THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY
DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING
RELAXED SYSTEM LAB

Tensor Model-, MoE- and Long Sequence- Parallel Training

COMP6211J

Binhang Yuan

Recall Data & Pipeline Parallelism

RELAXED
SYSTEM LAB

- Data Parallelism:
  - **Memory issue**: each device needs to maintain a complete copy of the model (parameters, gradients, and optimizer status).
  - **Statistical efficiency**: if the global batch size is too large, it may affect the convergence rate
- Pipeline Parallelism:
  - **Bubble overhead:** the pipeline parallelism efficiency decreases as the number of stages increases.

RELAXED
SYSTEM LAB

Tensor Model Parallelism

TransformerBlocks$(x \in R^{B\times L\times D}) \rightarrow x' \in \mathbb{R}^{B\times L\times D}$

RELAXED SYSTEM LAB

- B is the batch size;
- L is the sequence length;
- D is the model dimension;
- Multi-head attention: $D = n_H \times H$
- H is the head dimension;
- n_h is the number of heads.

Computation	Input	Output
$Q = XW^Q$	$X \in \mathbb{R}^{B\times L\times D}$, $W^Q \in \mathbb{R}^{D\times D}$	$Q \in \mathbb{R}^{B\times L\times D}$
$K = XW^K$	$X \in \mathbb{R}^{B\times L\times D}$, $W^K \in \mathbb{R}^{D\times D}$	$K \in \mathbb{R}^{B\times L\times D}$
$V = XW^V$	$X \in \mathbb{R}^{B\times L\times D}$, $W^V \in \mathbb{R}^{D\times D}$	$V \in \mathbb{R}^{B\times L\times D}$
$[Q_1, Q_2 \dots, Q_{n_h}] = \text{Partion}_{-1}(Q)$	$Q \in \mathbb{R}^{B\times L\times D}$	$Q_i \in \mathbb{R}^{B\times L\times H}, i = 1, \dots n_h$
$[K_1, K_2 \dots, K_{n_h}] = \text{Partion}_{-1}(K)$	$K \in \mathbb{R}^{B\times L\times D}$	$K_i \in \mathbb{R}^{B\times L\times H}, i = 1, \dots n_h$
$[V_1, V_2 \dots, V_{n_h}] = \text{Partion}_{-1}(V)$	$V \in \mathbb{R}^{B\times L\times D}$	$V_i \in \mathbb{R}^{B\times L\times H}, i = 1, \dots n_h$
$\text{Score}_i = \text{softmax}(\frac{Q_i K_i^T}{\sqrt{H}}), i = 1, \dots n_h$	$Q_i, K_i \in \mathbb{R}^{B\times L\times H}$	$\text{score}_i \in \mathbb{R}^{B\times L\times L}$
$Z_i = \text{score}_i\ V_i, i = 1, \dots n_h$	$\text{score}_i \in \mathbb{R}^{B\times L\times L}, V_i \in \mathbb{R}^{B\times L\times H}$	$Z_i \in \mathbb{R}^{B\times L\times H}$
$Z = \text{Merge}_{-1}([Z_1, Z_2 \dots, Z_{n_h}])$	$Z_i \in \mathbb{R}^{B\times L\times H}, i = 1, \dots n_h$	$Z \in \mathbb{R}^{B\times L\times D}$
$\text{Out} = ZW^O$	$Z \in \mathbb{R}^{B\times L\times D}$, $W^O \in \mathbb{R}^{D\times D}$	$\text{Out} \in \mathbb{R}^{B\times L\times D}$
$A = \text{Out}\ W^1$	$\text{Out} \in \mathbb{R}^{B\times L\times D}$, $W^1 \in \mathbb{R}^{D\times 4D}$	$A \in \mathbb{R}^{B\times L\times 4D}$
$A' = \text{relu}(A)$	$A \in \mathbb{R}^{B\times L\times 4D}$	$A' \in \mathbb{R}^{B\times L\times 4D}$
$X' = A'W^2$	$A' \in \mathbb{R}^{B\times L\times 4D}$, $W^2 \in \mathbb{R}^{4D\times D}$	$X' \in \mathbb{R}^{B\times L\times D}$

Tensor Model Parallelism

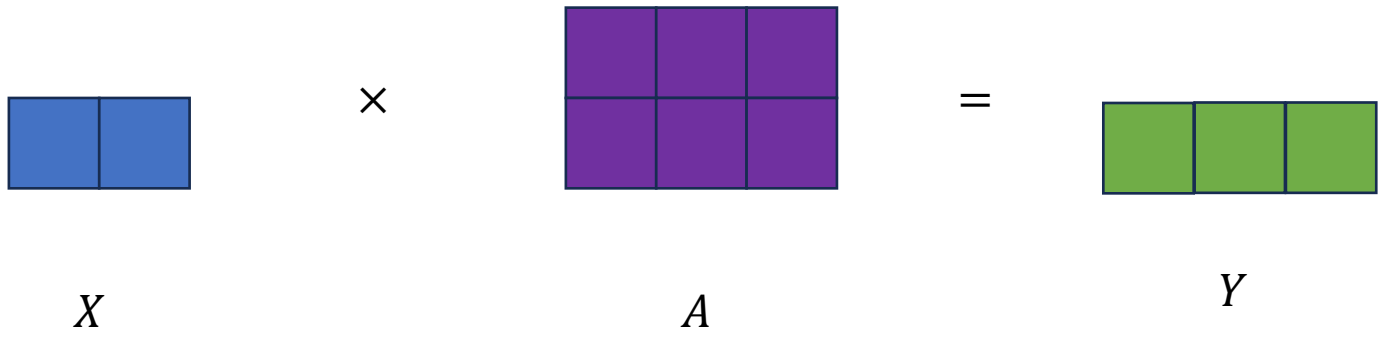
RELAXED
SYSTEM LAB

- High-level idea:
  - The tensor is split up into multiple chunks;
  - Instead of having the whole tensor reside on a single GPU, each shard of the tensor resides on its designated GPU.
  - Each shard is processed separately and in parallel on different GPUs.
  - The results are synchronized at the end of the step.

Partition the Matrix Multiplication

RELAXED SYSTEM LAB

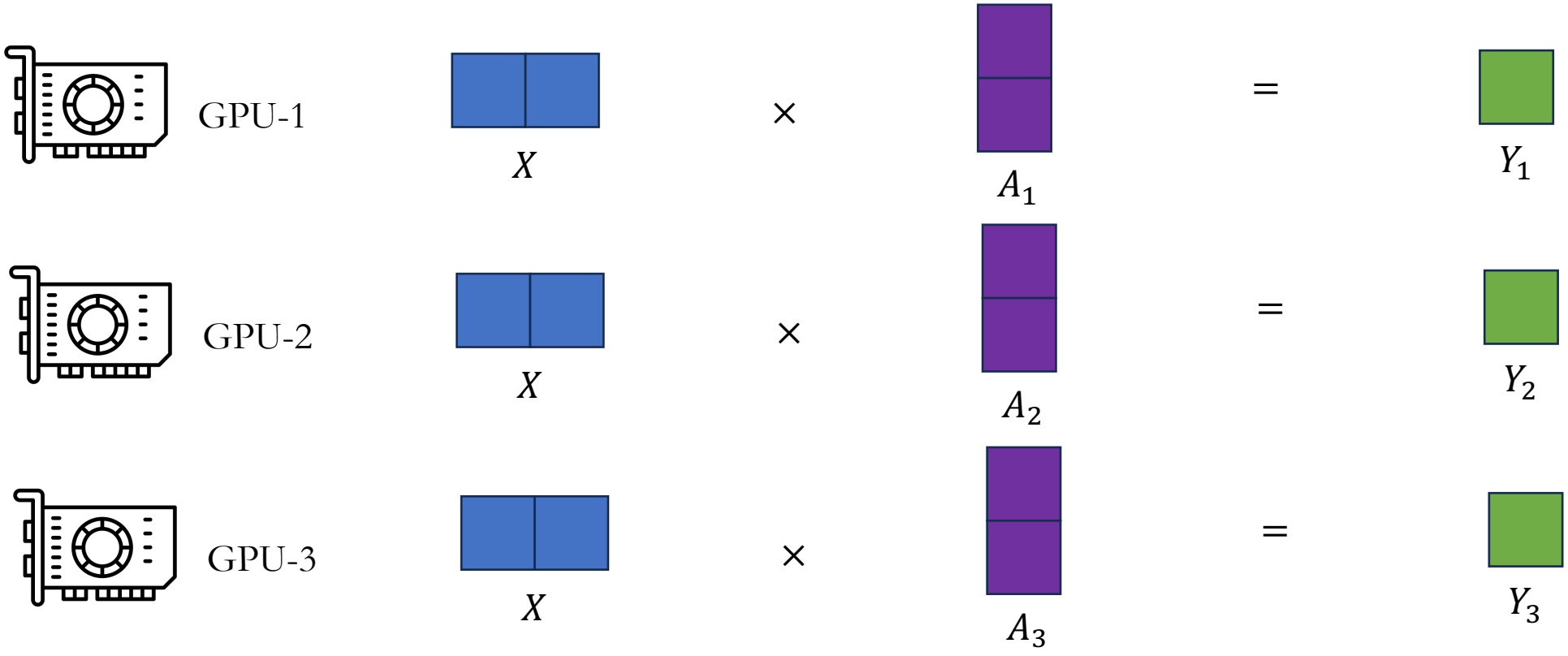
- Distribute the matrix multiplication:



Partition the Matrix Multiplication

RELAXED SYSTEM LAB

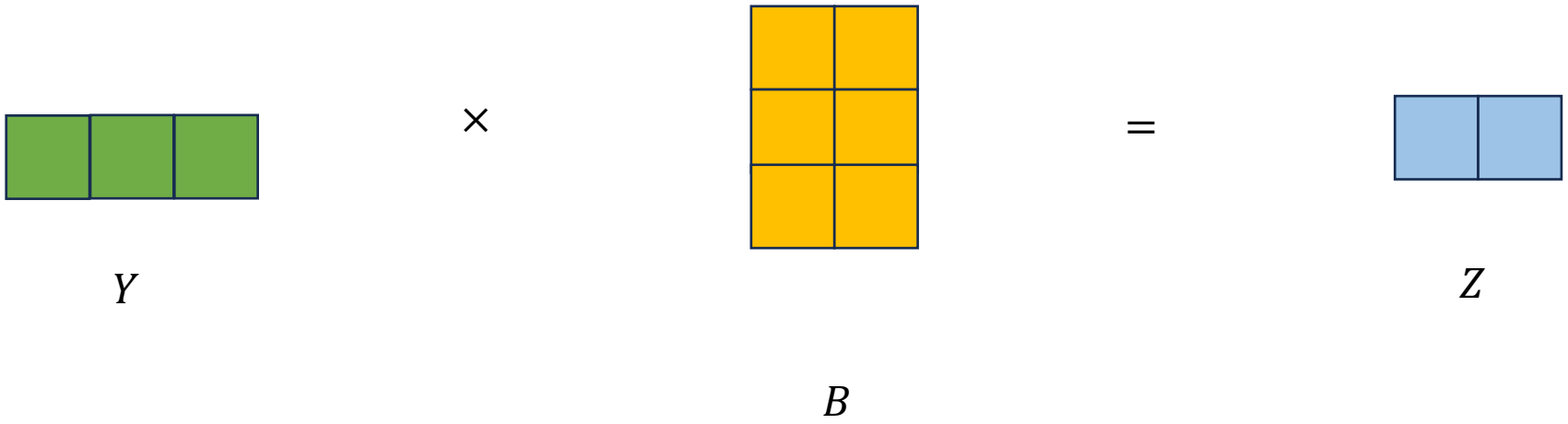
- Distribute the matrix multiplication:



Partition the Matrix Multiplication

RELAXED
SYSTEM LAB

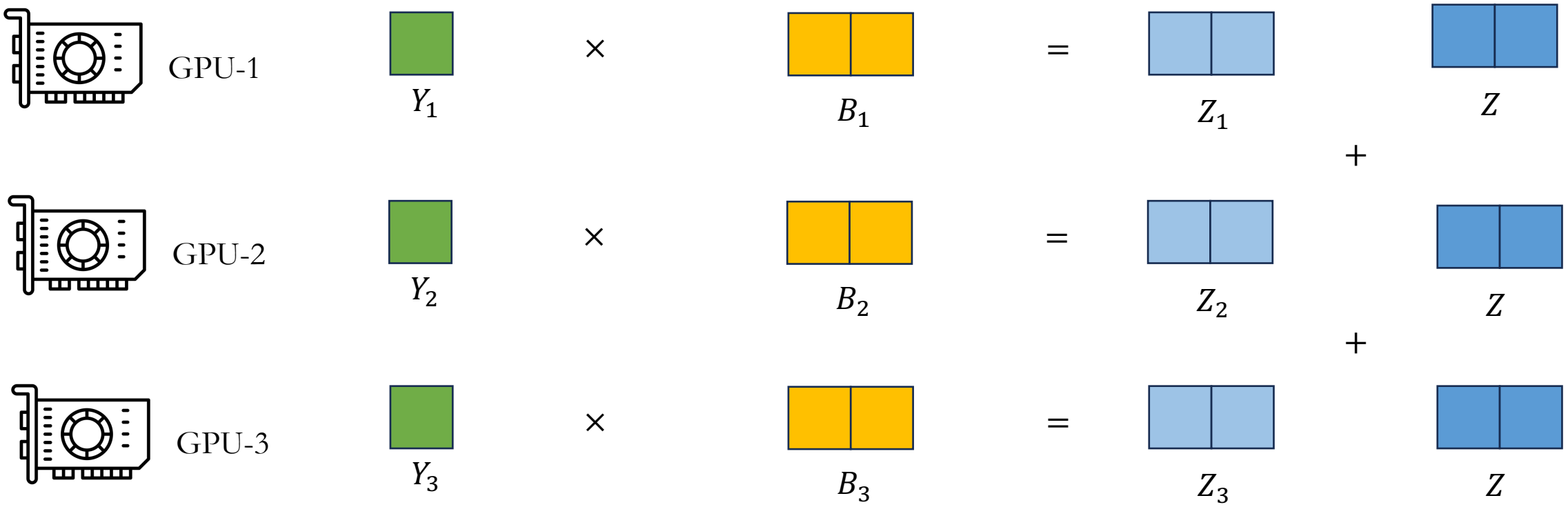
- Distribute the matrix multiplication:



Partition the Matrix Multiplication

RELAXED SYSTEM LAB

- Distribute the matrix multiplication:



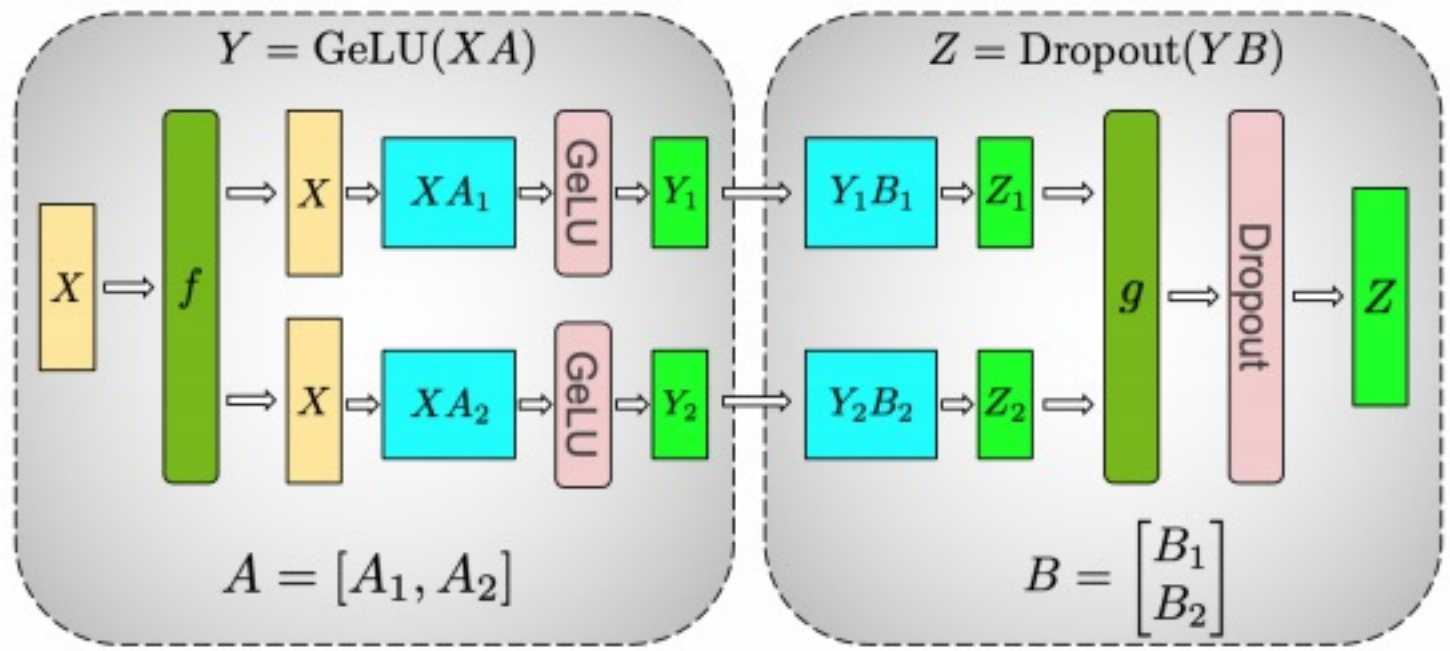
Tensor Model Parallelism

RELAXED
SYSTEM LAB

- Split the first weight matrix col-wisely;
- Split the second weight matrix row-wisely;
- Duplicate the input on each GPU;
- Apply the computation as we illustrated above;
- Aggregate the outputs after the local computation.

MLP in Tensor Model Parallelism

RELAXED SYSTEM LAB

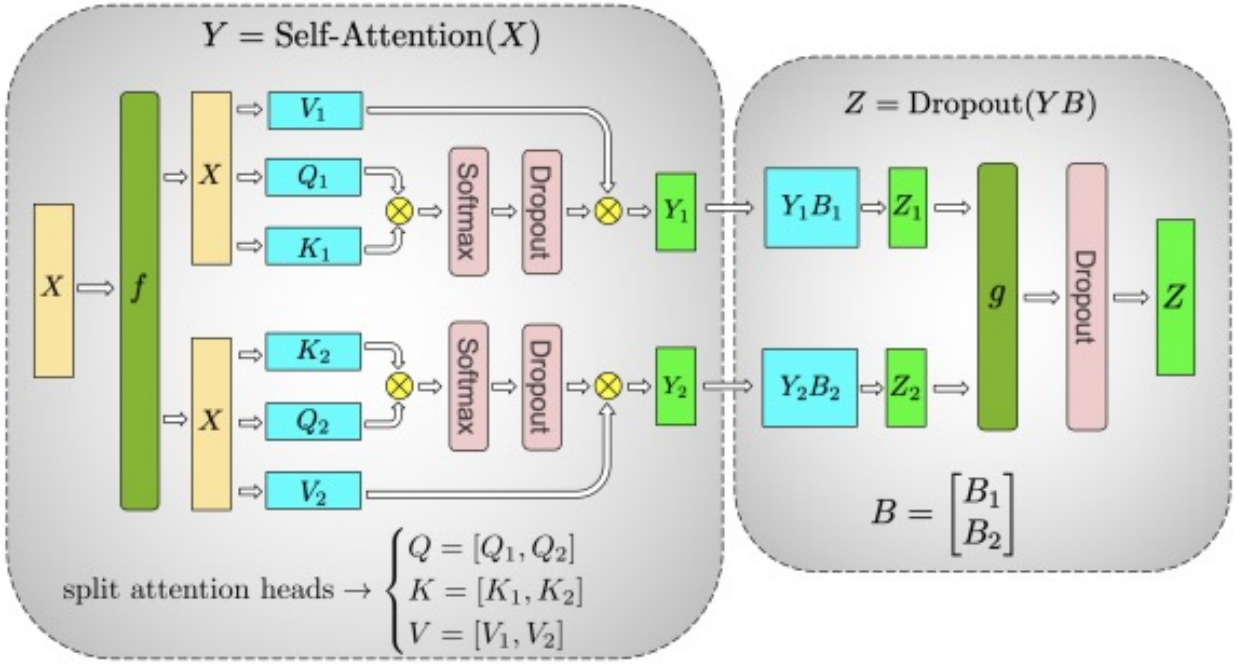


(a) MLP

- f is the identity operator in the forward pass and the **AllReduce** operator in the backward pass.
- g is the **AllReduce** operator in the forward pass and the identity operator in the backward pass.

Multi-Head Attention in Tensor Model Parallelism

RELAXED SYSTEM LAB



(b) Self-Attention

- f is the identity operator in the forward pass and the **AllReduce** operator in the backward pass.
- g is the **AllReduce** operator in the forward pass and the identity operator in the backward pass.

TransformerBlocks in Tensor Model Parallelism

RELAXED SYSTEM LAB

- B is the batch size;
- L is the sequence length;
- D is the model dimension;
- Multi-head attention: $D = n_H \times H$
- H is the head dimension;
- n_H is the number of heads.
- d_{tp} is the tensor parallel degree: $d_{tp} \leq n_H$.

Computation	Input	Output
$Q = XW^Q$	$X \in \mathbb{R}^{B\times L\times D}, W^Q \in \mathbb{R}^{D\times \frac{D}{d_{tp}}}$	$Q \in \mathbb{R}^{B\times L\times \frac{D}{d_{tp}}}$
$K = XW^K$	$X \in \mathbb{R}^{B\times L\times D}, W^K \in \mathbb{R}^{D\times \frac{D}{d_{tp}}}$	$K \in \mathbb{R}^{B\times L\times \frac{D}{d_{tp}}}$
$V = XW^V$	$X \in \mathbb{R}^{B\times L\times D}, W^V \in \mathbb{R}^{D\times \frac{D}{d_{tp}}}$	$V \in \mathbb{R}^{B\times L\times \frac{D}{d_{tp}}}$
$\left[Q_1, Q_2 \dots, Q_{\frac{n_H}{d_{tp}}}\right] = \text{Partion}_{-1}(Q)$	$Q \in \mathbb{R}^{B\times L\times \frac{D}{d_{tp}}}$	$Q_i \in \mathbb{R}^{B\times L\times H}, i = 1, \dots \frac{n_H}{d_{tp}}$
$\left[K_1, K_2 \dots, K_{\frac{n_H}{d_{tp}}}\right] = \text{Partion}_{-1}(K)$	$K \in \mathbb{R}^{B\times L\times \frac{D}{d_{tp}}}$	$K_i \in \mathbb{R}^{B\times L\times H}, i = 1, \dots \frac{n_H}{d_{tp}}$
$\left[V_1, V_2 \dots, V_{\frac{n_H}{d_{tp}}}\right] = \text{Partion}_{-1}(V)$	$V \in \mathbb{R}^{B\times L\times \frac{D}{d_{tp}}}$	$V_i \in \mathbb{R}^{B\times L\times H}, i = 1, \dots \frac{n_H}{d_{tp}}$
$\text{Score}_i = \text{softmax}(\frac{Q_i K_i^T}{\sqrt{H}}), i = 1, \dots \frac{n_H}{d_{tp}}$	$Q_i, K_i \in \mathbb{R}^{B\times L\times H}$	$\text{score}_i \in \mathbb{R}^{B\times L\times L}$
$Z_i = \text{score}_i\, V_i, i = 1, \dots \frac{n_H}{d_{tp}}$	$\text{score}_i \in \mathbb{R}^{B\times L\times L}, V_i \in \mathbb{R}^{B\times L\times H}$	$Z_i \in \mathbb{R}^{B\times L\times H}$
$Z = \text{Merge}_{-1}\left(\left[Z_1, Z_2 \dots, Z_{\frac{n_H}{d_{tp}}}\right]\right)$	$Z_i \in \mathbb{R}^{B\times L\times H}, i = 1, \dots \frac{n_H}{d_{tp}}$	$Z \in \mathbb{R}^{B\times L\times \frac{D}{d_{tp}}}$
$\text{Out} = ZW^O$	$Z \in \mathbb{R}^{B\times L\times \frac{D}{d_{tp}}}, W^O \in \mathbb{R}^{\frac{D}{d_{tp}}\times D}$	$\text{Out} \in \mathbb{R}^{B\times L\times D}$
AllReduce(Out)	$\text{Out} \in \mathbb{R}^{B\times L\times D}$	$\text{Out} \in \mathbb{R}^{B\times L\times D}$

TransformerBlocks in Tensor Model Parallelism

RELAXED SYSTEM LAB

- B is the batch size;
- L is the sequence length;
- D is the model dimension;
- Multi-head attention: $D = n_H \times H$
- H is the head dimension;
- n_H is the number of heads.
- d_{tp} is the tensor parallel degree: $d_{tp} \leq n_H$.

Computation	Input	Output
$A = \text{Out}\, W^1$	$\text{Out} \in \mathbb{R}^{B \times L \times D}$, $W^1 \in \mathbb{R}^{D \times \frac{4D}{d_{tp}}}$	$A \in \mathbb{R}^{B \times L \times \frac{4D}{d_{tp}}}$
$A' = \text{relu}(A)$	$A \in \mathbb{R}^{B \times L \times \frac{4D}{d_{tp}}}$	$A' \in \mathbb{R}^{B \times L \times \frac{4D}{d_{tp}}}$
$x' = A'W^2$	$A' \in \mathbb{R}^{B \times L \times \frac{4D}{d_{tp}}}$, $W^2 \in \mathbb{R}^{\frac{4D}{d_{tp}} \times D}$	$X' \in \mathbb{R}^{B \times L \times D}$
AllReduce(X')	$X' \in \mathbb{R}^{B \times L \times D}$	$X' \in \mathbb{R}^{B \times L \times D}$

Tensor Model Parallelism in Megatron-LM

https://github.com/NVIDIA/Megatron-LM

Entrance of the Training Scripts

RELAXED SYSTEM LAB

```
model = GPTModel(
    config=config,
    transformer_layer_spec=transformer_layer_spec,
    vocab_size=args.padded_vocab_size,
    max_sequence_length=args.max_position_embeddings,
    pre_process=pre_process,
    post_process=post_process,
    fp16_lm_cross_entropy=args.fp16_lm_cross_entropy,
    parallel_output=True,
    share_embeddings_and_output_weights=not args.untie_embeddings_and_output_weights,
    position_embedding_type=args.position_embedding_type,
    rotary_percent=args.rotary_percent,
)
```

https://github.com/NVIDIA/Megatron-LM/blob/main/pretrain_gpt.py#L60

Launch Scripts

RELAXED SYSTEM LAB

```
GPT_ARGS="
    --tensor-model-parallel-size 2 \
    --pipeline-model-parallel-size 2 \
    --sequence-parallel \
    --num-layers 24 \
    --hidden-size 1024 \
    --num-attention-heads 16 \
    --seq-length 1024 \
    --max-position-embeddings 1024 \
    --micro-batch-size 4 \
    --global-batch-size 16 \
    --lr 0.00015 \
    --train-iters 500000 \
    --lr-decay-iters 320000 \
    --lr-decay-style cosine \
    --min-lr 1.0e-5 \
    --weight-decay 1e-2 \
    --lr-warmup-fraction .01 \
    --clip-grad 1.0 \
    --fp16
"
```

https://github.com/NVIDIA/Megatron-LM/blob/main/examples/pretrain_gpt_distributed_with_mp.sh#L28

Parallel Strategies

RELAXED
SYSTEM LAB

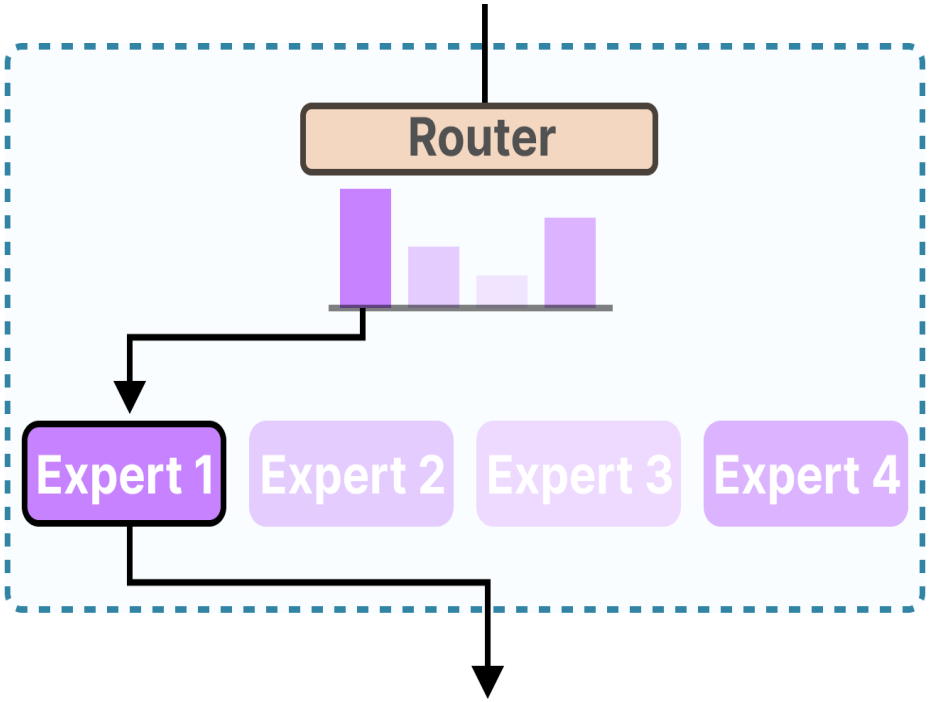
- Data Parallelism:
  - **Memory issue**: each device needs to maintain a complete copy of the model (parameters, gradients, and optimizer status).
  - **Statistical efficiency**: if the global batch size is too large, it may affect the convergence rate
- Pipeline Parallelism:
  - **Bubble overhead:** the pipeline parallelism efficiency decreases as the number of stages increases.
- Tensor model parallelism:
  - **Limited** to transformer architectures.
  - **Communication intensive:** each TransformerBlock requests two **AllReduce**s in the forward pass and two **AllReduce**s in the backward pass.

MoE Parallelism

Mixture of Expert

RELAXED SYSTEM LAB

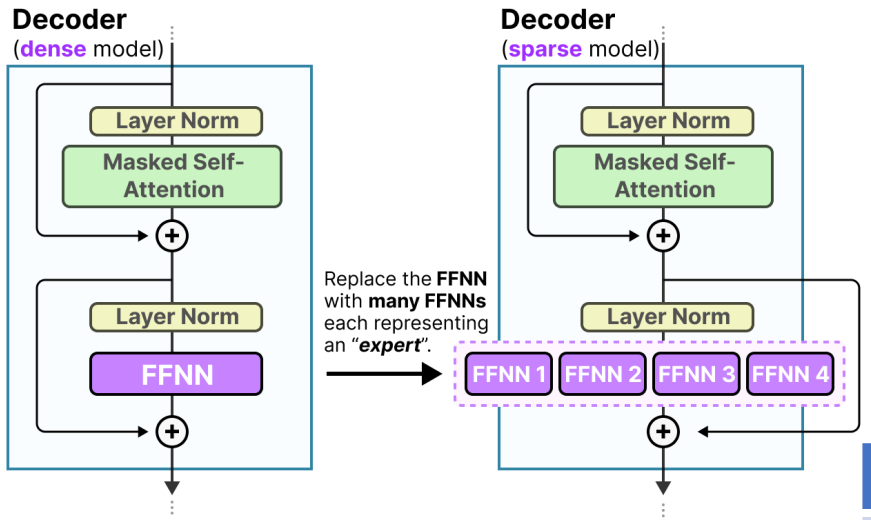
- Intuitive idea of MoE:
  - Divide a large model or layer into multiple smaller sub-networks, known as "experts," each specializing in different aspects of the input data or task.
- MoE components:
  - **Router** (Gating Network): This component determines which experts to activate for a given input.
  - **Experts**: individual neural sub-networks trained to handle specific subsets or patterns within the data.



- Benefit:
  - Unlike traditional dense models, where all parameters are activated for every input, MoE models use conditional computation to activate only a subset of experts relevant to a specific input.

Replace MLP with MoE in TransformerBlocks

RELAXED SYSTEM LAB



- B is the batch size;
- L is the sequence length;
- D is the model dimension;
- E is the number of experts;
- K is the number of activated experts;
- $H_E \ll D$ is the intermediate dimension of each expert.
- Noted that this formulation is only for explaining the computation, in practice we use the routing results as the input for each expert.

Dense MLP

Computation	Input	Output
$A = \text{Out}\, W^1$	$\text{Out} \in \mathbb{R}^{B\times L\times D}$, $W^1 \in \mathbb{R}^{D\times 4D}$	$A \in \mathbb{R}^{B\times L\times 4D}$
$A' = \text{relu}(A)$	$A \in \mathbb{R}^{B\times L\times 4D}$	$A' \in \mathbb{R}^{B\times L\times 4D}$
$X' = A'W^2$	$A' \in \mathbb{R}^{B\times L\times 4D}$, $W^2 \in \mathbb{R}^{4D\times D}$	$X' \in \mathbb{R}^{B\times L\times D}$

MoE

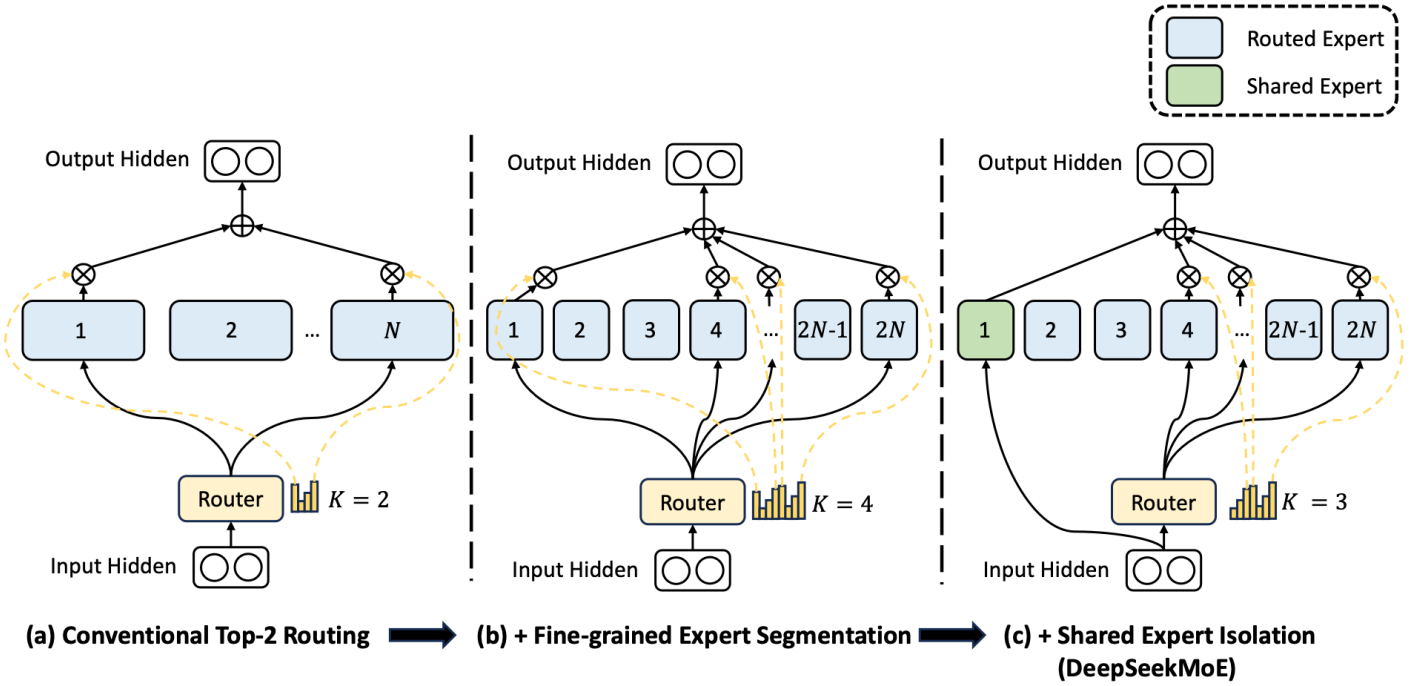
Computation	Input	Output
$S = \text{softmax}(\text{Out}\, W^G)$	$\text{Out} \in \mathbb{R}^{B\times L\times D}$, $W^G \in \mathbb{R}^{D\times E}$	$S \in \mathbb{R}^{B\times L\times E}$
$G_{i,j,k} = \begin{cases} S_{i,j,k} \text{ if } S_{i,j,k} \text{ in TopK}(S_{i,j,:}) \\ 0, \text{otherwise} \end{cases}$	$S \in \mathbb{R}^{B\times L\times E}$	$G \in \mathbb{R}^{B\times L\times E}$
$A_k = \text{Out}\, W_k^1, k = 1,2,\dots,E$	$\text{Out} \in \mathbb{R}^{B\times L\times D}$, $W_k^1 \in \mathbb{R}^{D\times H_E}$	$A_k \in \mathbb{R}^{B\times L\times H_E}$
$A_k{}' = \text{relu}(A_k), k = 1,2,\dots,E$	$A_k \in \mathbb{R}^{B\times L\times H_E}$	$A_k{}' \in \mathbb{R}^{B\times L\times H_E}$
$B_k = A_k' W^2, k = 1,2,\dots,E$	$A_k' \in \mathbb{R}^{B\times L\times H_E}$, $W_k^2 \in \mathbb{R}^{H_E\times D}$	$B_k \in \mathbb{R}^{B\times L\times D}$
$X' = \sum_{k=1}^{E} G_{:,:,k} * B_k$	$G \in \mathbb{R}^{B\times L\times E}$, $B_k \in \mathbb{R}^{B\times L\times D}$	$X' \in \mathbb{R}^{B\times L\times D}$

DeepSeek MoE

RELAXED SYSTEM LAB

- **Finely segmentation**: segmenting the experts into mN ones and activating mK from them is better than segmenting the experts into N ones and activating K from them, which allows for a more flexible combination of activated experts;
- **Shared expert**: isolating some experts as shared ones, aiming at capturing common knowledge and mitigating redundancy in routed experts.

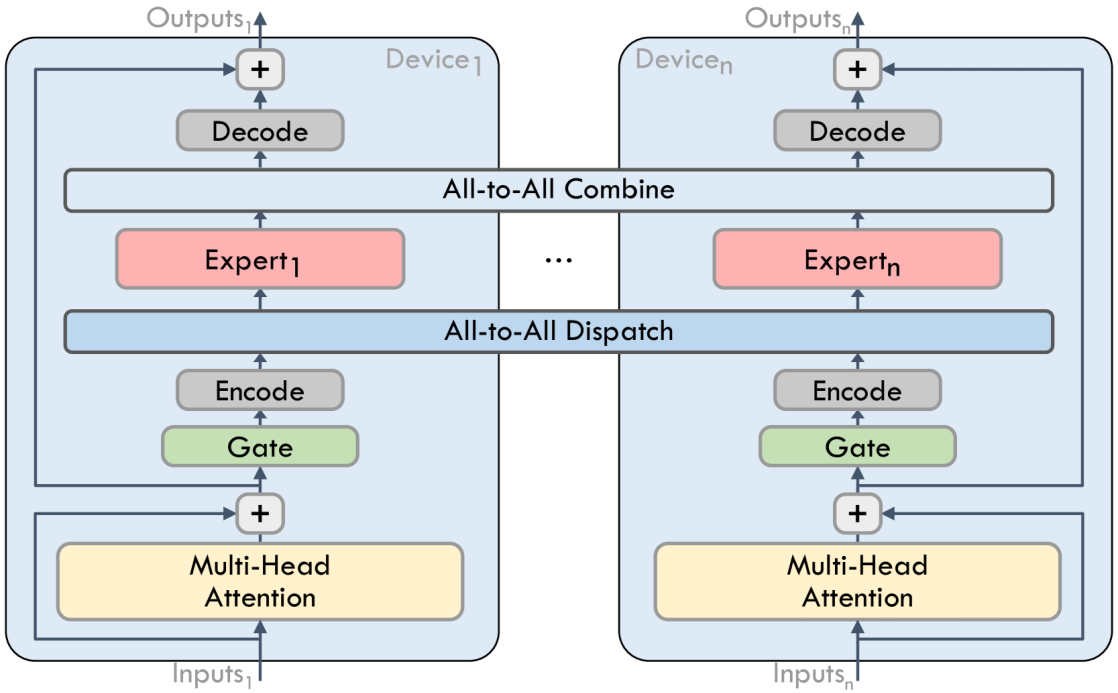
deepseek



MoE Parallelism

RELAXED SYSTEM LAB

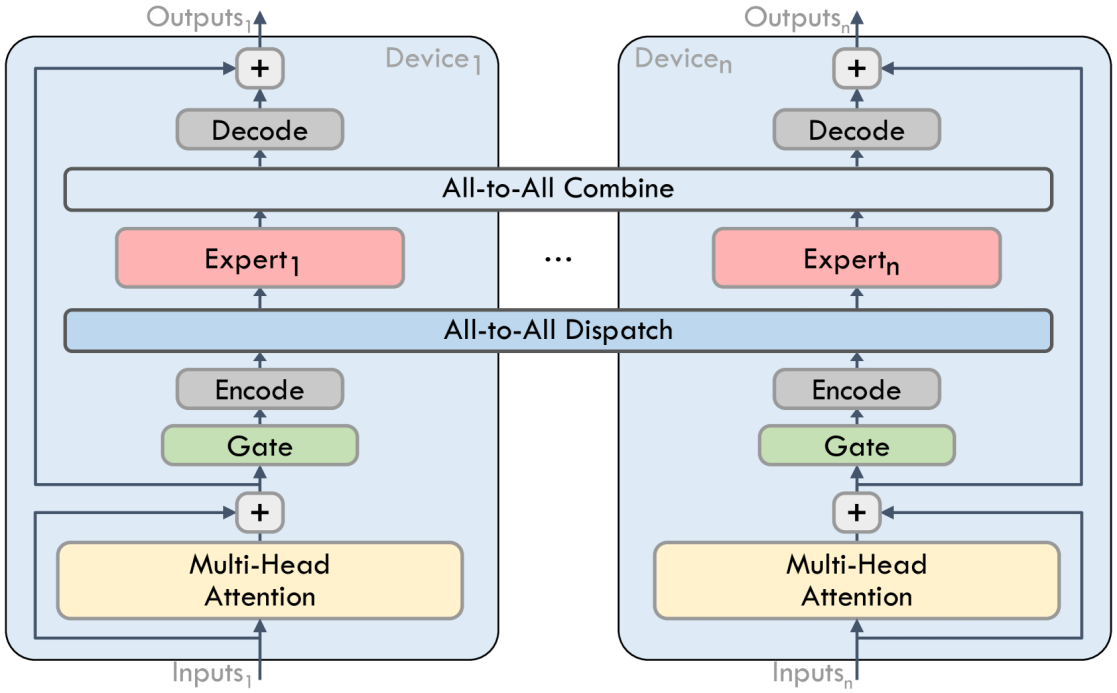
- How to parallelize the MoE training?
- Basic idea: extend standard data parallelism:
  - The experts (FFNs) are placed on different GPUs, e.g., if there is E expert and the expert parallel degree is d_{EP}, then each GPU handles $\frac{E}{d_{EP}}$ experts in parallel;
  - The rest parts of the model are duplicated on those GPUs running standard data parallelism.



MoE Parallelism

RELAXED SYSTEM LAB

- In the forward pass:
  - Two **AlltoAll** operations to communicate the activations:
    - One **AlltoAll** operation dispatches the routed activations in the current data batch to the corresponding experts;
    - One **AlltoAll** operation combines the computed expert output in the data batch that needs to be processed by the device.
  - Notice that there could be a little additional overhead to first share the shape of the dispatch tensors.



AlltoAll Communication

RELAXED SYSTEM LAB

torch.distributed.all_to_all(*output_tensor_list*, *input_tensor_list*, *group=None*, *async_op=False*) [SOURCE]

Scatters list of input tensors to all processes in a group and return gathered list of tensors in output list.

Complex tensors are supported.

Parameters

- **output_tensor_list** (*list*[*Tensor*]) – List of tensors to be gathered one per rank.
- **input_tensor_list** (*list*[*Tensor*]) – List of tensors to scatter one per rank.
- **group** (*ProcessGroup, optional*) – The process group to work on. If None, the default process group will be used.
- **async_op** (*bool, optional*) – Whether this op should be an async op.

Returns

Async work handle, if async_op is set to True. None, if not async_op or if not part of the group.

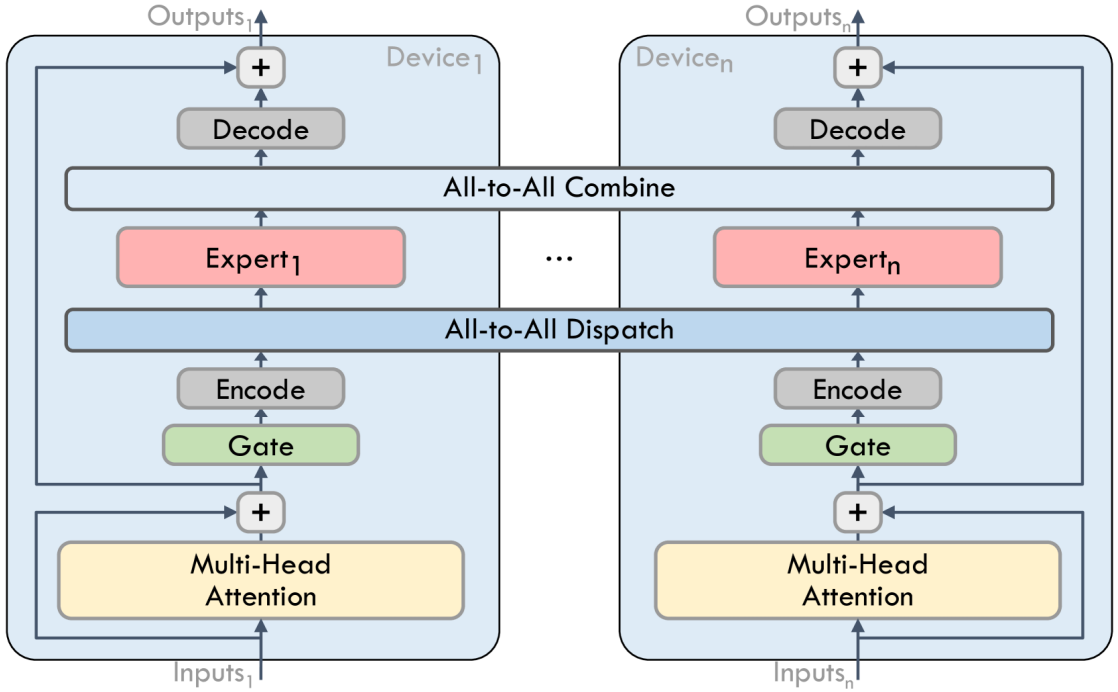
```
>>> input
tensor([0, 1, 2, 3, 4, 5])                                       # Rank 0
tensor([10, 11, 12, 13, 14, 15, 16, 17, 18])                     # Rank 1
tensor([20, 21, 22, 23, 24])                                     # Rank 2
tensor([30, 31, 32, 33, 34, 35, 36])                             # Rank 3
>>> input_splits
[2, 2, 1, 1]                                                     # Rank 0
[3, 2, 2, 2]                                                     # Rank 1
[2, 1, 1, 1]                                                     # Rank 2
[2, 2, 2, 1]                                                     # Rank 3
>>> output_splits
[2, 3, 2, 2]                                                     # Rank 0
[2, 2, 1, 2]                                                     # Rank 1
[1, 2, 1, 2]                                                     # Rank 2
[1, 2, 1, 1]                                                     # Rank 3
>>> input = list(input.split(input_splits))
>>> input
[tensor([0, 1]), tensor([2, 3]), tensor([4]), tensor([5])]                   # Rank 0
[tensor([10, 11, 12]), tensor([13, 14]), tensor([15, 16]), tensor([17, 18])] # Rank 1
[tensor([20, 21]), tensor([22]), tensor([23]), tensor([24])]                 # Rank 2
[tensor([30, 31]), tensor([32, 33]), tensor([34, 35]), tensor([36])]         # Rank 3
>>> output = ...
>>> dist.all_to_all(output, input)
>>> output
[tensor([0, 1]), tensor([10, 11, 12]), tensor([20, 21]), tensor([30, 31])]   # Rank 0
[tensor([2, 3]), tensor([13, 14]), tensor([22]), tensor([32, 33])]           # Rank 1
[tensor([4]), tensor([15, 16]), tensor([23]), tensor([34, 35])]              # Rank 2
[tensor([5]), tensor([17, 18]), tensor([24]), tensor([36])]                  # Rank 3
```

Each chunk is **NOT** necessary to have the same shape.

MoE Parallelism

RELAXED SYSTEM LAB

- In the backward pass:
  - Two **AlltoAll** operations to communicate the corresponding gradients of the activations back to the original device.
  - **AllReduce** operations to synchronize the gradients of non-expert model weights.



MoE Load Balance

RELAXED SYSTEM LAB

- Automatically learned routing strategies may encounter the issue of load imbalance:
  - Routing collapse: the model always selects only a few experts, preventing other experts from sufficient training.
  - Computation inefficiency: the computation load can vary in different devices, where the device handles the most tokens becomes the bottleneck.
- Solution: add some load balance loss during training (T is the total tokens in a batch, E is the number of experts, $S_{t,i}$ is the routing score for token t of expert i):

$$\mathcal{L}_{bal} = \sum_{i=1}^{E} f_i P_i$$

$$f_i = \frac{E}{KT} \sum_{t=1}^{T} \mathbb{I}(\text{Token } t \text{ selects Expert } i),$$

$$P_i = \sum_{t=1}^{T} S_{t,i}$$

Summary of MoE

RELAXED
SYSTEM LAB

- Most of the state-of-the-art model is based on MoE architectures:
  - E.g., Deepseek-V3, Mixtral, rumor about OpenAI GPT-4.
- MoE parallelism can be viewed as an extension of data parallelism:
  - Experts are distributed across different devices;
  - Non-expert parts are running standard data parallelism.
- Issue about load-balance.

Parallelism for Long Sequence Training

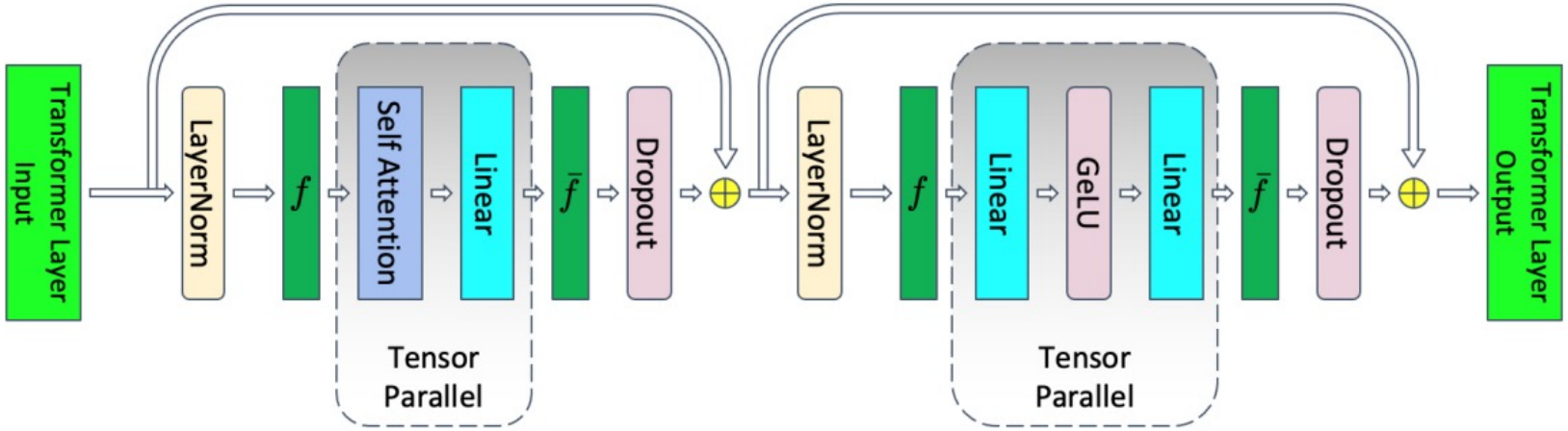
Issue about Long Context

RELAXED SYSTEM LAB

- The current LLM can be equipped with an extremely long context length, e.g., 128K, or 1M tokens;
- Even we have only one sample in the batch, there is heavy computations. We have to extend the current parallel strategies to:
  - Distributed the computation load;
  - Reduce the memory footprint.

Megatron Sequence Parallelism

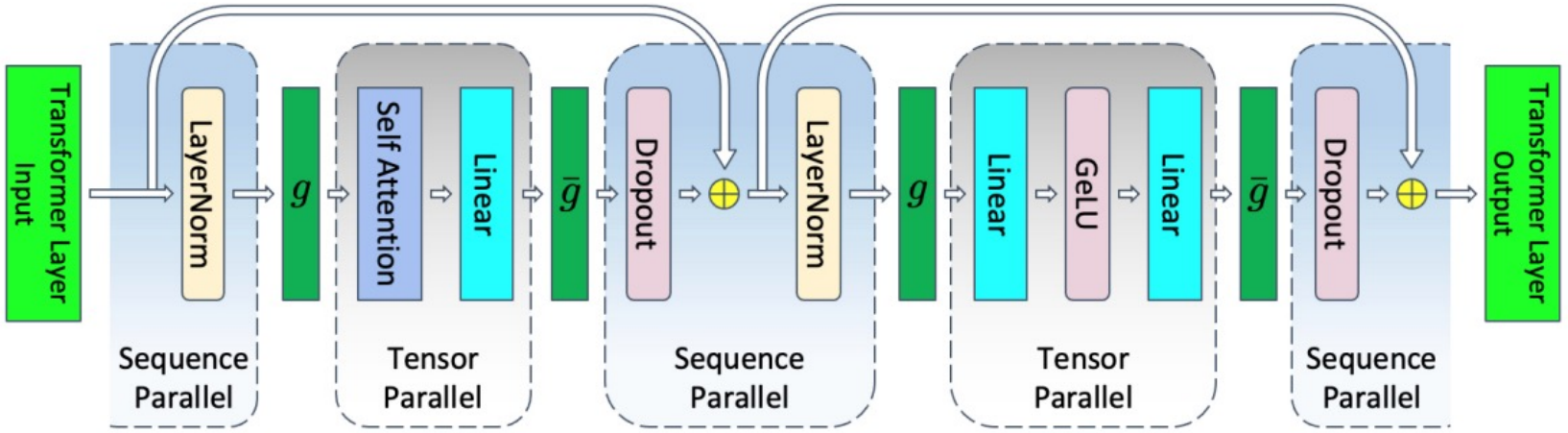
RELAXED SYSTEM LAB



In standard tensor model parallelism:
f is no operation in the forward pass and **AllReduce** in the backward pass.
$\bar{f}$ is **AllReduce** in the forward pass and no operation in the backward pass.

- Key observation:
  - All the activations in the non-tensor parallel regions of a transformer layer are duplicated, e.g., after the **AllReduce** operation.
  - These operations are independent along the sequence dimension.
  - This characteristic allows us to partition these regions along the *sequence dimension*.

Megatron Sequence Parallelism



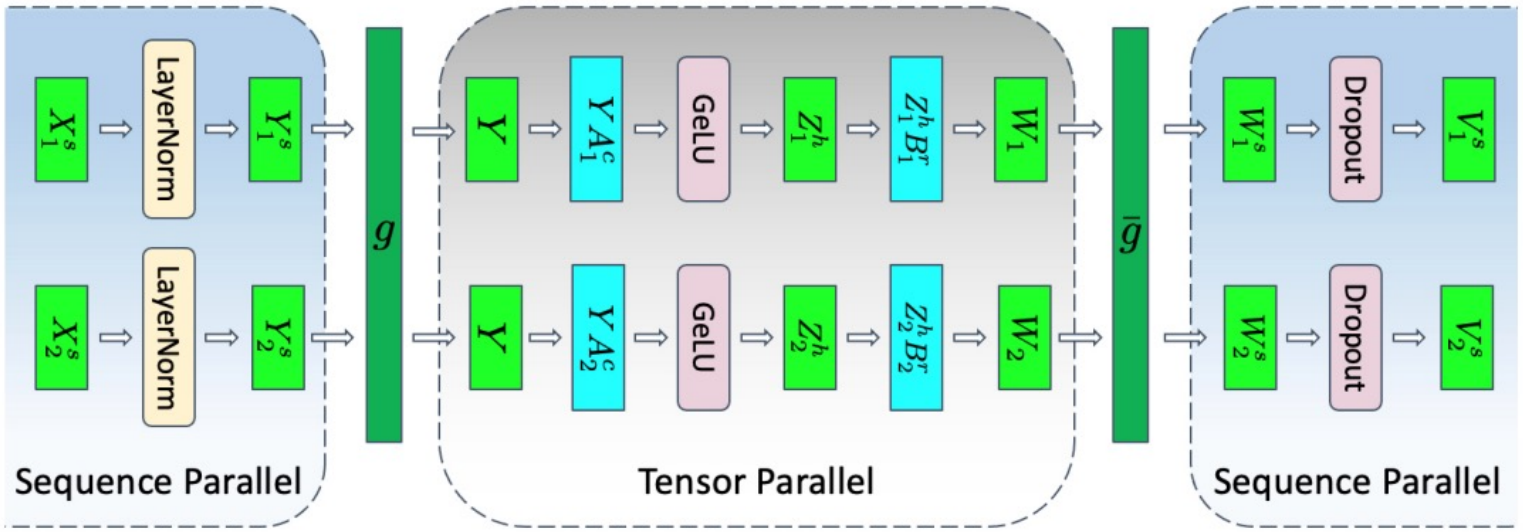
In tensor model parallelism combined with sequence parallelis:
g is **AllGather** operation in the forward pass and **ReduceScatter** in the backward pass.
$\bar{g}$ is **ReduceScatter** in the forward pass and **AllGather** operation in the backward pass.

- Sequence parallelism is an extension of the previous tensor model parallelism:
- Partitioning along the sequence dimension reduces the memory required for the activations. This extra level of parallelism introduces new collective communication paradigm.

Megatron Sequence Parallelism

RELAXED SYSTEM LAB

- This is the concrete partition of the MLP with a parallel degree as 2.



g is **AllGather** operation in the forward pass and **ReduceScatter** in the backward pass.
$\bar{g}$ is **ReduceScatter** in the forward pass and **AllGather** operation in the backward pass.

Deepspeed-Ulysses

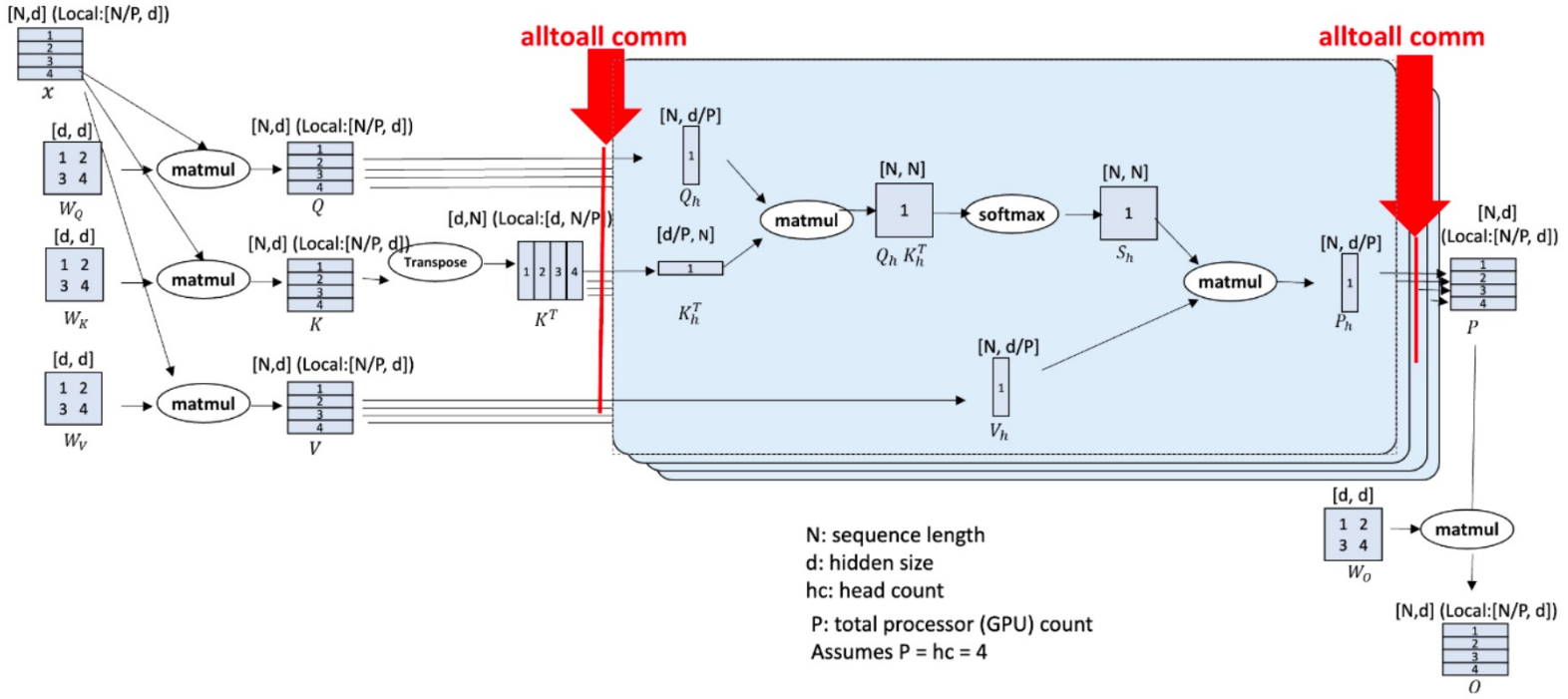
RELAXED SYSTEM LAB

- Limitation of Megatron sequence parallelism: In Megatron sequence parallelism, it has to be combined with tensor model parallelism.
- Deepspeed proposed another way of distributing the long sequence parallel training:
  - A modification of data parallelism: instead of partition the batch by data samples, Ulysses partitions the batch by sequence dimension.
  - Model parameters are duplicated among all devices.
  - Activation tensors along the sequence dimension across multiple GPUs.
  - Everything except attention computation is straight-forward. The core question is about *how to accomplish the attention computation if we split the sequence?*

Deepspeed-Ulysses

RELAXED SYSTEM LAB

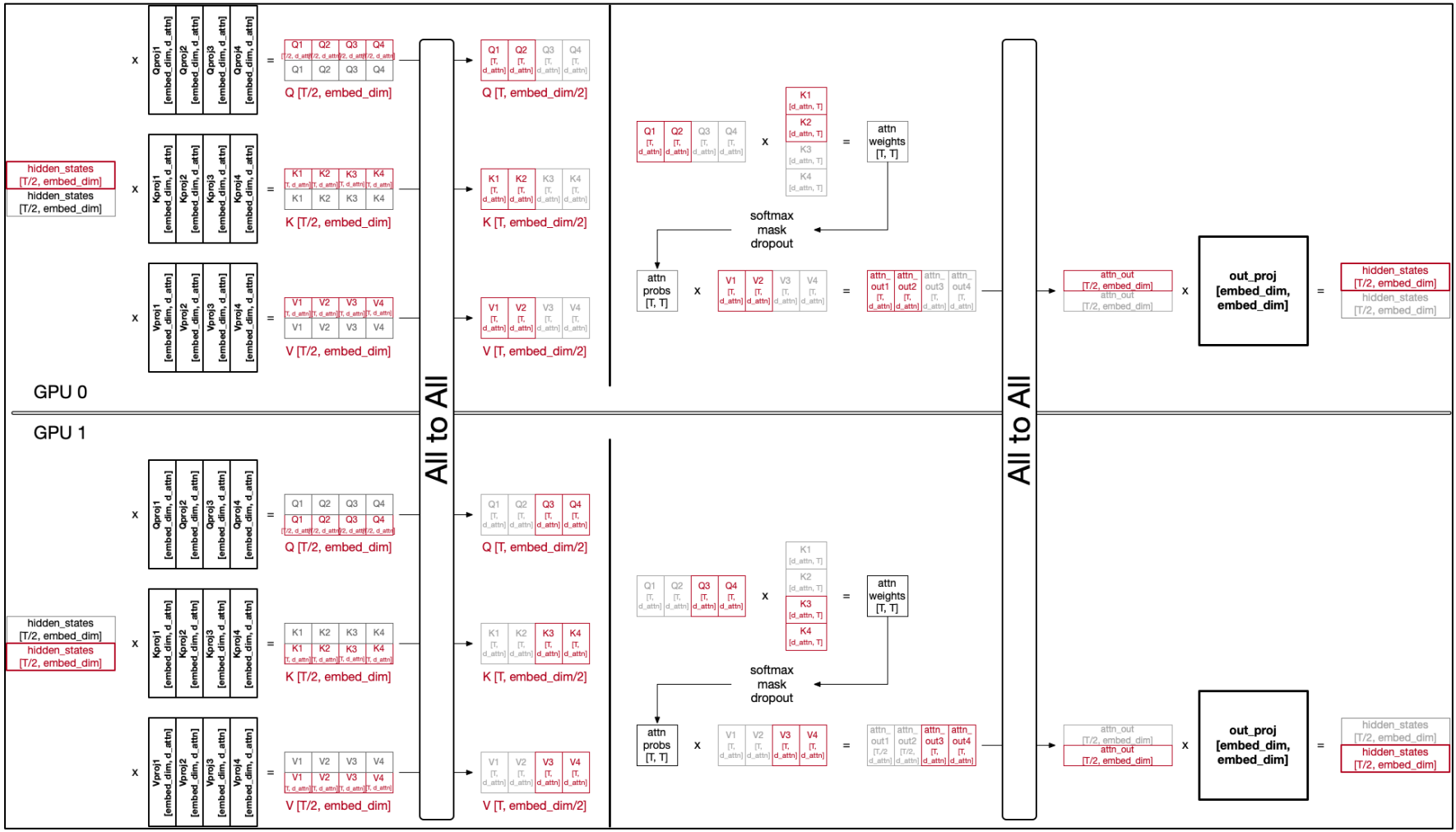
- **Core idea：**
  - Partition the computation of attention heads among different GPUs;
  - Use one All-to-All to shuffle the input Query, Key, Value;
  - Use one All-to-All to collect the corresponding output.



Deepspeed-Ulysses

RELAXED SYSTEM LAB

- **Core idea:**
  - Partition the computation of attention heads among different GPUs;
  - Use one All-to-All to shuffle the input Query, Key, Value;
  - Use one All-to-All to collect the corresponding output.



https://insujang.github.io/2024-09-20/introducing-context-parallelism

Deepspeed-Ulysses Communication

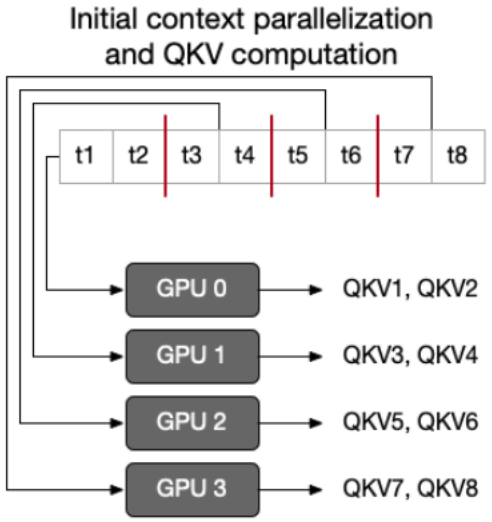
RELAXED SYSTEM LAB

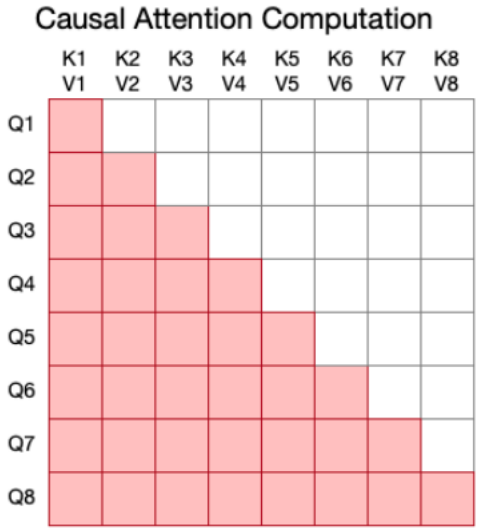
- Forward pass:
  - Before computing the attention mechanism, one **AlltoAll** operation redistributes the partitioned queries, keys, and values such that each GPU receives the full sequence data for the device's subset of attention heads.
  - After computing the attention mechanism, one **AlltoAll** operation to recover the partition of activations along the sequence dimension.
- Backward pass:
  - Two corresponding **AlltoAll** operations to send back the corresponding gradients of the activations.
  - Standard **AllReduce** operations for all gradient synchronization of the model parameters in data parallelism.

Ring Attention/Megatron Context Parallelism

RELAXED SYSTEM LAB

- Limitation of Deepspeed-Ulysses: the parallel degree is limited by the number of attention heads, we cannot add more devices to further scaling out the computation.
- Ring attention computation for the attention mechanism:
  - Split the data by sequence dimension;
  - Iteratively accumulate local attention results by iterating Q and K/V as a nested loop;
  - Each GPU holds a portion of queries, and sends its keys and values to the next GPU and receives them from the previous GPU (ring).



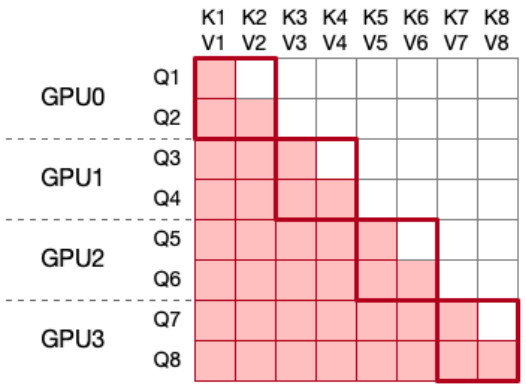


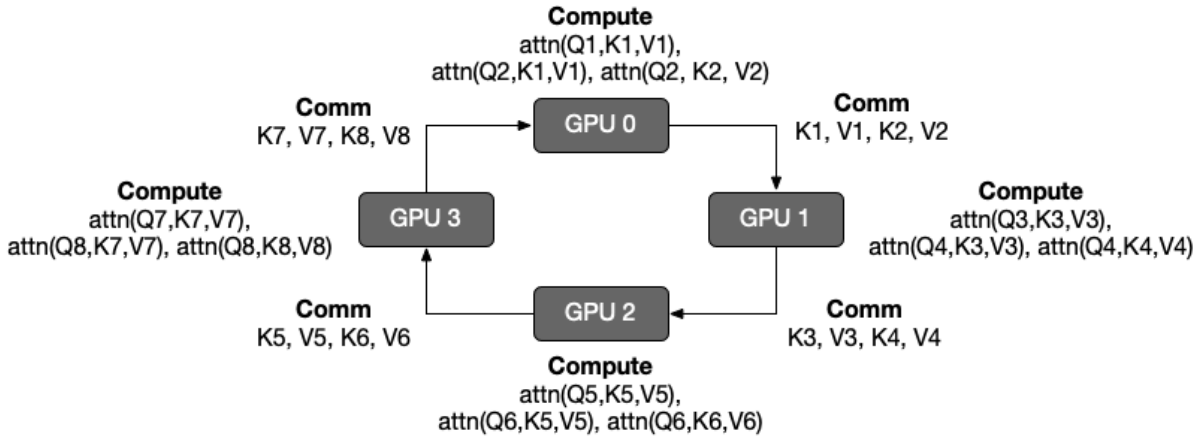
https://insujang.github.io/2024-09-20/introducing-context-parallelism

Ring Attention

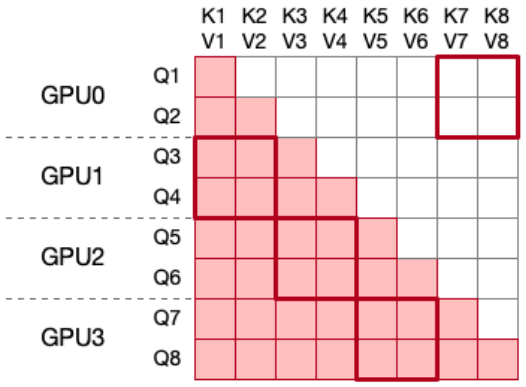
RELAXED SYSTEM LAB

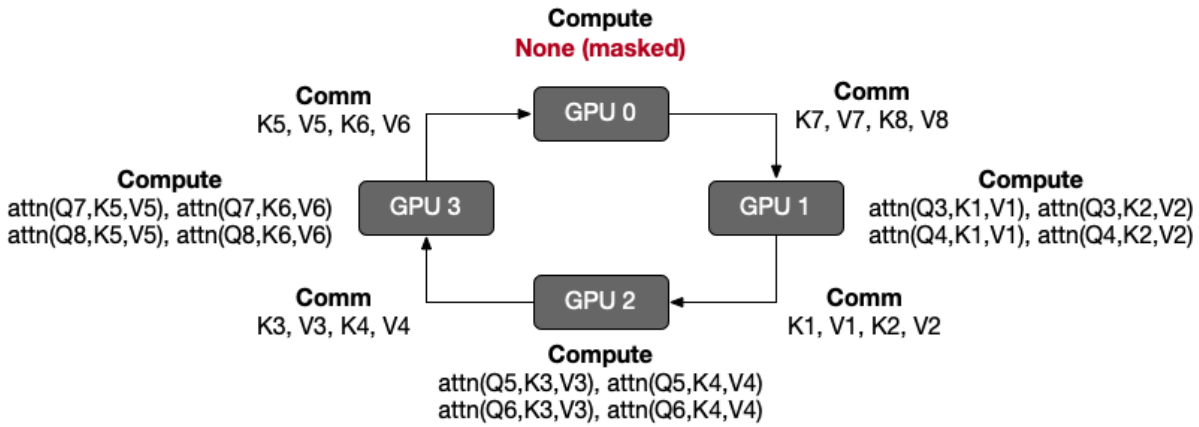
Round 1





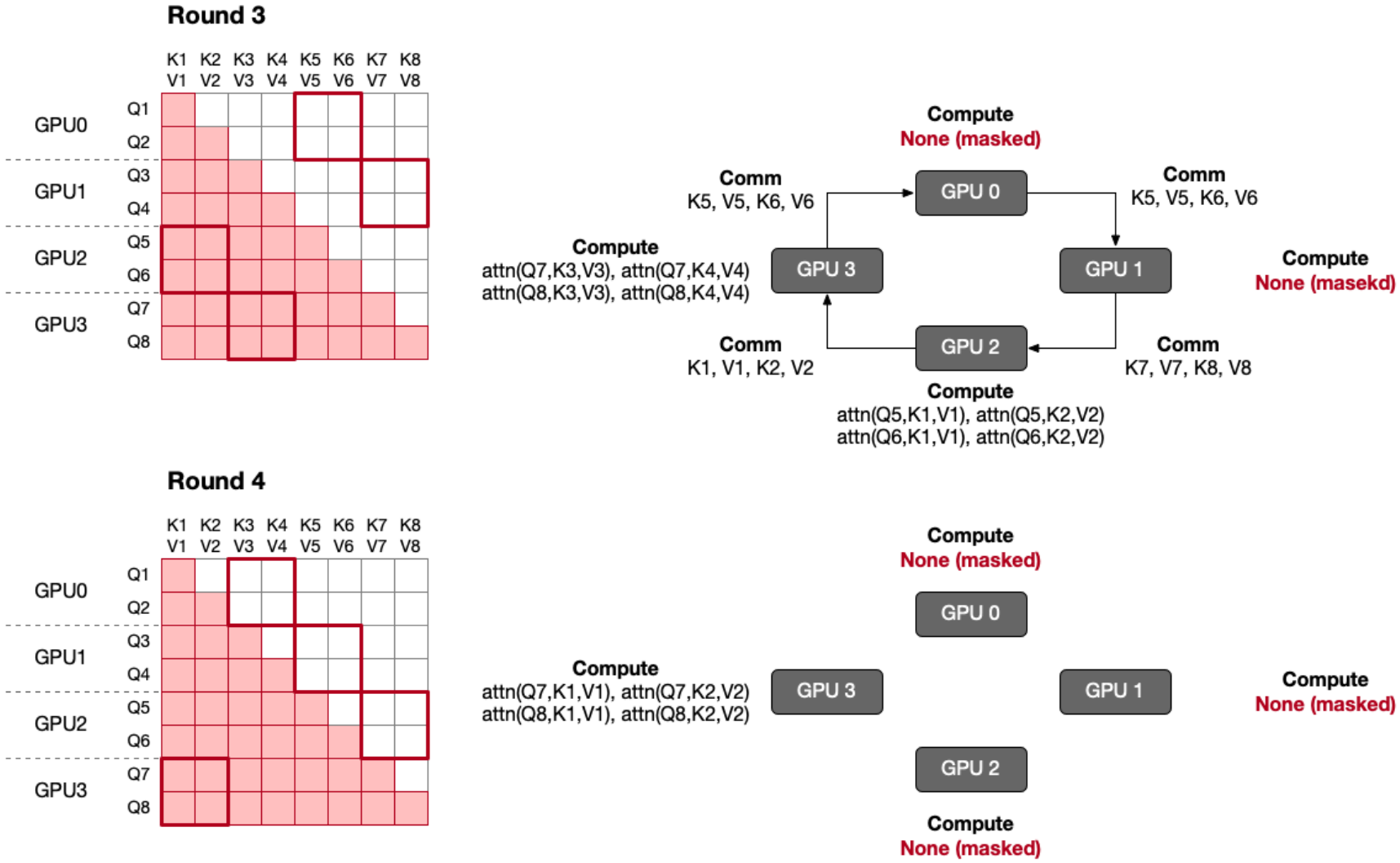
Round 2





Ring Attention

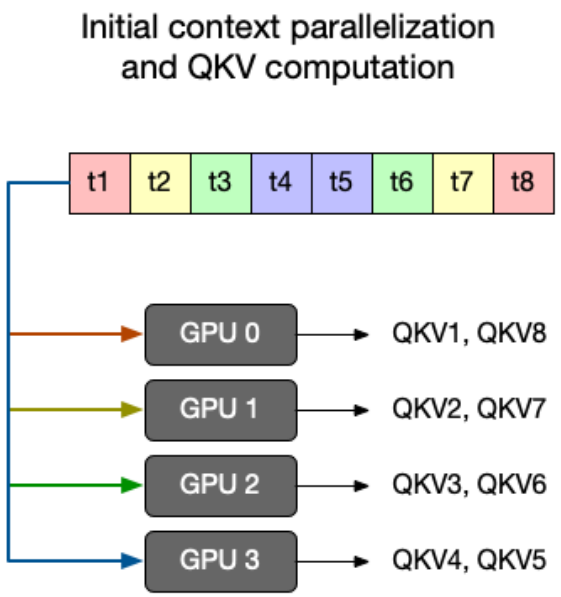
RELAXED SYSTEM LAB

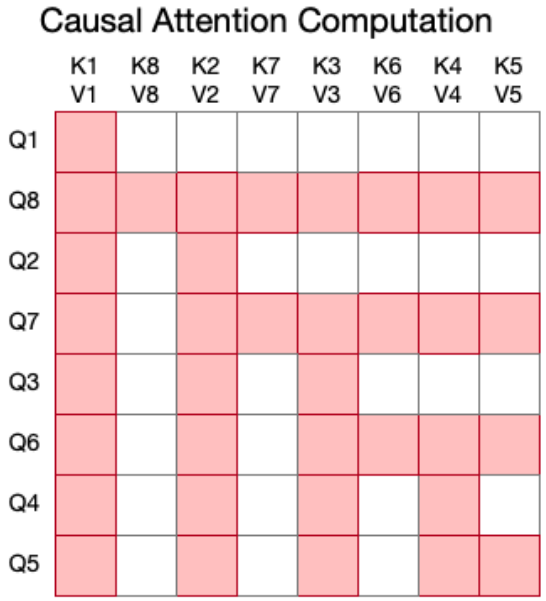


Megatron Context Parallelism

RELAXED SYSTEM LAB

- A trivial issue to be fixed in Ring Attention: the load-balance in each iteration:
- Megatron context parallelism implementation: an optimization not to compute unnecessary masked parts to balance the workflow.

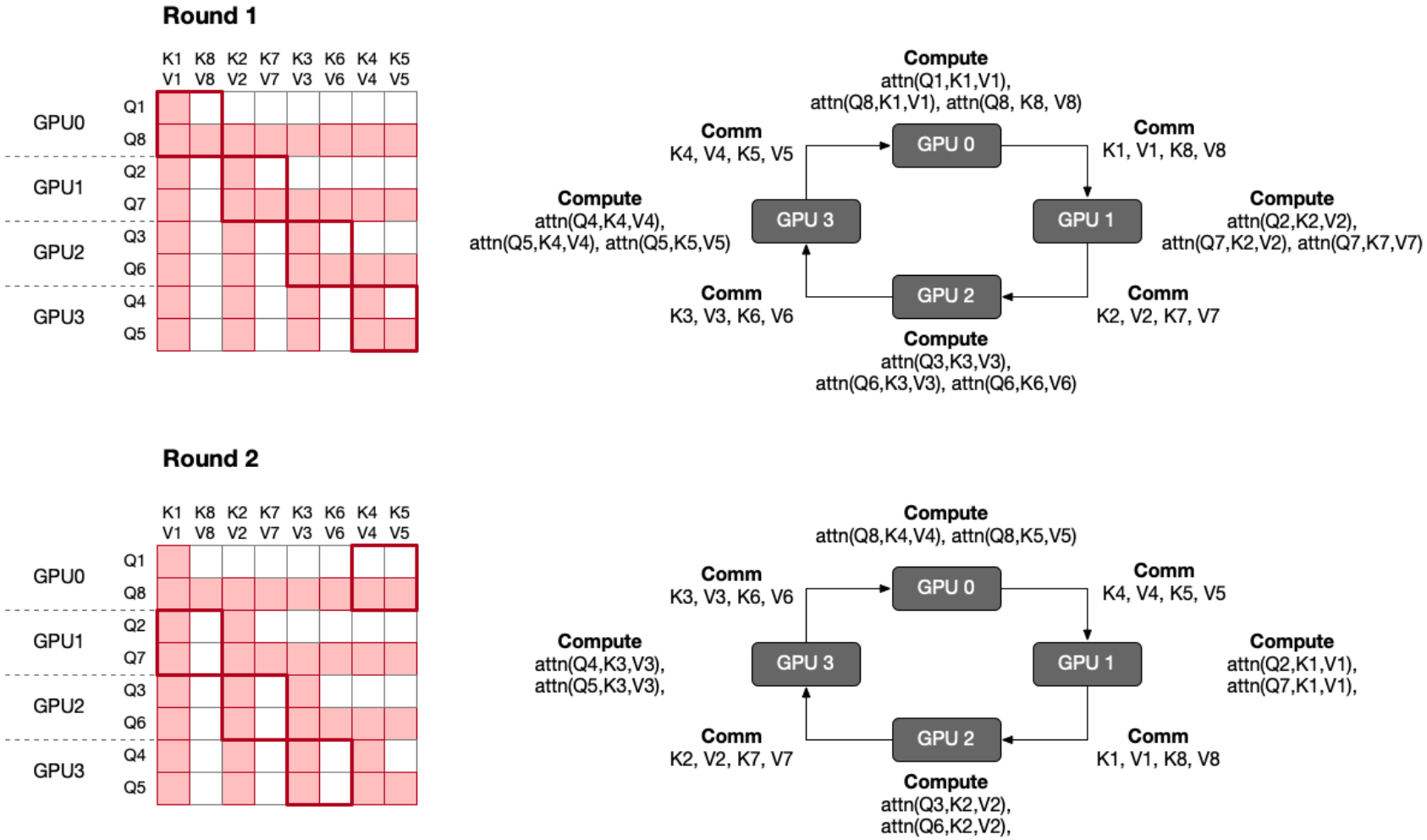




https://insujang.github.io/2024-09-20/introducing-context-parallelism

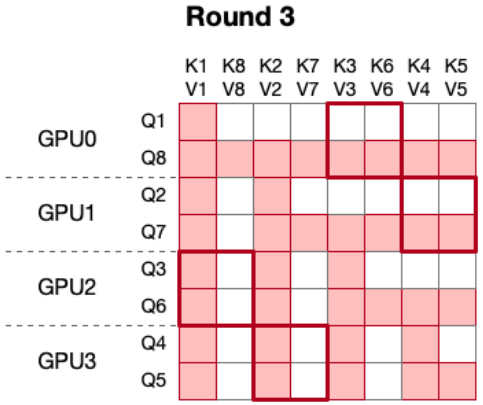
Megatron Context Parallelism

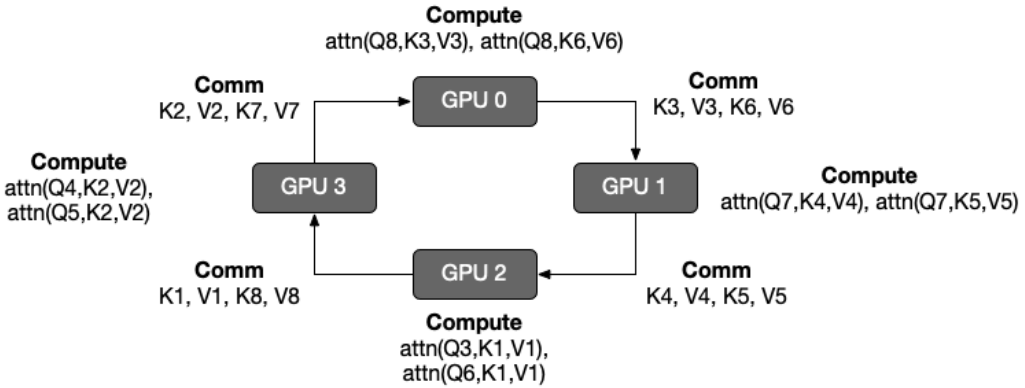
RELAXED SYSTEM LAB

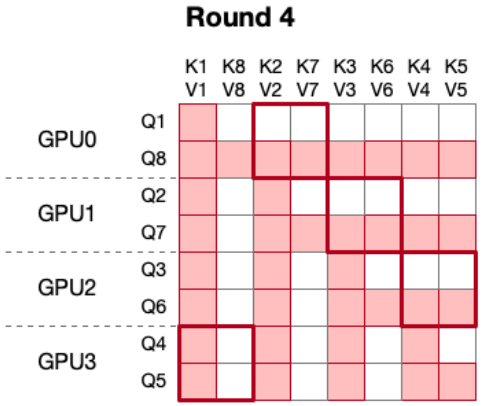


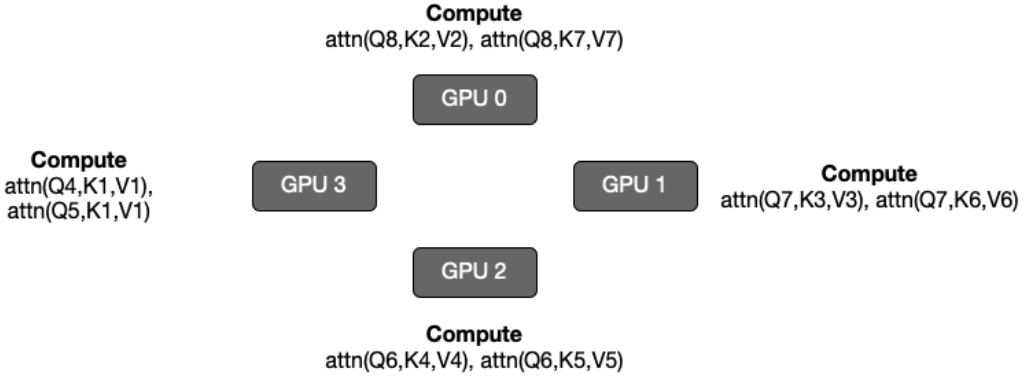
Megatron Context Parallelism

RELAXED SYSTEM LAB









References

- https://newsletter.maartengrootendorst.com/p/a-visual-guide-to-mixture-of-experts
- https://huggingface.co/blog/moe
- https://arxiv.org/abs/2401.06066
- https://arxiv.org/pdf/2205.05198
- https://arxiv.org/pdf/2309.14509
- https://insujang.github.io/2024-09-20/introducing-context-parallelism/