 2020)	4.6	13.0
	Imputer(DP)(Chan et al., 2020)	4.0	**11.1**
	Jasper (333M) (Li et al., 2019)	**3.86**	11.95
Transducers	Transformer-T (45.7M) (Yeh et al., 2019)	6.47	15.79
	ConvT-T (67M) (Huang et al., 2020)	3.5	8.3
	Transformer-T (139M) (Zhang et al., 2020)	**3.0**	**7.7**
Streamable Seq2Seq	Triggered Attention (Moritz et al., 2019)	7.4	19.2
	Mocha (Kim et al., 2019)	6.30	18.41
	Mocha (Lee et al., 2020)	5.15	16.45
	DecGRC (Lee et al., 2020)	5.87	17.04
	CIF (Dong & Xu, 2020)	3.96	11.19
	SAGMM-tr (121M) (single-head)	3.73	9.92
	SAGMM-tr (121M) (multi-head)	**3.52**	**9.29**

Table 4: The experiment results on (a) SAGMM-tr with the fixed window length and (b) long-form speech recognition on "test-long" set. (sh) and (mh) denote the single-head and multi-head attention, respectively.

(a)

	test-clean	**test-other**
SAGMM-tr (sh)	3.73	9.92
SAGMM-tr (mh)	**3.52**	**9.29**
SAGMM-tr (sh,fixed)	3.67	9.76
SAGMM-tr (mh,fixed)	4.45	10.34
+fine-tuning	3.60	9.42

(b)

	test-clean	**test-long**
Soft attention	**3.20**	32.77
GMM	3.71	24.71
SAGMM-tr (sh)	3.73	**5.60**
SAGMM-tr(mh)	3.52	8.13

plots are shown in Appendix A.4. In soft attention, several heads attends to the speech absence frames constantly for all decoder steps. These heads might help utterance-level normalization on attention context vectors. The truncated GMM model failed to learn the alignment and attended to an wide range of encoder tokens. Finally, SAGMM-tr attention learned monotonic alignments successfully. Due to the monotonic constraint, all heads in SAGMM-tr did not attend silence. The future work should explore the role of heads attending silence in soft attention and introduce them to the SAGMM-tr attention. The SAGMM-tr attention plots in lower layers are more blurred. We suppose that the lower layers find the relevant subsets in the sequence and the higher layers use the context vector from lower layers to select the most relevant tokens in the subset.

The multi-head SAGMM-tr model showed more blurred alignments compared to the single-head model. Our hypothesis for this phenomenon is that several heads attended larger window to provide context information. The fixed window length scheme described in equation 17 - 20 or regularization on σ_i would be also helpful to minimize the latency of online inference. In this paper, we tested the fixed window algorithm. We started with the SAGMM-tr models trained for the online ASR experiment and measured the WERs before and after fine-tuning with the constant window width $(c = 15 \text{ frames})$. From the results in table 4 (a), SAGMM-tr attention mechanism can be also adopted to the models with fixed attention window width.

Finally, we concatenated utterances from the same speaker in "test-clean" set to build "test-long" set for the long-form speech recognition. The average length of utterances in the test-long set was 54 seconds. In the SAGMM-tr model, the beam search algorithm was slightly modified from Algorithm 1 to suppress the EOS token until the attention window covers $\nu_{h,J}$. The performance of GMM attention did not improved by the same modification since GMM attention attends to $\nu_{h,J}$ before the end of sentence.

From the table 4 (b), SAGMM-tr outperformed the conventional soft and GMM attention models in long-form speech recognition. Comparing the SAGMM-tr models, the multi-head SAGMM-tr showed worse performance than the single-head model. The performance degradation of multi-head mechanism on "test-long" set might come from accumulated attention windows range mismatches. Future works should explore techniques to regularize the attention window ranges in multi-headed models.

4.3 EXPERIMENTS ON A NON-MONOTONIC TASK

The proposed algorithm focuses on strict monotonic tasks which do not allow reordering. However, the self-attention layers in the encoder could reorder the semantics in input sequences before monotonic alignments from the SAGMM-tr. We conducted machine translation experiments on the WMT EN-DE environment to show the performance of SAGMM-tr attention in non-monotonic tasks. While the machine translation is a non-monotonic task, various approaches have been proposed to improve performance of online inference and simultaneous translation (Arivazhagan et al., 2019; Elbayad et al., 2020). In this paper, we conduct simple experiments to figure out if the GMM attention can deals with non-monotonic tasks.

We trained the encoder-decoder model similar to the transformer-base in Vaswani et al. (2017) except the head size 4 of the encoder-decoder and decoder self-attention. We trained model with 4.5M pairs of sentences and measured the BLEU score on the newstest2013 set after 100K training steps. For uni-directional encoder, the block-wise mask with $M = 5$ is applied to SAGMM-tr model with bi-directional encoder and fine-tuned for additional 40K steps.

Table 5 shows the performance of soft and SAGMM-tr attention models on the newstest2013 set. As expected, the performance of SAGMM-tr did not match that of the conventional transformer models with soft attention. The uni-directional encoder also deteriorates the performance of SAGMM-tr similar to speech recognition experiments. Since SAGMM-tr does not consider the local reordering, the proposed algorithm has difficulty in learning locally non-monotonic functions. Our future works will improve the performance of SAGMM-tr on local reordering tasks by positive constraint relaxation on Δ_i.

Table 5: The BLEU scores on the newstest2013 set for the WMT EN-DE environment.

	EN-DE
Transformer (Vaswani et al., 2017)	25.8
Soft attention (Ours)	25.7
SAGMM-tr (bi-enc)	24.0
SAGMM-tr (uni-enc)	23.7

5 CONCLUSION

We have proposed the SAGMM which attends the subset of source sequences according to the normal distribution on the weighted encoder output axis, considering both contents and order of elements in sequences. We have also proposed SAGMM-tr for online/real-time inference applications. From the results on various speech recognition tasks, the proposed attention mechanism is shown to be able to learn the monotonic alignments between source and target sequences without a human supervision. The performance of transformer with SAGMM-tr improved for online and long-form speech recognition without performance degradation in the standard offline ASR task. In future works, we would like to adopt the SAGMM-based attention mechanisms for natural language processing tasks which allow local reordering during the sequence generation. We are also interested in latency minimization for online inference by controlling μ and σ in both the training and inference stages.

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A APPENDIX

A.1 BLOCK-WISE MASK FOR ENCODER SELF-ATTENTION LAYER

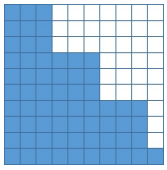

Figure 4: Encoder self-attention mask between query (vertical axis) and key (horizontal axis) in $M = 3$ case.

The block-wise uni-directional mask was adopted for encoder self-attention layers to block future context more than M tokens. 4 shows the block-wise masking with $M = 3$ case. In the experiment with SAGMM-tr, we chose $M = 30$ whose gmaximum latency is comparable to other studies with uni-directional encoders (Zhang et al., 2020; Dong et al., 2019). The blcok-wise masking is different from lookahead operation since encoder outputs from the block-wise masking are not guaranteed to look future M token depends on their position in block while the lookahead operation provides maximum future context for all encoder outputs.

A.2 PSEUDO CODE FOR ONLINE INFERENCE WITH SAGMM-TR ATTENTION

Algorithm 1: Decoding process of SAGMM-tr attention mechanism for a h-th head.

Data: encoder key and value vectors K_j^h, V_j^h for $j \in \{1, 2, ...J\}$, $i = 1$, $\mu_0^h = \nu_0^h = 0$, $y_0 = SOS$
while $y_{i-1} \neq EOS$ **do**
  $Q_i^h = \text{feedforward}\left(y_{i-1}\right)$ `/* Lower decoder layers */`
  $\Delta_i^h, \sigma_i^h, \phi_i^h = \text{GMMparam}\left(Q_i^h\right), \quad \mu_i^h = \mu_{i-1}^h + \min\left(\max\left(\Delta_i^h, 0\right), 3\right)$ `/* equation 4 */`
  $pos_s^h, = \mu_i^h - 2\sqrt{\sigma_i^h}, \;\; pos_e^h = \mu_i^h + 2\sqrt{\sigma_i^h}, Attend^h = \mathbf{0}$
  for $j = 1$ *to* J **do**
    $\delta_j^h = \text{sigmoid}\left(K_j^h W_\delta^h\right), \quad \nu_j^h = \nu_{j-1}^h + \delta_j^h$
    if $\nu_j^h > pos_e^h$ **then**
      Break
    else if $\nu_j^h > pos_s^h$ **then**
      $\alpha^h_{SAGMM\text{-}tr\|_{i,j}} = \delta_j^h \; N_{tr}\left(\nu_j^h; \mu_i^h, \sigma_i^h\right)$ `/* equation 14, 15 */`
      $Attend^h = Attend^h + \alpha^h_{SAGMM\text{-}tr\|_{i,j}} V_j^h$
  $y_i = \text{Output}\left(\text{Decoder}\left(\text{softmax}_h\left(\phi_i^h\right) Attend^h\right)\right), \quad i = i + 1$

A.3 EXPERIMENT CONFIGURATIONS

For all speech recognition experiments, the 80-dimensional log-Mel filterbank features were extracted with a 25ms window and shifted every 10ms. Each input vector stacked 3 log-Mel feature vectors, downsampled to 30ms frame rate.

In the speech command dataset experiment, We trained the multi-headed transformer Vaswani et al. (2017); Dong et al. (2018) with soft attention and SAGMM attention for encoder-decoder alignments. We adopt the

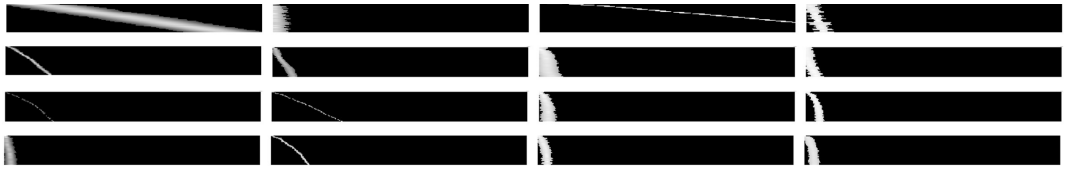

Figure 5: Attention alignments plots from multi-head truncated GMM model.

relative positional encoding for both the encoder and decoder self-attention (Dai et al., 2019). The encoder consisted of 6 layers of self-attention block with 512 nodes and 2,048 filter size, respectively. The decoder was constructed by stacking 3 self-attention block with the same node and filter sizes. The number of heads for encoder self attention, encoder-decoder attention, and decoder self attention were $\{8, 4, 4\}$, respectively. We employed label smoothing of value $\epsilon_{ls} = 0.15$, and applied parallel scheduled sampling with probability 0.2 after 100k (Duckworth et al., 2019). We used the Adam optimizer with $\beta_1 = 0.9$, $\beta_2 = 0.98$ and $\epsilon = 10^{-9}$). The learning rate was linearly increased to 0.1 until 16k steps and set constant in following training steps. We used the tensorflow framework and trained the model until 500K step with 4 m40 GPUs. We averaged 5 last checkpoints before the inference. The dropout ratio for attention weights, rectified linear units, output of sub-layers, and neural network input after positional encoding were 0.2, 0.1, 0.2, and 0.2, respectively. The Specaug algorithm Park et al. (2019) was also applied during training. The width of beam was set to 4 in all experiments. The output token segments are grepheme of the reference.

In the LibriSpeech experiment, The learning rate was linearly increased to 0.1 until 16k steps and set constant until the model converges on dev-clean dataset. Then, we lowered learning rate to 0.02 and fine-tuned until the model converges. We used the tensorflow framework and the model is trained from 7 to 10 days on 8 p40 GPUs. We averaged $\{5, 10, 15\}$ last checkpoints before the performance evaluation. The 1K wordpiece vocabularies extracted from training dataset is used for output token segmentation. Other parameters are the same with those in the speech command dataset experiment.

A.4 ATTENTION PLOT FOR VARIOUS ENCODER-DECODER MODELS

To show the SAGMM-tr is able to learn alignments between encoder and decoders, we plot the attention score for single and multi-head models. We used the utterance "Chapter eleven ¡long pause¿ the morrow brought a very sober looking morning the sun making only a few efforts to appear and Catherine augured from it everything most favourable to her wishes" in LibriSpeech.

The truncated GMM model fails to learn the true alignment attended several distinct windows in 5. Surprisingly, the performance of truncated GMM was 4.03% and 10.16% for test-clean and test-other, respectively. The decent performance of truncated GMM implies that the GMM learns to attend as many frames as possible instead of learning alignments between sequences. Therefore, the truncated GMM attention is not suitable for streaming inference.

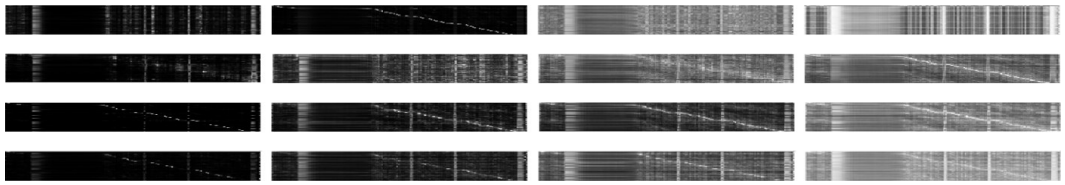

Figure 6: Attention alignments plots from multi-head soft attention model.

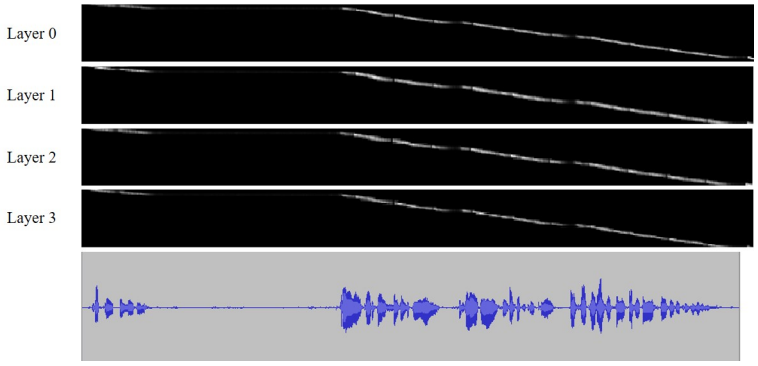

Figure 7: Attention alignments plots for single-head SAGMM-tr for the utterance "Chapter eleven ¡long pause¿ the morrow brought a very sober looking morning the sun making only a few efforts to appear and Catherine augured from it everything most favourable to her wishes" in LibriSpeech. The attention plot in time domain longer than the original wave due to **1**-vector concatenation for EOS 2.4

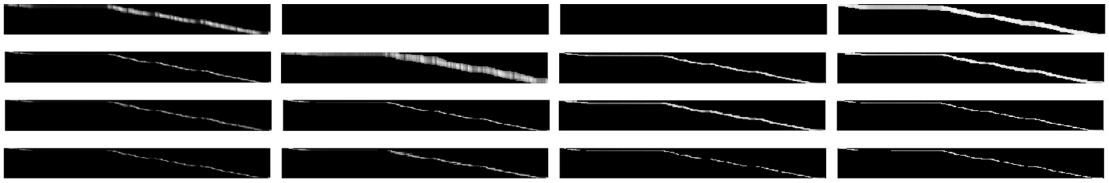

Figure 8: Attention alignments plots from multi-head SAGMM-tr model with adaptive window width. The empty plots denote the pruned head in the first layer

Figure 9: Attention alignments plots from multi-head SAGMM-tr attention model with fixed window width. The empty plots denote the pruned head in the first layer

In the soft attention model, the several heads learns monotonic alignments between inputs and outputs as shown in Figure 6. However, other heads attend to the whole speech presence or absence intervals. We assume these heads help utterance-level normalization. While a few heads show monotonicity, the soft attention is not suitable for online inference due to softmax operation over all frames.

The attention alignment figure for single and multi-headed SAGMM-tr model is shown in Figures 7, 8 and 9. From the figures, both models learn the optimal alignments between input wave and transcription and distinguish the word boundaries without relying on human knowledge. The width of attention windows in multi-head SAGMM-tr with adaptive window width are longer than those in the single-head model. The additional objective function for regularizing σ_i would be helpful to reduce the window length in figure 8.

In the multi-head model with fixed window length, the model learns the multi-head monotonic alignment without increasing the window width. Considering the attention window width as a hyperparameter from external knowledge, it is shown that additional information could improve the model latency in SAGMM-tr while the model can also be trained without human knowledge.

A.5 ABLATION STUDIES

We tested the three ablation experiments on SAGMM-tr attention in Figure 6. First, we tested the model without CTC loss on encoder output. The CTC loss improves the word error rate performances of model similar to previous studies, but the model showed decent performance without the CTC loss. Second, we tested the SAGMM-tr model with uni-directional encoder without initialization from the bi-directional encoder. The result shows slightly worse performance compared to the original SAGMM-tr. Finally, we train the SAGMM model in the training and decoded with the SAGMM-tr decoding scheme without fine-tuning. The performance degradation in 6 shows that the mismatch between training and test stages should be removed by the fine-tuning with truncated normal distribution.

Table 6: The word error rate (%) of ablation experiments for SAGMM-tr attention mechanism in LibriSpeech.

	test-clean	**test-other**
SAGMM-tr	3.52	9.29
SAGMM-tr w/o CTC loss	3.84	9.86
SAGMM-tr uni-encoder from scratch	3.69	9.79
SAGMM-tr w/o truncated attention fine-tuning	3.76	9.96

A.6 ATTENTION PLOTS FOR SAGMM-TR IN MACHINE TRANSLATION EXPERIMENTS

We plot the first three decoder layers of the SAGMM-tr model with bi-directional encoder for an example utterance “The patient really needs to be made to understand the degree of risk of his cancer, by offering him the options available, not necessarily treating prostate cancers that are not long-term life threatening, and opting instead, in such cases, for active monitoring of the disease.” and model output “Der Patient muss wirklich verstanden werden, um den Grad des Risikos seines Krebses zu verstehen, indem er ihm die Möglichkeiten zur Verfügung stellt, nicht notwendigerweise mit Prostatakrebs umzugehen, die nicht langfristiges Leben bedrohen und sich stattdessen in solchen Fällen für eine aktive Überwachung der Krankheit entscheiden.”.

We also plot the first three encoder-decoder attention and encoder-self attention layers of the SAGMM-tr model with uni-directional encoder for an example utterance “The patient really needs to be made to understand the degree of risk of his cancer, by offering him the options available, not necessarily treating prostate cancers that are not long-term life threatening, and opting instead, in such cases, for active monitoring of the disease.” and model output “Der Patient muss wirklich verstanden werden, um das Risiko seines Krebses zu verstehen, indem er ihm die Möglichkeiten zur Verfügung stellt, nicht notwendigerweise mit Prostatakrebs umzugehen, die nicht langfristiges Leben bedrohen, und stattdessen in solchen Fällen für eine aktive Überwachung der Krankheit zu entscheiden.”.

From the figures 10, 11 and 12, the transformers with SAGMM-tr approximates the machine translation task as a strict monotonic task and finds optimal alignments under the assumption. Since the machine translation is not strictly monotonic task, the performance of the SAGMM-tr attention deteriorates compared to the soft attention. However, the transformer with SAGMM-tr attention and uni-directional encoder enables online inference for simultaneous translation.

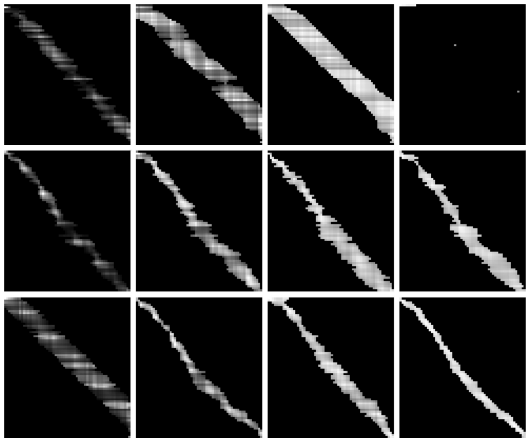

Figure 10: Encoder-decoder attention alignments plots from multi-head SAGMM-tr model with bi-directional encoder in machine translation experiment.

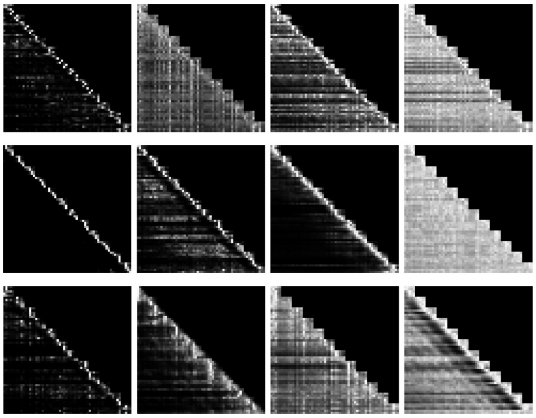

Figure 11: Encoder self-attention alignments plots from multi-head SAGMM-tr model with uni-directional encoder in machine translation experiment.

A.7 DECODED EXAMPLES OF SOFT ATTENTION AND SAGMM MODELS ON SPEECH COMMAND AND LIBRISPEECH DATASETS

Table 7 and 8 show the decoded examples from the models with unseen sequence lengths. From the tables, soft attention has difficulty to generate the sequences that are significantly shorter or longer than the training corpus distribution. In contrast, the SAGMM-tr is robust to the sequence length mismatch and generates the transcription to arbitrary length.

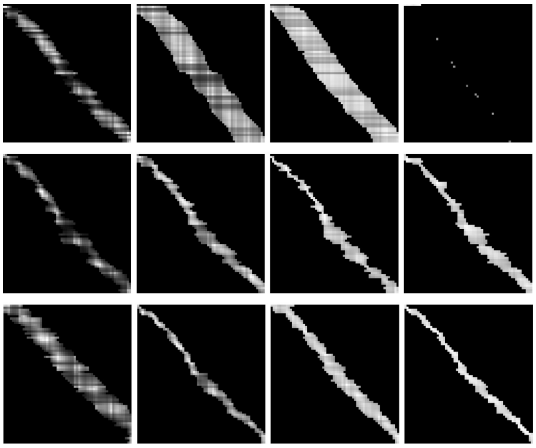

Figure 12: Encoder-decoder attention alignments plots from multi-head SAGMM-tr model with uni-directional encoder in machine translation experiment.

Table 7: The example results for attention-based models in concatenated speech command dataset.

	Transcription
Reference	seven three stop
Soft attention	seven three stop stop
SAGMM	seven three stop
Reference	two right two no cat bird right left tree four tree one wow marvin left
Soft attention	two right two no cat bird right left marvin left
SAGMM	two right two no cat bird right left tree four tree one wow marvin left

Table 8: The example results for attention-based models in test-clean-long set from LibriSpeech dataset. (sh) and (mh) denote the single-head and multi-head attention, respectively.

	Transcription
Reference	it was idle for him to move himself to be generous towards them to tell himself that if he ever came to their gates stripped of his pride beaten and in beggar's weeds that they would be generous towards him loving him as themselves idle and embittering finally to argue against his own dispassionate certitude that the commandment of love bade us not to love our neighbour as ourselves with the same amount and intensity of love but to love him as ourselves with the same kind of love the phrase and the day and the scene harmonized in a chord words was it their colours they were voyaging across the deserts of the sky a host of nomads on the march voyaging high over ireland westward bound the europe they had come from lay out there beyond the irish sea europe of strange tongues and valleyed and woodbegirt and citadelled and of entrenched and marshalled races
Soft attention	it was idle for him to move himself to be generous towards them to tell himself that if he ever came to their gates stripped of his pride beaten and in beggars weeds that they would be generous towards him loving him as themselves to love him as ourselves with the same amount and intensity of love the europe they had come from lay out there beyond the irish sea europe of strange tongues and valleyed and martialed races
SAGMM-tr(sh)	it was idle for him to move himself to be generous towards them to tell himself that if he ever came to their gates stripped of his pride beaten and in beggars weeds that they would be generous towards him loving him as themselves idle and embittering finally to argue against his own dispassionate certitude that the commandment of love bade us not to love our neighbour as ourselves with the same amount and intensity of love but to love him as ourselves with the same kind of love the phrase and the day and the scene harmonized in accord words was it their colors they were voyaging across the deserts of the sky a host of no mads on the march voyaging high over ireland westward bound the europe they had come from lay out there beyond the irish sea europe of strange tongues and valleys and wood be girt and set and of intrenched and marshalled races
SAGMM-tr(mh)	it was idle for him to move himself to be generous towards them to tell himself that if he ever came to their gates stripped of his pride beaten and in beggar's weeds that they would be generous towards him loving him as themselves idle and embittering finally to argue against his own dispassionate certitude that the command of love bade us not to love our neighbour as ourselves with the same amount and intensity of love but to him as ourselves with the same kind of love the phrase and the day and the scene harmonized in accord words was it their colors they were voyaging across the deserts of the sky a host of no mads on the march voyaging high over ireland westward bound the europe they had come from lay there beyond the irish sea europe of strange tongues and valleyed and wood girt and citadel and of intrenched and marched and races