Sequence Parallelism: Long Sequence Training from System Perspective

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Abstract

Transformer achieves promising results on various tasks. However, self-attention suffers from quadratic memory requirements with respect to the sequence length. Existing work focuses on reducing time and space complexity from an algorithm perspective. In this work, we propose sequence parallelism, a memory-efficient parallelism to solve this issue from system perspective instead. With sequence parallelism, we no longer require a single device to hold the whole sequence. Besides, using efficient attention with linear complexity, our sequence parallelism enables us to train transformer with infinite long sequence. Experiments show that sequence parallelism performs well when scaling with batch size and sequence length. Compared with tensor parallelism, our approach achieved 13.7× and 3.0× maximum batch size and sequence length respectively when scaling up to 64 NVIDIA P100 GPUs. With efficient attention, sequence can handle sequence with over 114K tokens, which is over 27× longer than existing efficient attention works holding the whole sequence on a single device.

1. Introduction

Transformer-based language models (Radford et al., 2019; Brown et al., 2020; Devlin et al., 2018) have achieved impressive performance on various natural language understanding and generation tasks (*e.g.,* Q&A (Qu et al., 2019; Yang et al., 2020), relation extraction (Xue et al., 2020b;a; Zhou et al., 2020) and dialogue system (Ni et al., 2021)). Recently, Transformer also achieved promising results on computer vision tasks (Dosovitskiy et al., 2020; Zhang et al., 2020; 2021) and even on bioinformatics tasks (Elnaggar et al., 2020; Wang et al., 2021). These Transformer-based models learn powerful context-aware representation by applying self-attention to all pairs of tokens from the input sequence. This mechanism captures long-term dependencies at the token level for sequence modeling. However, self-attention suffers from quadratic memory requirements with respect to sequence length. Existing works focusing on long sequence modeling devote to solve this problem from algorithm perspective. That is, these works mainly try to reduce the time and space complexity of attention. In this paper, we focus on solving the long sequence training problem from system perspective. Existing system requires us to hold the whole sequence in one GPU, which limits the length of input sequence. Unfortunately, the long sequence is common in real-world applications. For instance, when we train Transformer for medical image classification, each image is much larger than it is in usual (*e.g.,* 512×512×512 vs 256×256×3). Then, each medical image has much more tokens (*i.e.,* over 512×). Each input sequence is much longer than usual. In this case, it is challenging to hold the whole sequence within single GPU.

In this paper, we designed and implemented sequence parallelism, which aims at breaking the limitation that we must store the whole sequence in one GPU. The proposed system can train transformer-based models with longer sequences and a larger batch size. Specifically, we first split the input sequence into multiple chunks along the sequence dimension and feed each sub-sequence chunk to one corresponding GPU. Each GPU thus only holds a part of the full sequence, *i.e.,* a sub-sequence. To apply self-attention to the tokens from different chunks, the main challenge is to compute attention scores and outputs across GPUs efficiently. To tackle this problem, we proposed Ring Self-Attention (RSA), which circulates key and value embeddings across GPUs in a ring manner. In this case, each device is just required to keep the attention embeddings corresponding to its own sub-sequence. As a result, our sequence parallelism is memory-efficient, especially for long input sequences.

To model long sequences, existing works mainly focus on efficient attention (*e.g.,* (Zaheer et al., 2020)) with linear instead of quadratic space complexity. In this paper, we aim to solve the long sequence modeling problem from the distributed system perspective. We evaluated our system on both vanilla attention to verify our system is a general

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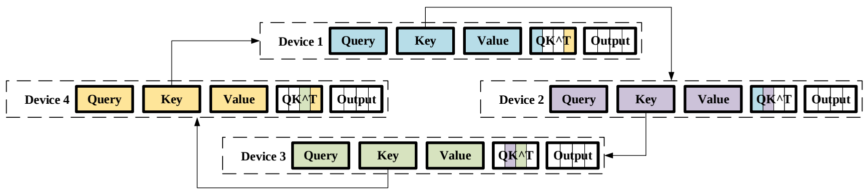
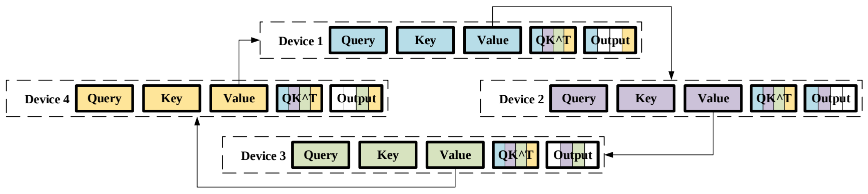
Work presented at the ES-FoMo Workshop at ICML 2023., Honolulu, Hawaii, USA. PMLR 202, 2023. Copyright 2023 by the author(s).



(a) Transmitting key embeddings among devices to calculate attention scores.



(b) Transmitting value embeddings among devices to calculate the output of attention layers.

Figure 1: Ring Self-Attention.

solution, and evaluated on efficient attention setting to show the upper bound sequence length. Existing pipeline parallelism (Huang et al., 2018) and tensor parallelism (Shoeybi et al., 2019)) are designed to cope with a larger model size instead of longer sequences. However, when the sequence is long, the challenge is, existing parallelism must keep the whole sequence on one single device. Even if splitting model along hidden and attention-head dimension (*i.e.,* tensor parallelism) or depth dimension (*i.e.,* pipeline parallelism) can still process longer sequences to some extent, the attention-head and depth are much smaller than sequence length (*e.g.,* 12 vs 512), which limits the training scalability and the maximum length of the input sequence. In contrast, our approach splits the whole sequence into multiple devices, enabling it to fit longer input data.

Contributions (1) Our system breaks the length limitation of Transformer model training. Sequence parallelism splits long sequences into multiple chunks and feeds them into different devices. With linear space complexity attention, sequence parallelism can help us train the attention model with infinite long sequences. (2) To our best knowledge, our work first proposed to use distributed system to handle long sequence training for attention-based models. Our implementation is fully based on PyTorch and is compatible with data parallelism, pipeline parallelism, and tensor parallelism without any extra compiler or library. This makes it possible to integrate sequence parallelism with data parallelism, pipeline parallelism and tensor parallelism into 4D parallelism, and pave the way to train large-scale models with long sequences.

2. Sequence parallelism

We propose sequence parallelism for training Transformer with longer sequences. Input sequences are split into multiple chunks and the sub-sequences are fed to different corresponding devices. All devices are holding the same trainable parameters but different sub-sequence input chunks. We will introduce and analyze sequence parallelism in detail below. We use the following notation in this section: (1) B: batch size; (2) L: sequence length; (3) H: hidden size of linear layers; (4) A: attention head size; (5) Z: number of attention heads; (6) N: number of GPUs.

To distribute sub-sequences to multiple devices, the main challenge is calculating attention scores across devices. Therefore, we propose Ring Self-Attention (RSA) to compute attention output in a distributed setting. There are two steps in RSA to obtain the final output. Please note, we only consider bidirectional self-attention here to introduce RSA succinctly. We treat all heads equally so it can be extended to multi-head attention directly.

Given query embeddings $\{q_1^1, q_2^1, ..., q_L^N\}$, key embeddings $\{k_1^1, k_2^1, ..., k_L^N\}$ and value embeddings $\{v_1^1, v_2^1, ..., v_L^N\}$, where q_s^n represents the key embedding of the s^{th} token in the the sequence which is on n^{th} device. We define all key embeddings on n^{th} device as K^n. In RSA, n^{th} device holds the corresponding query embeddings Q^n, key embeddings K^n and value embeddings V^n. The embeddings on n^{th} device correspond to the n^{th} chunk whose sub-sequence length is L/N. Our goal is to obtain $Attention^n(Q^n, K, V)$ which is the self-attention layer output on n^{th} device. To this end, as shown in Figure 1(a), we first transmit the key embeddings among devices to calculate the attention scores QK^T in a circular fashion. Such communication needs to be conducted $N-1$ times to make sure the query embeddings of each sub-sequence can multiply all the key embeddings. To be more specific, each device will compute the partial attention scores based on its local query and key embeddings first. Then, it will receive different key embeddings from the previous device and calculate the partial attention scores with respect to the new key embeddings for each ring-style communication. As a result, all query embeddings $\{Q^1, Q^2, ..., Q^N\}$ collected their corresponding attention scores $\{S^1, S^2, ..., S^N\}$ on their own devices.

In the second stage of RSA, we can calculate the self-attention layer output $\{O^1, O^2, ..., O^N\}$ based on $\{S^1, S^2, ..., S^N\}$ and $\{V^1, V^2, ..., V^N\}$. Since computing O^n requires S^n and all value embeddings, as we described in Figure 1(b), we transmit all value embeddings instead of key embeddings in a similar way. For O^n, we calculate S^nV by $O^n = S^nV = \sum_{i=1}^{N} S_i^n V_i$, where $V_i = V^n$, S_i^n is S^n after column splitting, which means $S_i^n \in \mathbb{R}^{L/N \times L/N}$ but $S^n \in \mathbb{R}^{L/N \times L}$.

3. Experiments

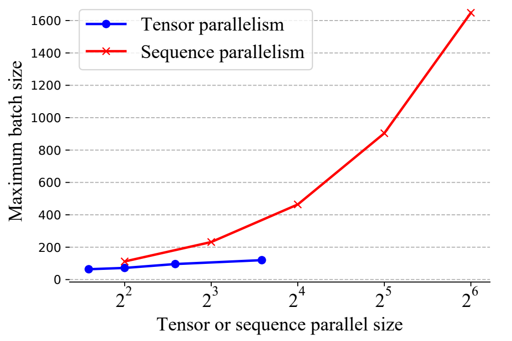
3.1. Experimental setup

We conducted our experiments on the Piz Daint supercomputer provided by Swiss National Supercomputing Center (CSCS). The Piz Daint supercomputer provides one P100 GPU (16GB GPU RAM) for each compute node and the compute nodes are connected by a high-bandwidth network. We chose two bidirectional language models, namely BERT Base and BERT Large, to evaluate our sequence parallelism. We also verified the convergence performance of sequence parallelism (see Appendix E). Since we are using the original model but different systems, the accuracy should be the same. The slight differences are from randomness.

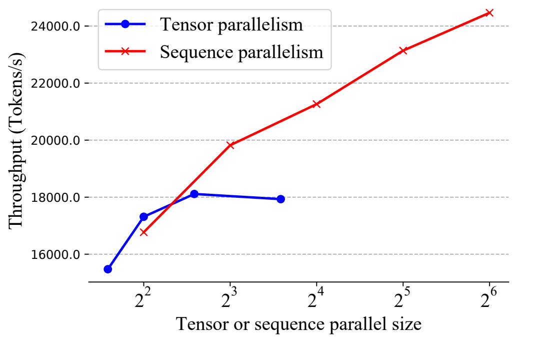
3.2. Maximum batch size

Since our sequence parallelism is memory-efficient to handle larger batch sizes, we first investigated the maximum batch size we can reach with sequence parallelism. In this section, for a comprehensive comparison, we scaled with tensor or sequence parallelism on BERT Base and BERT Large. We also fixed the tensor or parallel size and then scale them with pipeline parallelism to evaluate the verify the compatibility with pipeline parallelism. We used tokens per second as the metric for throughput. To this end, we trained BERT Base and BERT Large for 150 iterations in total, and then we calculate the mean tokens processed per second within the last 100 iterations.

Scaling with sequence/tensor parallelism We fixed all hyper-parameters except the batch size and the tensor parallelism or sequence parallelism size. We trained the model with a sequence length of 512 and no pipeline parallelism



(a) Maximum batch size of BERT Base scaling along tensor or sequence parallel size



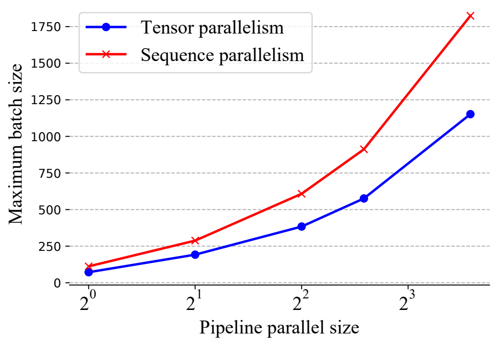
(b) Throughput of BERT Base scaling along tensor or sequence parallel size

Figure 2: Scaling with sequence/tensor parallelism

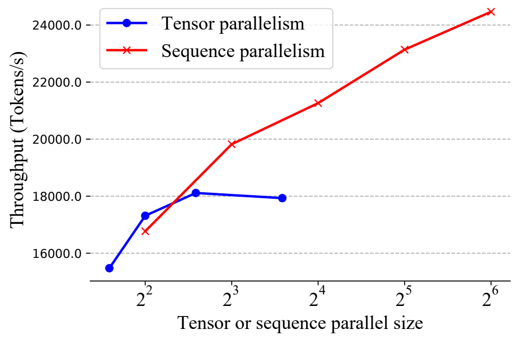
is used. The tensor parallelism size in Megatron is limited by the number of attention heads and hidden size, because these two hyper-parameters are required to be divisible by the tensor parallelism size. Among them, the number of attention heads is small so it limits the tensor parallelism. Thus, tensor parallelism size is a maximum of 12 for the BERT Base model in Megatron. In contrast, for our sequence parallelism, only the sequence length is required to be divisible by the sequence parallelism size, so that we can scale sequence parallelism to a larger size since it is a much larger hyper-parameter than the number of attention heads.

For BERT Base, our sequence parallelism outperforms tensor parallelism in terms of memory consumption. Figure 2(a) shows that our system on 64 GPUs can achieve 13.7× larger batch size than Megatron on 12 GPUs. Even if we combine data parallelism and tensor parallelism to scale up to 64 GPUs for Megatron, our system would still support a larger batch size. In Figure 2(b), we can observe sequence parallelism achieved comparable throughput with the same parallel size, and our system can extend to a larger parallel size to achieve better performance. For the results on BERT Large, please see Appendix F for details.

Scaling with pipeline parallelism To verify the compatibility with pipeline parallelism, we fixed the tensor parallelism and sequence parallelism size as 4 and scale the pipeline

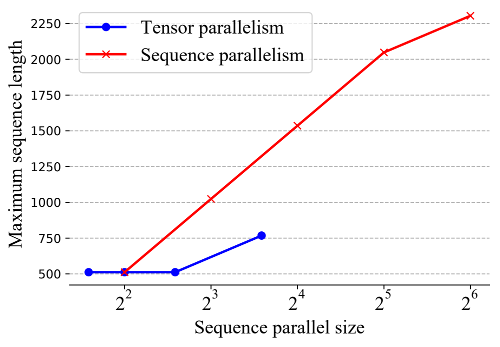


(a) Maximum batch size of BERT base scaling along pipeline parallel size.

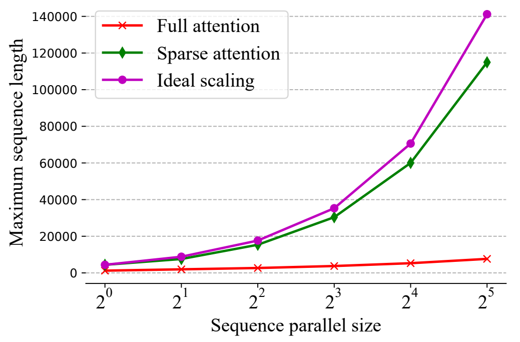


(b) Throughput of BERT base scaling along pipeline parallel size.

Figure 3: Scaling with pipeline parallelism



(a) Maximum sequence length on BERT base.



(b) Sequence length upper bound.

Figure 4: Scaling with sequence length.

parallel size. For BERT Base, we can observe that sequence parallelism outperforms tensor parallelism on the maximum batch size in Figure 3(a). It can be noted that sequence parallelism also achieved higher throughput when using more pipeline stages as shown in Figure 3(b). This is because Megatron incurs extra communication costs between pipeline stages. Megatron holds the activation for the full sequence on each device. Thus, it needs to split the activation, transmit the partial activation to the next device, and gather back the partial activation when sending the activation between pipelines. This incurs less communication overhead compared to transmitting the whole activation between pipelines. However, this still brings more communication costs than ours, as no splitting and all-gather operation is required for our sub-sequence intermediate activation. Therefore, our sequence parallelism achieved better throughput when scaling along with pipeline parallel size.

3.3. Maximum sequence length

Sequence parallelism is designed for training Transformer-based models with longer input sequences, so we investigated the maximum sequence length it can handle. Similarly, we still compared tensor parallelism without pipeline parallelism.

Compared with tensor parallelism We fixed batch size as 64 for BERT Base and no pipeline parallelism was used. We show the maximum sequence length in Figure 4(a). If we scale up to 64 GPUs, we can achieve around $3\times$ maximum sequence length on BERT Base. Another observation is splitting along the number of attention heads limits the input sequence length of tensor parallelism in Megatron, but our sequence parallelism can scale easily by splitting a sequence into multiple chunks. When using the same 16 GPUs, our sequence parallelism still can achieve $1.4\times$ larger sequence length than tensor parallelism. The gap is expected to widen if we use 32GB GPUs instead of 16GB GPUs.

Sequence length upper bound To investigate the maximum sequence length our system can handle on the cluster with 32 P100 GPUs. we set both data and pipeline parallel size as 1 and global batch size as 4. As efficient attention is widely used in long sequence training, we adapt Linformer (Wang et al., 2020), *i.e.,* one low-rank attention algorithm with linear time and space complexity. Our sequence parallelism is compatible with the efficient attention. More importantly, as shown in Table 3, for memory usage in efficient attention block, all terms including sequence length L is divided by number of devices N, which means **we can scale the sequence length to infinite long if we use efficient attention with linear complexity**. To investigate the sequence length upper bound of sequence length on the efficient attention setting, we conduct experiments with both efficient and full attention. As shown in Figure 4(b), if we use efficient attention on sequence parallelism, we can almost achieve ideal scaling. With 32 P100 GPUs, our sequence parallelism with efficient attention can handle the sequence with 114K tokens, which is over 27× longer than recent sparse attention papers holding the whole sequence on a single device (Zaheer et al., 2020; Wang et al., 2020).

4. Conclusion

In this paper, we proposed sequence parallelism for training transformer with longer sequence. Sequence parallelism is designed to break the limitation of sequence length on a single device. We have shown that sequence parallelism can handle longer sequence and is more memory-efficient than SoTA. In particular, sequence parallelism achieves 3.0× maximum sequence length and 13.7× maximum batch size than tensor parallelism when scaling up to 64 GPUs. Unlike both tensor and pipeline parallelism, sequence parallelism is not limited by the smaller hyper-parameters (*e.g.,* number of attention heads, number of layers). Therefore, our sequence parallelism can be adapted as long as the sequence length is divisible by sequence parallel size. With efficient attention, sequence parallelism can handle sequence with over 114K tokens, which is over 27× longer than existing efficient attention works holding the whole sequence on a single device. We used a language model (*i.e.,* BERT) to evaluate our system, but it can also be adapted to vision tasks. This work paves the way to process large images (Hou et al., 2019) by ViT (Dosovitskiy et al., 2020) as a larger image means more patches or longer sequences.

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A. Limitations

In order to perform communication between sub-sequences during training, the use of sequence parallelism can result in increased communication costs, which in turn can slow down the training process. However, by combining sequence parallelism with pipeline parallelism, this issue can be alleviated and the communication cost can be made comparable to advanced forms of model parallelism such as tensor parallelism. Nonetheless, sequence parallelism still incurs higher communication costs than vanilla data parallelism.

While sequence parallelism is effective for training of unidirectional attention models as well as training and inference of bidirectional attention models, it poses a challenge for unidirectional attention models inference due to the autoregressive decoding process. This means that different devices cannot compute in parallel, resulting in reduced throughput and decreased GPU utilization.

B. Discussion

Although there are other related works including DeepSpeed (Rasley et al., 2020), GShard (Lepikhin et al., 2020), GSPMD (Xu et al., 2021), etc., they are not our direct baseline in experiments. DeepSpeed is an efficient method to optimize memory footprint in data parallel training by using ZeRO Optimizer (Rajbhandari et al., 2021) and ZeRO-Offload (Ren et al., 2021). DeepSpeed and our method optimize training in different dimensions and they are actually compatible with each other. Our method is orthogonal to DeepSpeed just as how DeepSpeed can be integrated with Megatron. Thus, Megatron should be our baseline.

GShard and GSPMD are two libraries built for the TensorFlow community to partition model parameters in distributed training. GSPMD is developed based on GShard. These two methods rely on the static computation graph of TensorFlow to train larger models while we provide a plug-and-play tool based on PyTorch's dynamic computation graph to train on longer sequences. The difference in the computation paradigms makes them unsuitable as our baseline.

We also highlight again that, although sequence parallelism can perform decent on large model training, a more highly important use case is training mid-scale but very long sequence. One example is AlphaFold (Jumper et al., 2021), which uses only 86M parameters but is required to be trained with very long sequence (from 1K to 4K).

C. Multi-head attnetion

Multi-head attention is designed to jointly consider the information from different subspaces of embedding. Compared with self-attention below, multi-head attention has h query, key and value embeddings instead of the single one, where h denotes the number of heads. We obtain these embeddings with identical shapes by linear transformations. The multi-head attention can be described as:

$$MultiHead(Q, K, V) = Concat(head_1, ..., head_h)W^O \quad (1)$$

where $head_i = Attention(Q_i, K_i, V_i)$ and W denotes the linear transformations. All heads are concatenated and further projected by linear transformation W^O.

D. Modeling

We analyzed and compared our sequence parallelism with tensor parallelism in both theoretical modeling and experiments, although tensor parallelism is not our direct baseline. To our best knowledge, sequence parallelism is the first system designed for breaking the length limitation of sequence, so there is actually no direct baseline for sequence parallelism. Therefore, as a distributed training system designed for attention-based models, we compare it with a SoTA model parallelism. Tensor parallelism (Narayanan et al., 2021) is compatible with data parallelism, pipeline parallelism. Our sequence parallelism is also compatible with them. We expect our system can outperform tensor parallelism with and without pipeline parallelism. We leave integrating sequence parallelism with data parallelism, pipeline parallelism and tensor parallelism into 4D parallelism as our future work. Here, we mainly focus on memory usage and communication cost of tensor parallelism and our sequence parallelism.

D.1. Memory usage

For memory usage, according to the architecture of Transformer, the comparison is divided into two parts, MLP block and attention block. In this part, we consider multi-head attention instead of self-attention for a fair and accurate comparison. We assume the optimizer is Adam used in Megatron.

MLP block As shown in Table 1, for the MLP blocks, tensor parallelism stores the matrices after row or column-style splitting of the whole sequence. Our sequence parallelism stores the matrices without row or column-style splitting of only one single sub-sequence on each GPU. If we assume that our sequence parallelism is more memory-efficient:

$$\frac{32\mathrm{H}^2}{\mathrm{N}} + \frac{4\mathrm{BLH}}{\mathrm{N}} + \mathrm{BLH} > 32\mathrm{H}^2 + \frac{5\mathrm{BLH}}{\mathrm{N}} \quad (2)$$

We can find that, in MLP blocks, sequence parallelism is more memory-efficient when $\mathrm{BL} > 32\mathrm{H}$.

Multi-head attention block We compared the memory usage of multi-head attention block in Table 2. Tensor parallelism splits the attention heads here, but our sequence parallelism still splits the length dimension of the sequence data. By comparing the memory usages of multi-head attention block of the two parallelisms, we can find sequence parallelism is more memory-efficient if $\mathrm{BL} > 16\mathrm{AZ}$. As for communication, tensor parallelism needs an all-reduce operation in both the forward pass and backward pass when calculating the attention output. In our RSA, to facilitate tensor exchange between devices, our communication is equivalent to 2 all-reduce operations in the forward pass and 4 all-reduce operations in the backward pass. The extra communication cost of RSA can be offset by the lack of communication cost in the MLP block.

In both MLP block and multi-head attention block, sequence parallelism is more memory-efficient when we train Transformer with a longer sequence and a larger batch size.

D.2. Communication cost

Megatron-LM uses all-reduce in its MLP layer and self-attention layer while the communication overhead in sequence parallelism mainly lies in the self-attention layer. Using the same notation as given above, we are able to calculate the amount of data transferred in sequence parallelism and tensor parallelism.

In sequence parallelism, there is no communication in the MLP layer and communication only occurs in the self attention module. There are two ring-style P2P communication in the forward pass for calculating the attention score and attention output respectively. In the backward pass, there are two all-reduce collective communication and two ring-style P2P communication. The amount of data transferred is $2(N-1) * B * Z * (L/N) * A$ in the forward pass and $6(N-1) * B * Z * (L/N) * A$ in the backward pass. The combined amount of data transferred in calculating QK^T and AV will be $8(N-1) * B * Z * (L/N) * A$.

In tensor parallelism of Megatron-LM, the amount of data transferred in the forward pass and backward pass is the same as given by $2(N-1)*B*Z*(L/N)*A$. Since there are 4 collective communication in the forward and backward passes of the MLP layer and self-attention layer, the total communication cost will be $8(N-1) * B * Z * (L/N) * A$.

Thus, sequence parallelism has the same communication overhead compared with tensor parallelism in Megatron-LM. However, please note sequence parallelism has better compatibility with pipeline parallelism, which would further reduce the communication budget of sequence parallelism. In tensor parallelism, to save the communication bandwidth between pipeline stages which are often over different nodes, the tensor is split before transmitting to the next stage and

Table 1: MLP block memory usage comparison. M1 means the matrix before linear layer, and M2 is the trainable matrix of linear layer.

	GEMM	M1	M2	output	Memory
Tensor parallelism	1st linear	$(\mathrm{B}, \mathrm{L}, \mathrm{H})$	$(\mathrm{H}, \frac{4\mathrm{H}}{\mathrm{N}})$	$(\mathrm{B}, \mathrm{L}, \frac{4\mathrm{H}}{\mathrm{N}})$	$\frac{32\mathrm{H}^2}{\mathrm{N}} + \frac{4\mathrm{BLH}}{\mathrm{N}} + \mathrm{BLH}$
	2nd linear	$(\mathrm{B}, \mathrm{L}, \frac{4\mathrm{H}}{\mathrm{N}})$	$(\frac{4\mathrm{H}}{\mathrm{N}}, \mathrm{H})$	$(\mathrm{B}, \mathrm{L}, \mathrm{H})$	
Sequence parallelism	1st linear	$(\mathrm{B}, \frac{\mathrm{L}}{\mathrm{N}}, \mathrm{H})$	$(\mathrm{H}, 4\mathrm{H})$	$(\mathrm{B}, \frac{\mathrm{L}}{\mathrm{N}}, 4\mathrm{H})$	$32\mathrm{H}^2 + \frac{5\mathrm{BLH}}{\mathrm{N}}$
	2nd linear	$(\mathrm{B}, \frac{\mathrm{L}}{\mathrm{N}}, 4\mathrm{H})$	$(4\mathrm{H}, \mathrm{H})$	$(\mathrm{B}, \frac{\mathrm{L}}{\mathrm{N}}, \mathrm{H})$	

Table 2: Multi-head attention block memory usage comparison

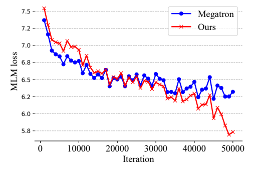
	Operation	M1	M2	output	Memory
Tensor parallelism	$Q/K/V$	$(\mathrm{B}, \mathrm{L}, \mathrm{H})$	$(\mathrm{H}, \frac{\mathrm{ZA}}{\mathrm{N}})$	$(\mathrm{B}, \frac{\mathrm{Z}}{\mathrm{N}}, \mathrm{L}, \mathrm{A})$	$\frac{16\mathrm{AZH}}{\mathrm{N}} + \frac{4\mathrm{BLZA}}{\mathrm{N}} + \frac{\mathrm{BZL}^2}{\mathrm{N}} + \mathrm{BLH}$
	QK^T	$(\mathrm{B}, \frac{\mathrm{Z}}{\mathrm{N}}, \mathrm{L}, \mathrm{A})$	$(\mathrm{B}, \frac{\mathrm{Z}}{\mathrm{N}}, \mathrm{L}, \mathrm{A})$	$(\mathrm{B}, \frac{\mathrm{Z}}{\mathrm{N}}, \mathrm{L}, \mathrm{L})$	
	AV	$(\mathrm{B}, \frac{\mathrm{Z}}{\mathrm{N}}, \mathrm{L}, \mathrm{L})$	$(\mathrm{B}, \frac{\mathrm{Z}}{\mathrm{N}}, \mathrm{L}, \mathrm{A})$	$(\mathrm{B}, \frac{\mathrm{Z}}{\mathrm{N}}, \mathrm{L}, \mathrm{A})$	
	Linear	$(\mathrm{B}, \frac{\mathrm{Z}}{\mathrm{N}}, \mathrm{L}, \mathrm{A})$	$(\frac{\mathrm{AZ}}{\mathrm{N}}, \mathrm{H})$	$(\mathrm{B}, \mathrm{L}, \mathrm{H})$	
Sequence parallelism	$Q/K/V$	$(\mathrm{B}, \frac{\mathrm{L}}{\mathrm{N}}, \mathrm{H})$	$(\mathrm{H}, \mathrm{AZ})$	$(\mathrm{B}, \mathrm{Z}, \frac{\mathrm{L}}{\mathrm{N}}, \mathrm{A})$	$16\mathrm{AZH} + \frac{4\mathrm{BZLA}}{\mathrm{N}} + \frac{\mathrm{BZL}^2}{\mathrm{N}} + \frac{\mathrm{BLH}}{\mathrm{N}}$
	Ring-QK^T	$(\mathrm{B}, \mathrm{Z}, \frac{\mathrm{L}}{\mathrm{N}}, \mathrm{A})$	$(\mathrm{B}, \mathrm{Z}, \frac{\mathrm{L}}{\mathrm{N}}, \mathrm{A})$	$(\mathrm{B}, \mathrm{Z}, \frac{\mathrm{L}}{\mathrm{N}}, \mathrm{L})$	
	Ring-AV	$(\mathrm{B}, \mathrm{Z}, \frac{\mathrm{L}}{\mathrm{N}}, \mathrm{L})$	$(\mathrm{B}, \mathrm{Z}, \frac{\mathrm{L}}{\mathrm{N}}, \mathrm{A})$	$(\mathrm{B}, \mathrm{Z}, \frac{\mathrm{L}}{\mathrm{N}}, \mathrm{A})$	
	Linear	$(\mathrm{B}, \mathrm{Z}, \frac{\mathrm{L}}{\mathrm{N}}, \mathrm{A})$	$(\mathrm{AZ}, \mathrm{H})$	$(\mathrm{B}, \frac{\mathrm{L}}{\mathrm{N}}, \mathrm{H})$	

all-gathered after transmission. As tensor has already been split along the sequence dimension in sequence parallelism, there is no need to split and all-gather between pipeline stages. Thus, sequence parallelism can have one less all-gather operation per pipeline stage.

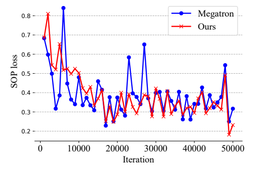
D.3. Memory Usage of Efficient Attention

E. Convergence performance

We verified the convergence performance of sequence parallelism. Since sequence parallelism is just a distributed implementation of long sequence training, there is no change in model architecture, We expect sequence parallelism can achieve the same accuracy and convergence performance as training without sequence parallelism. We used the Wikipedia dataset (Devlin et al., 2018) and evaluated Megatron and our model on the development set every 1k iterations. We trained the BERT Large model for 50k iterations with the default hyper-parameters used by Megatron. Our goal here is to verify the correctness of our implementation so we trained the model for fewer steps. We set parallel size as 4 for tensor parallelism in Megatron and sequence parallelism in our model. No pipeline was used for both models. In Figure 5, Our sequence parallelism shows good convergence on both the masked language modeling (MLM) loss and the sentence order prediction (SOP) loss. Compared with Megatron, sequence parallelism has a similar trend in



(a) Convergence performance of MLM loss



(b) Convergence performance of SOP loss

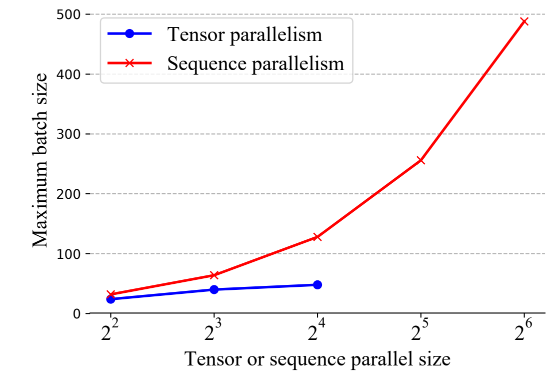
Figure 5: Convergence performance comparison between tensor parallelism and ours

Table 3: Efficient attention block memory usage. K is the projection dimension in Linformer (Wang et al., 2020)

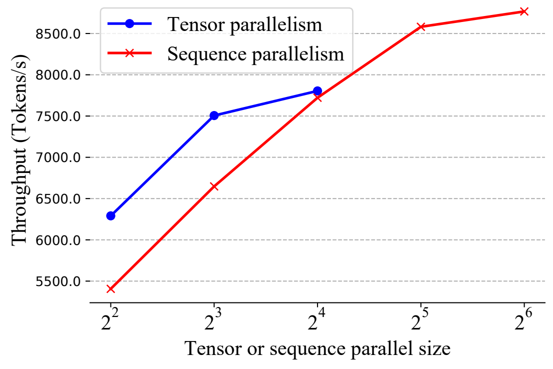
	Operation	M1	M2	output	Memory
	$Q/K/V$	$(\mathrm{B}, \frac{\mathrm{L}}{\mathrm{N}}, \mathrm{H})$	$(\mathrm{H}, \mathrm{AZ})$	$(\mathrm{B}, \mathrm{Z}, \frac{\mathrm{L}}{\mathrm{N}}, \mathrm{A})$	
Linformer Sequence parallelism	Projection	$(\mathrm{B}, \mathrm{Z}, \frac{\mathrm{L}}{\mathrm{N}}, \mathrm{A})$	$(\frac{\mathrm{L}}{\mathrm{N}}, \mathrm{K})$	$(\mathrm{B}, \mathrm{Z}, \mathrm{K}, \mathrm{A})$	$2\mathrm{AZH} + \frac{2\mathrm{BZLA}}{\mathrm{N}}$
	Ring-QK^T	$(\mathrm{B}, \mathrm{Z}, \frac{\mathrm{L}}{\mathrm{N}}, \mathrm{A})$	$(\mathrm{B}, \mathrm{Z}, \mathrm{K}, \mathrm{A})$	$(\mathrm{B}, \mathrm{Z}, \frac{\mathrm{L}}{\mathrm{N}}, \mathrm{K})$	$+\frac{\mathrm{BZLK}}{\mathrm{N}} + \frac{\mathrm{BLH}}{\mathrm{N}}$
	Ring-AV	$(\mathrm{B}, \mathrm{Z}, \frac{\mathrm{L}}{\mathrm{N}}, \mathrm{K})$	$(\mathrm{B}, \mathrm{Z}, \mathrm{K}, \mathrm{A})$	$(\mathrm{B}, \mathrm{Z}, \frac{\mathrm{L}}{\mathrm{N}}, \mathrm{A})$	$+2\mathrm{BZKA}$
	Linear	$(\mathrm{B}, \mathrm{Z}, \frac{\mathrm{L}}{\mathrm{N}}, \mathrm{A})$	$(\mathrm{AZ}, \mathrm{H})$	$(\mathrm{B}, \frac{\mathrm{L}}{\mathrm{N}}, \mathrm{H})$	

convergence and achieved lower values for both MLM loss and SOP loss for 50k iterations.

F. Scaling with sequence/tensor parallelism



(a) Maximum batch size of BERT Large scaling along tensor or sequence parallel size

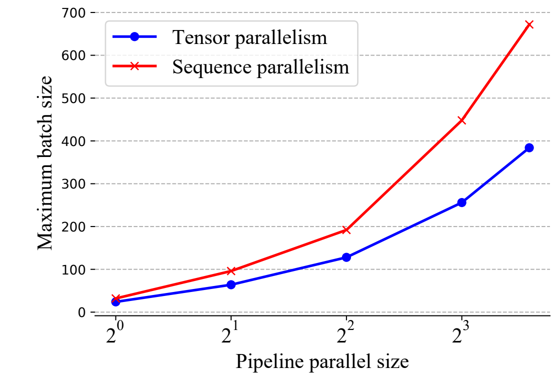


(b) Throughput of BERT Large scaling along tensor or sequence parallel size

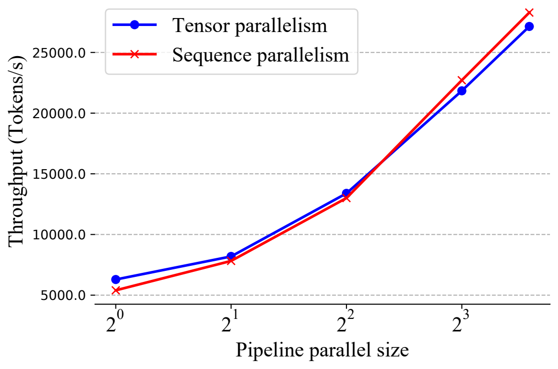
Figure 6: Scaling with sequence/tensor parallelism

Compared with BERT Base setting, the only difference is, the tensor parallel size is a maximum of 16 for the BERT Large model in Megatron-LM. In Figure 6(a), our method achieved 2.7 times larger batch size for BERT Large on 16 GPUs, and the batch size of sequence parallelism on 64 GPUs is 10.2 times larger than that of tensor parallelism on 16 GPUs. In Figure 6(b), observe that our sequence parallelism achieved comparable throughput with the same parallel size, and more importantly, our system can extend to a larger parallel size to achieve better performance.

G. Scaling with pipeline parallelism



(a) Maximum batch size of BERT Large scaling along pipeline parallel size



(b) Throughput of BERT Large scaling along pipeline parallel size

Figure 7: Scaling with pipeline parallelism

For BERT Large, sequence parallelism achieved higher maximum batch size than tensor parallelism in Figure 7(a). Sequence parallelism also performs better on throughput when using more pipeline stages as shown in Figure 7(b).

H. Maximum sequence length

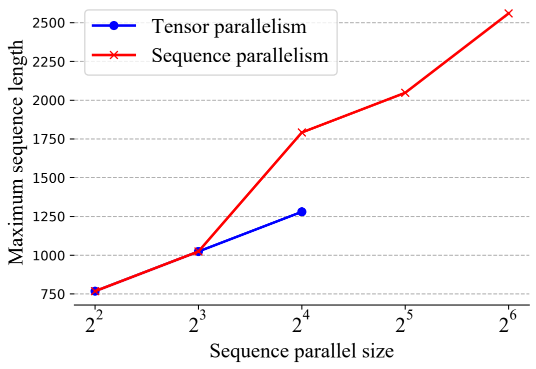


Figure 8: Maximum sequence length on BERT Large

BERT Large Similarly, we compared tensor parallelism without pipeline parallelism. We fixed batch size as 16 for BERT Large and did not use pipeline parallelism. As shown in Figure 8. When we scale up to 64 GPUs, we can achieve around 2× maximum sequence length and scale better through splitting a sequence into multiple chunks on BERT Large.

I. Weak scaling

Strong scaling limits the upper bound of batch size and sequence length within a single device, so we mainly discuss weak scaling in this section. We scale the batch size and sequence length separately when increasing the number of nodes. We fixed the pipeline parallelism size as 8. In Table 4, sequence parallelism achieved almost constant memory usage when scaling along with the global batch size, which outperforms tensor parallelism by a large margin. As for weak scaling along the sequence length, our method still uses much less memory with comparable throughput.

Table 4: Weak scaling results. Parallel size is the tensor or sequence parallel size. Batch size denotes global batch size, respectively. Memory and Token/sec denote max allocated memory/MB and tokens processed per second. OOM means that CUDA out of memory occurs.

Parallel size	Batch size	Sequence length	Tensor parallelism		Sequence parallelism	
			Memory	Token/sec	Memory	Token/sec
1	64	512	8477.28	9946.15	8477.53	9261.04
2	128	512	9520.47	15510.19	8478.76	13938.22
4	256	512	12232.52	20701.96	8481.26	21269.91
8	512	512	OOM	OOM	8490.75	26401.64
1	64	256	3707.39	9752.61	3707.01	9340.13
2	64	512	4993.43	14195.17	4670.64	13144.16
4	64	1024	8175.93	19879.27	6601.88	18243.82
8	64	2048	14862.09	22330.5	10536.38	21625.51