Efficient LLMs

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Large Language Models: Introduction and Recent Advances

Semester 1,
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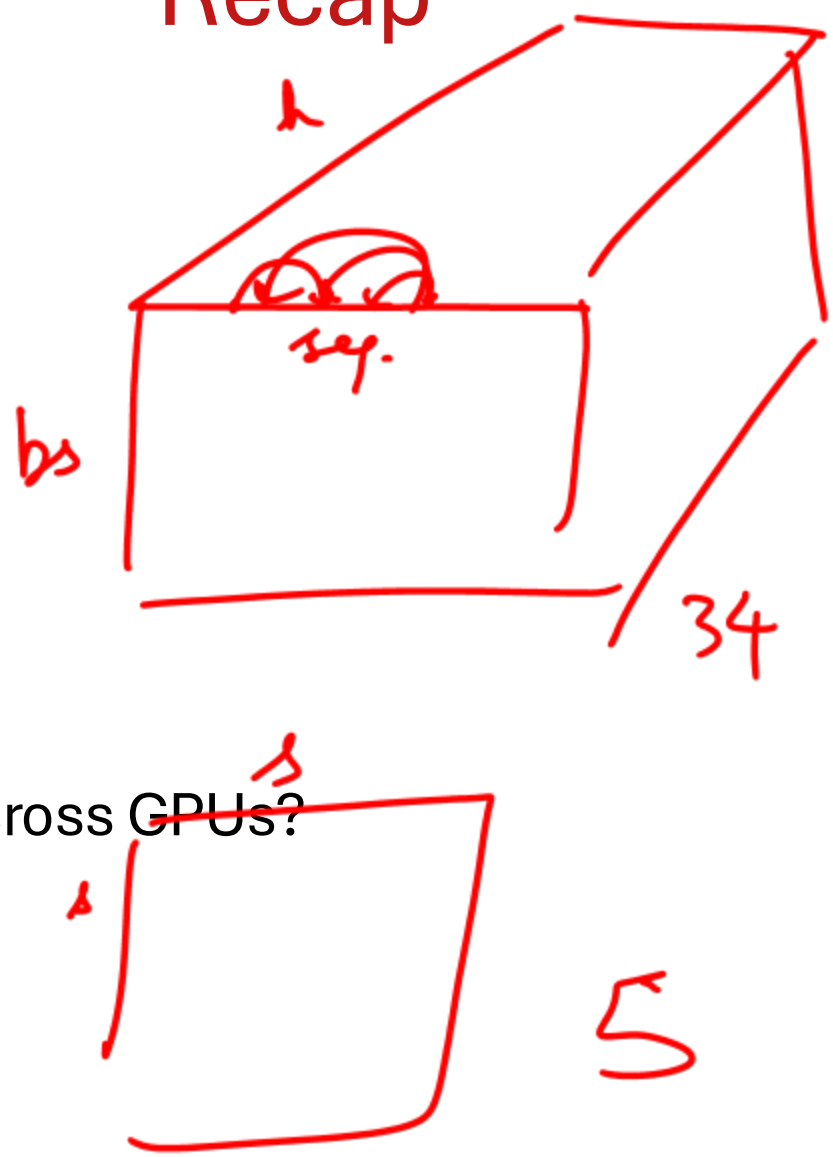
ELL881 · AIL821

Recap

- How to train big models on big data?
- What's in the GPU memory during training?
  i. Model weights ; ii. Param gradients iii. Optim states iv. Activations
- What is the size of params / grads / optim states?
- What is the size of activations?
- How to reduce activation memory?
  - Activation re-computation *aka* Gradient checkpointing
- How to increase batch size?
  - Gradient accumulation (run fwd / bwd *k* times before optim.step())
- Can we parallelize grad. Accumulation?
- Can we shard the optim. states, grads, and model params across GPUs?



Command: `torchrun --nproc_per_node 2 train.py`

```python
from torch.distributed.fsdp import fully_shard, FSDPModule
model = Transformer()
for layer in model.layers:
    fully_shard(layer)
fully_shard(model)

assert isinstance(model, Transformer)
assert isinstance(model, FSDPModule)
print(model)
#  FSDPTransformer(
#    (tok_embeddings): Embedding(...)
#    ...
#    (layers): 3 x FSDPTransformerBlock(...)
#    (output): Linear(...)
#  )
```

```python
for _ in range(epochs):
    x = torch.randint(0, vocab_size, (batch_size, seq_len), device=device
    loss = model(x).sum()
    loss.backward()
    optim.step()
    optim.zero_grad()
```

```python
from torch.utils.data import DataLoader

train_loader = DataLoader(
    dataset,
    batch_size=32,
)
```

for batch in train_loader:

```python
from torch.utils.data import DataLoader

train_loader = DataLoader(
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)
```
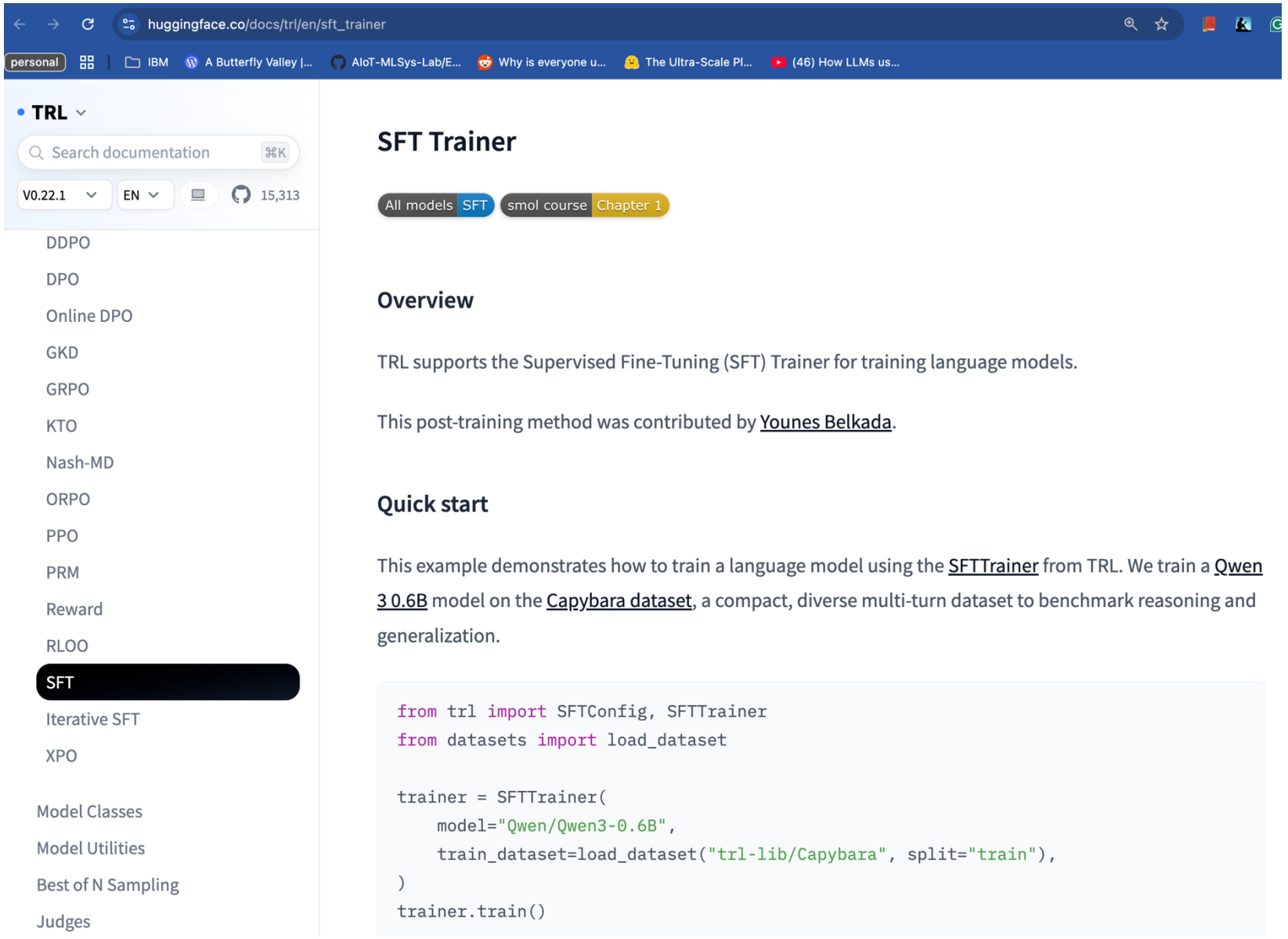

```python
from torch.utils.data import DataLoader, DistributedSampler
import torch.distributed as dist

dist.init_process_group("nccl")
rank = dist.get_rank()
world_size = dist.get_world_size()

train_sampler = DistributedSampler(
    dataset, num_replicas=world_size, rank=rank,
    shuffle=True,           # shuffle at each epoch
)
train_loader = DataLoader(
    dataset,
    batch_size=local_batch_size,  # per-GPU batch size
    sampler=train_sampler,
)
```



trl

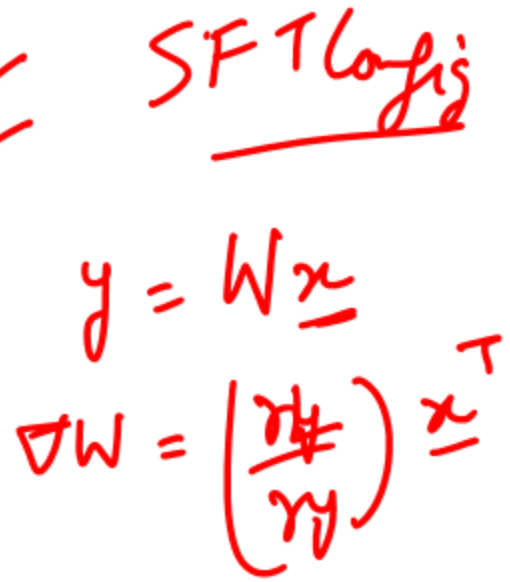
SFTTrainer

`torchrun` is low-level PyTorch-native

`accelerate` is high-level and automates much of the distributed setup.

https://huggingface.co/docs/trl/en/sft_trainer

```
accelerate launch --config_file <path/to/acc/config> trl/scripts/sft.py \
  --model_name_or_path Qwen/Qwen2-0.5B \
  --dataset_name trl-lib/Capybara \
  --learning_rate 2.0e-5 \
  --num_train_epochs 1 \
  --per_device_train_batch_size 2 \
  --gradient_accumulation_steps 8 \
  --gradient_checkpointing \
  --eos_token '<|im_end|>' \
  --eval_strategy steps \
  --eval_steps 100 \
  --output_dir Qwen2-0.5B-SFT \
```



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https://huggingface.co/docs/trl/main/en/distributing_training

https://github.com/huggingface/trl/blob/main/trl/scripts/sft.py

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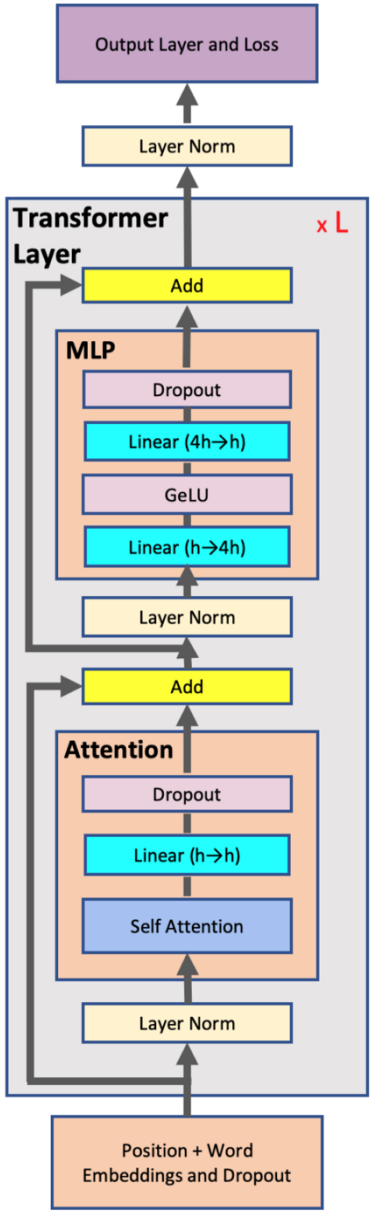
- How to increase batch size?
  - Gradient accumulation (run fwd / bwd *k* times before optim.step())
- Can we parallelize grad. Accumulation?
- Can we shard the optim. states, grads, and model params across GPUs?
- Still not sufficient for big models (e.g 70B Llama). Can we split one input sequence across GPUs?

Let us revisit activation memory



Total	$\mathbf{34 * seq * bs * h + 5 * n_{heads} * seq^2 * bs}$
MLP Block	$\mathbf{19 * seq * bs * h}$
D/o mask	$1 * seq * bs * h$
Linear *(4h -> h)*	$8 * seq * bs * h$
GELU	$8 * seq * bs * h$
Linear *(h -> 4h)*	$2 * seq * bs * h$
Layer Norm	$\mathbf{2 * seq * bs * h}$
Attention Block	$\mathbf{11 * seq * bs * h + 5 * n_{heads} * seq^2 * bs}$
Layer Norm	$\mathbf{2 * seq * bs * h}$

Memory for Activations

$$m_{act} = L * \left(\begin{array}{c} 34 * seq * bs * h \\ + \\ 5 * n_{heads} * seq^2 * bs \end{array} \right)$$

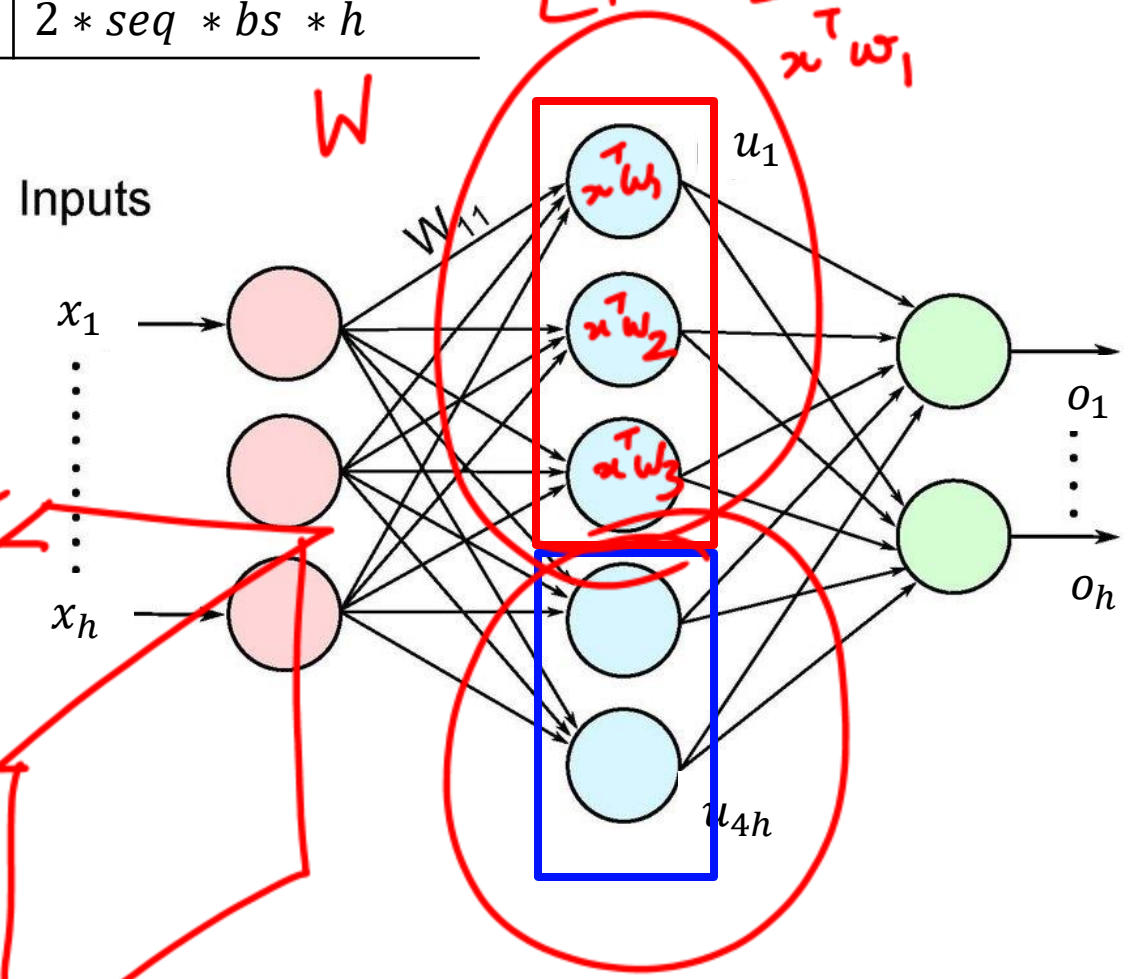
- Scales Linearly with batch size
- Quadratically with the sequence length

Korthikanti etal. 2022, Reducing Activation Recomputation in Large Transformer Models

MLP Block

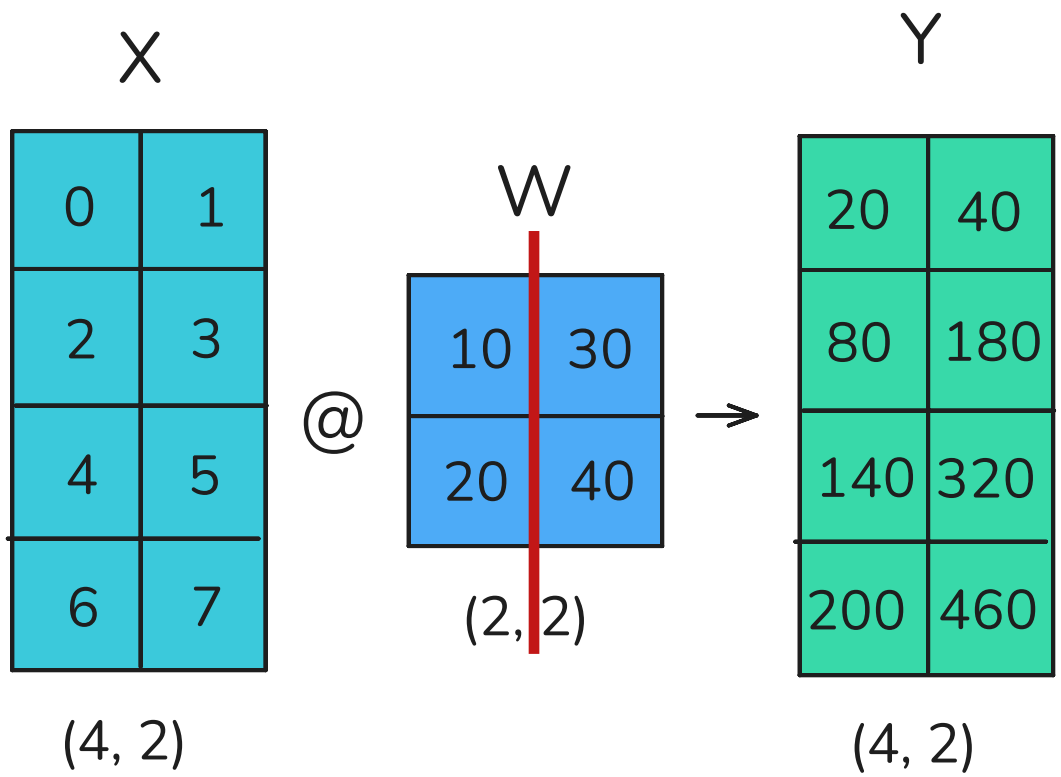
Linear *(4h -> h)*	$8 * seq * bs * h$
GELU	$8 * seq * bs * h$
Linear *(h -> 4h)*	$2 * seq * bs * h$

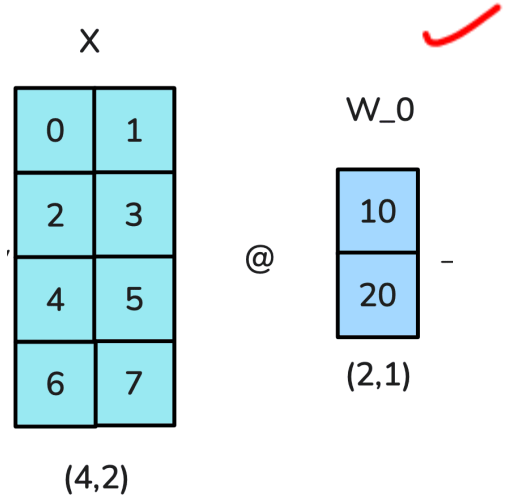
- neurons are independent of
- Can we compute them independently on different GPUs?
- How will it split the weight matrix?

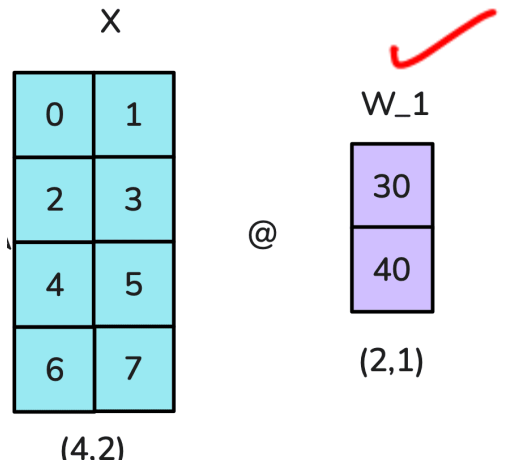


1. $A \cdot B = A \cdot [B_1 \quad B_2 \quad \cdots] = [AB_1 \quad AB_2 \quad \cdots]$

Column Linear

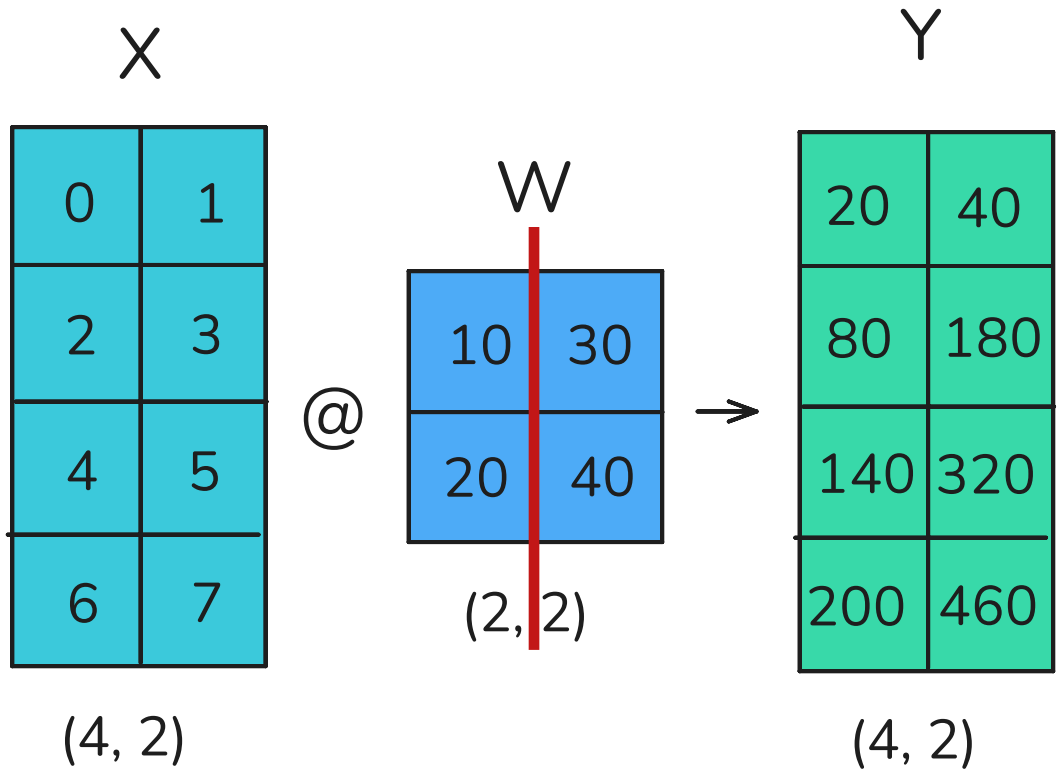


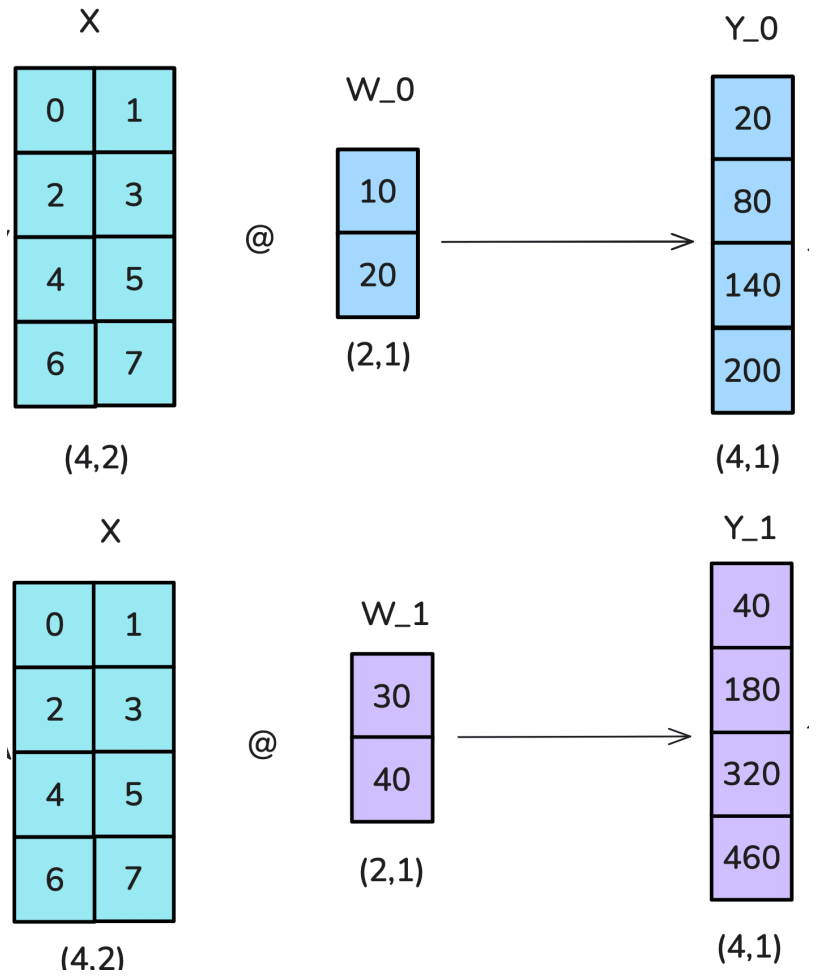




1. $A \cdot B = A \cdot \begin{bmatrix} B_1 & B_2 & \cdots \end{bmatrix} = \begin{bmatrix} AB_1 & AB_2 & \cdots \end{bmatrix}$

Column Linear





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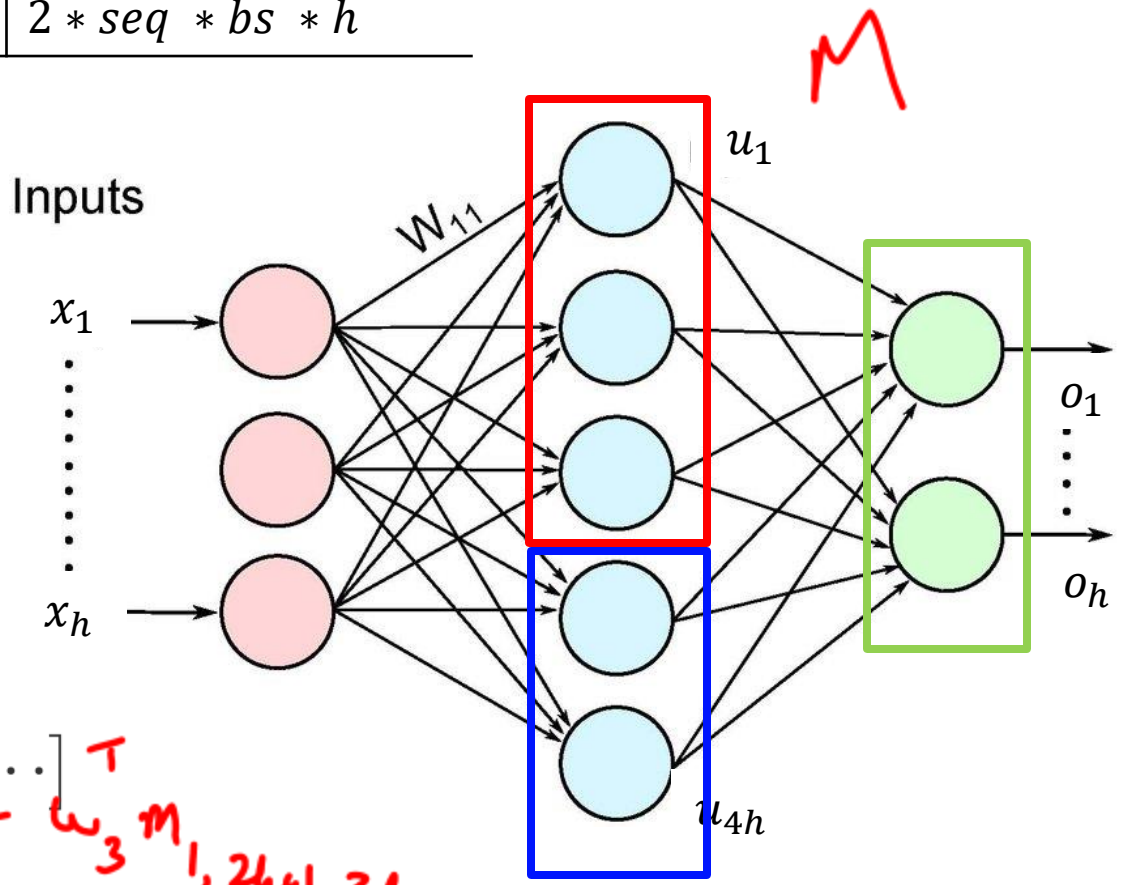
MLP Block

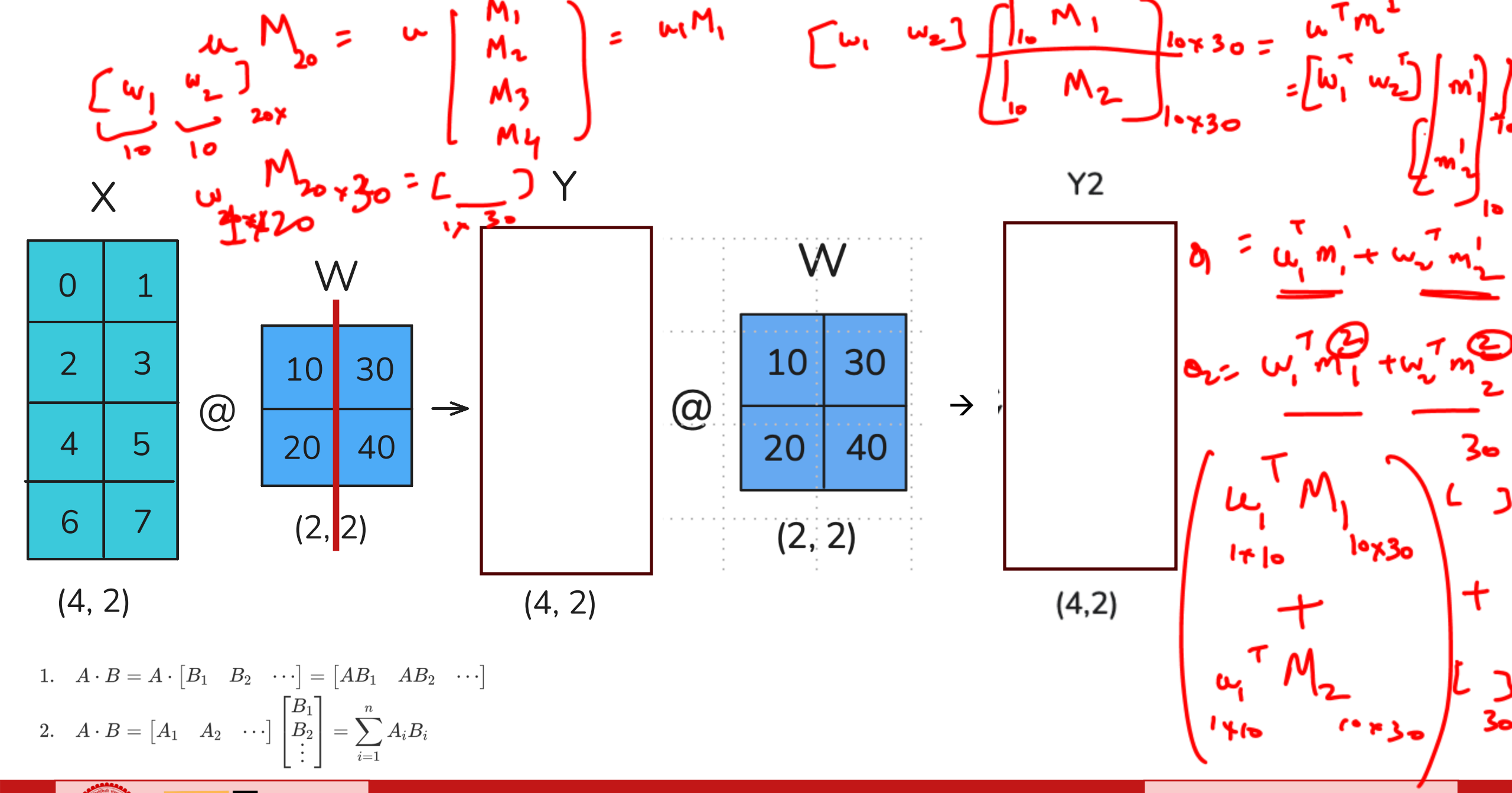
Linear *(4h -> h)*	$8 * seq * bs * h$
GELU	$8 * seq * bs * h$
Linear *(h -> 4h)*	$2 * seq * bs * h$

- Focus on the 2nd Linear Layer and output neurons
- Both [ ] and [ ] neurons contribute to all the output neurons
- Can we split the computation on two GPUs?



1. $A \cdot B = A \cdot [B_1 \; B_2 \; \ldots] = [AB_1 \; AB_2 \; \ldots]$

2. $A \cdot B = [A_1 \; A_2 \; \ldots] \begin{bmatrix} B_1 \\ B_2 \\ \vdots \end{bmatrix} = \sum_{i=1}^{n} A_i B_i$



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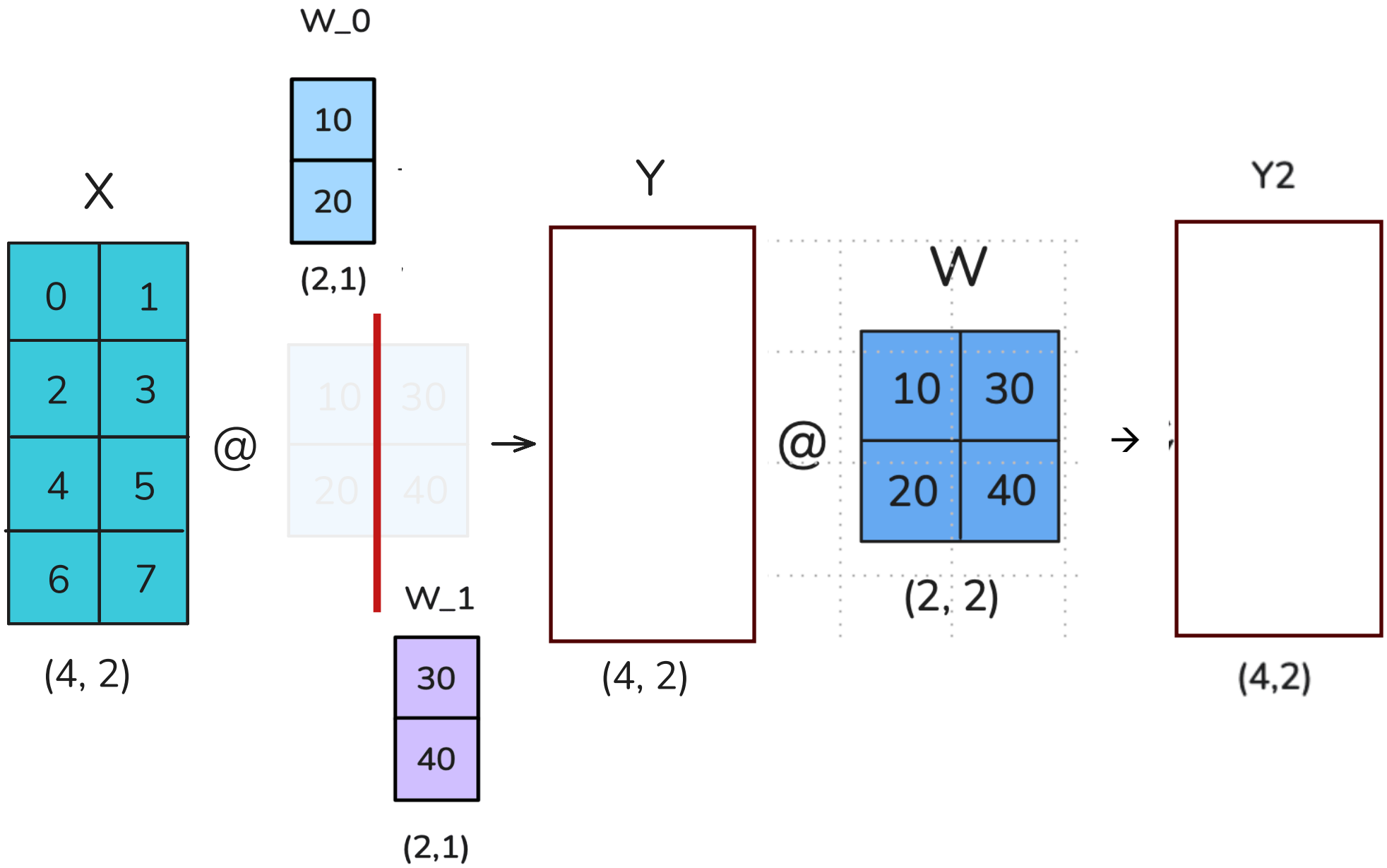
2. $A \cdot B = [A_1 \quad A_2 \quad \cdots] \begin{bmatrix} B_1 \\ B_2 \\ \vdots \end{bmatrix} = \sum_{i=1}^{n} A_i B_i$


W_0
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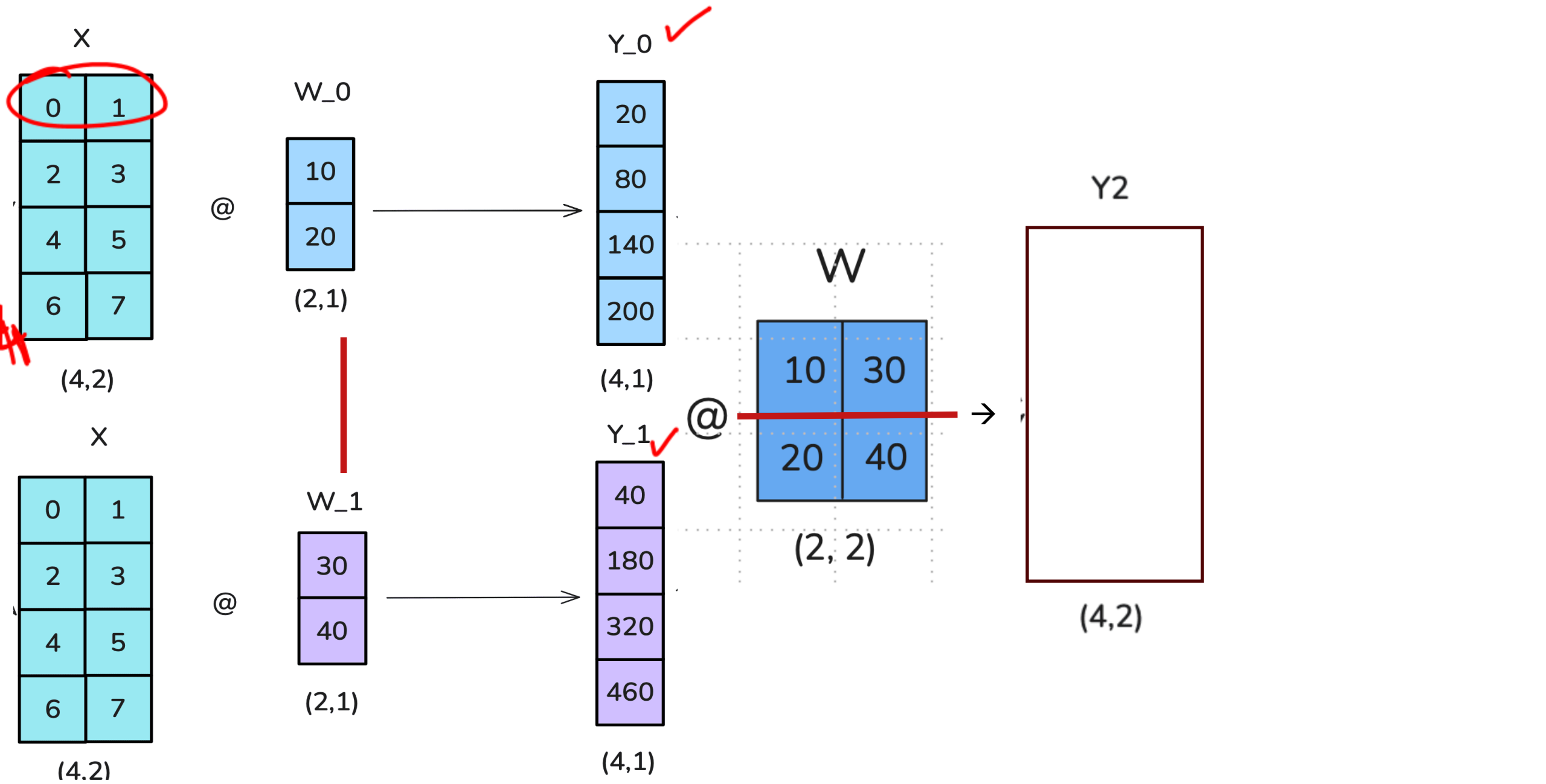
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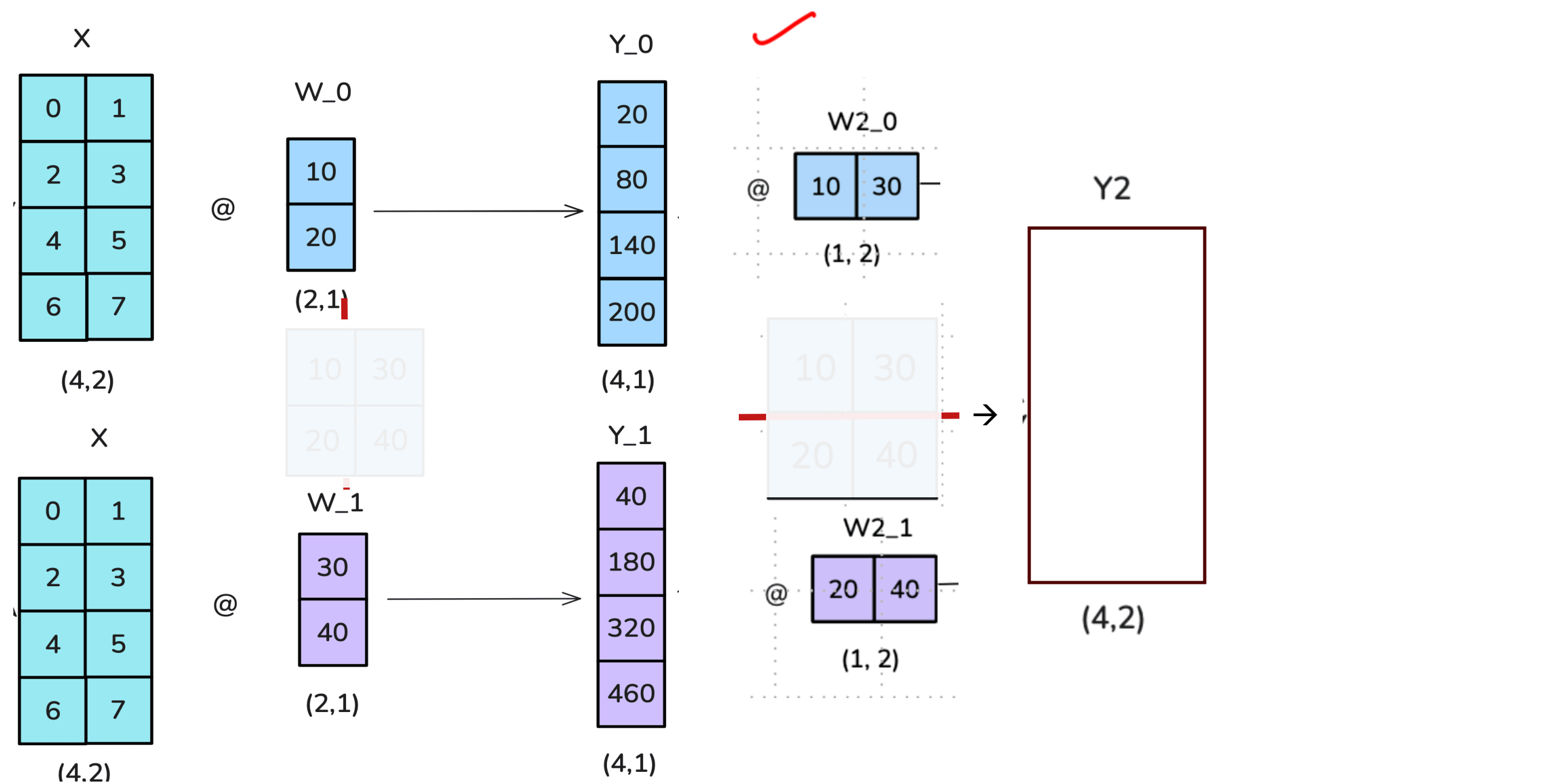
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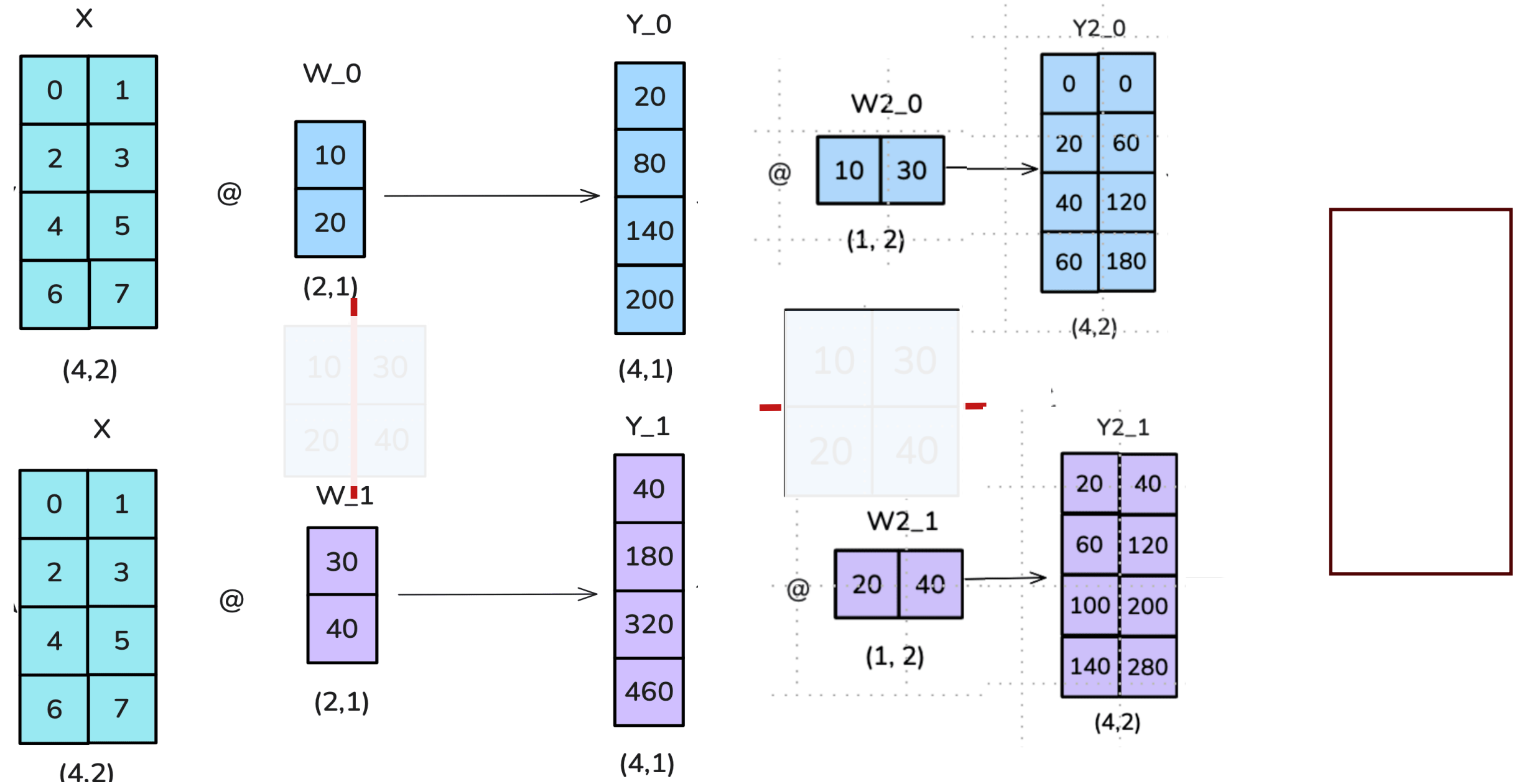
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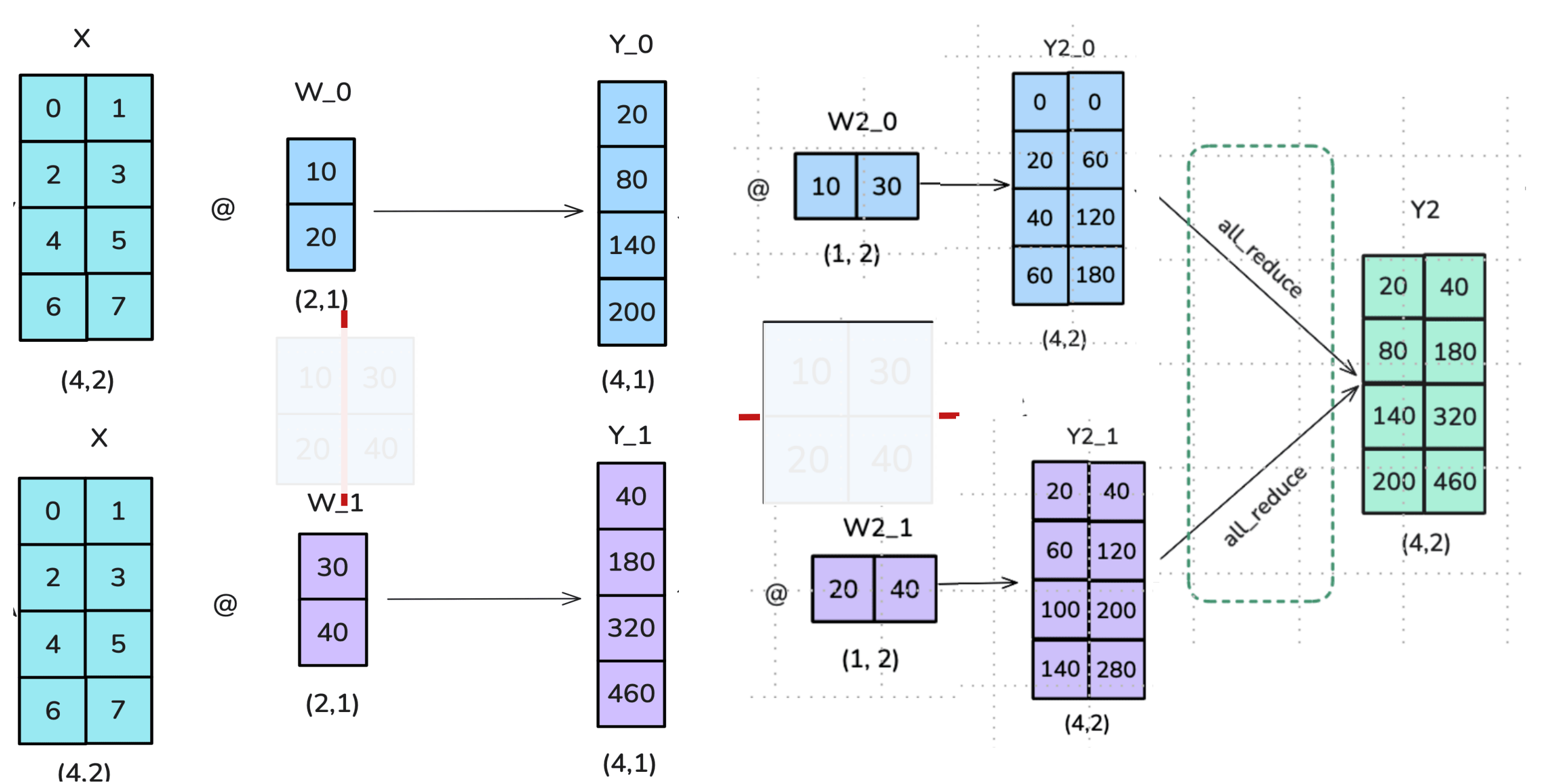
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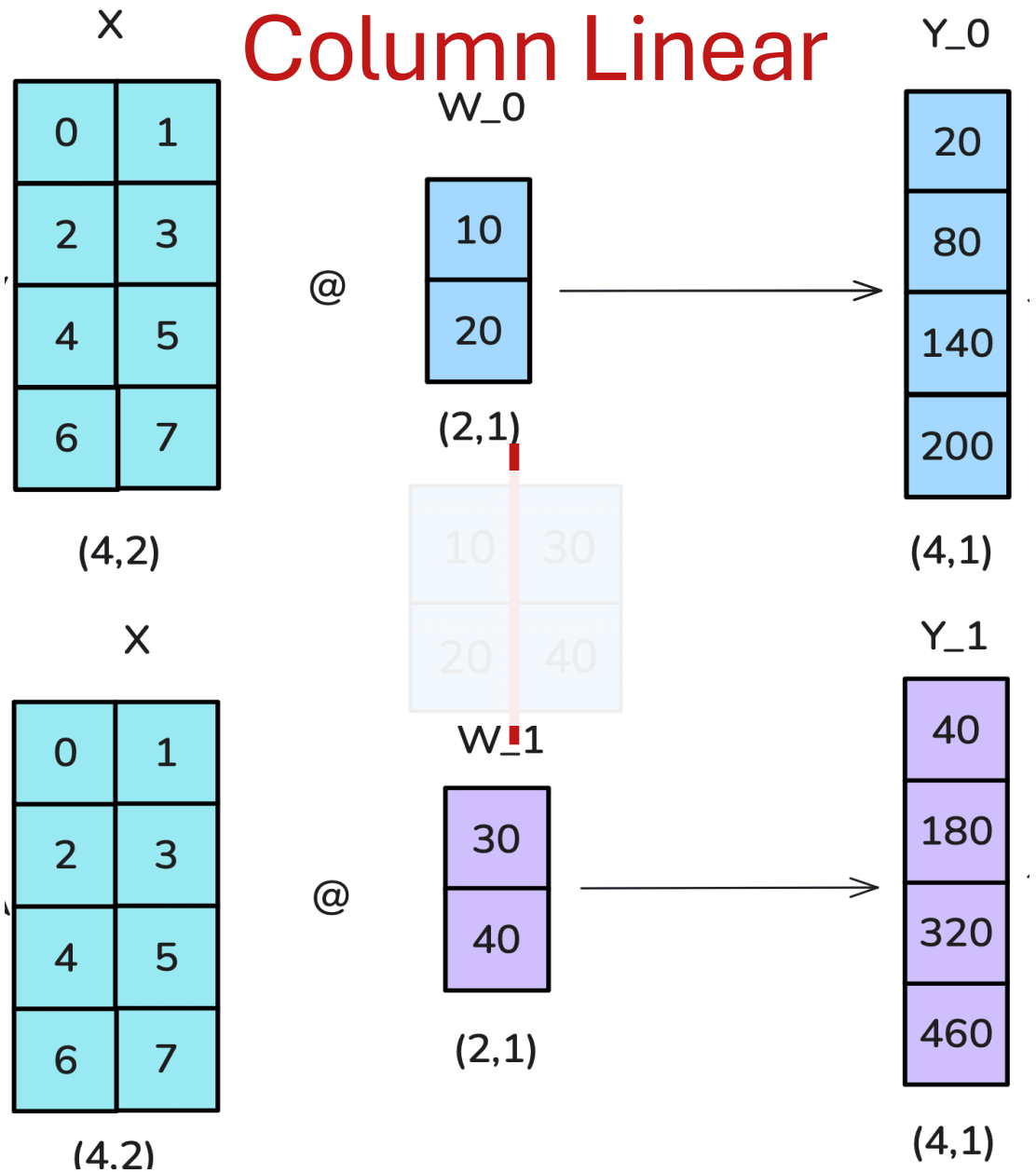
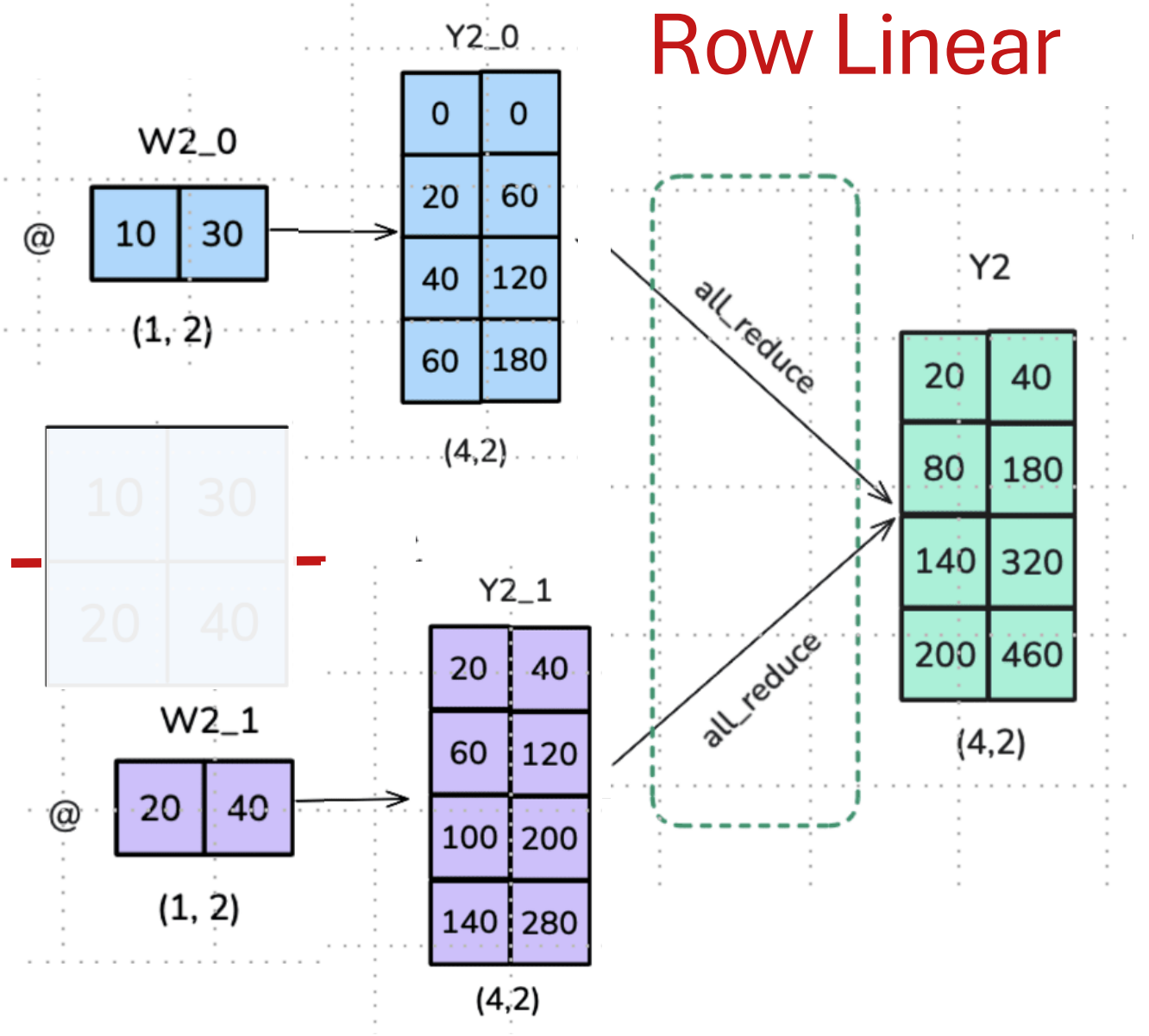
Column Linear

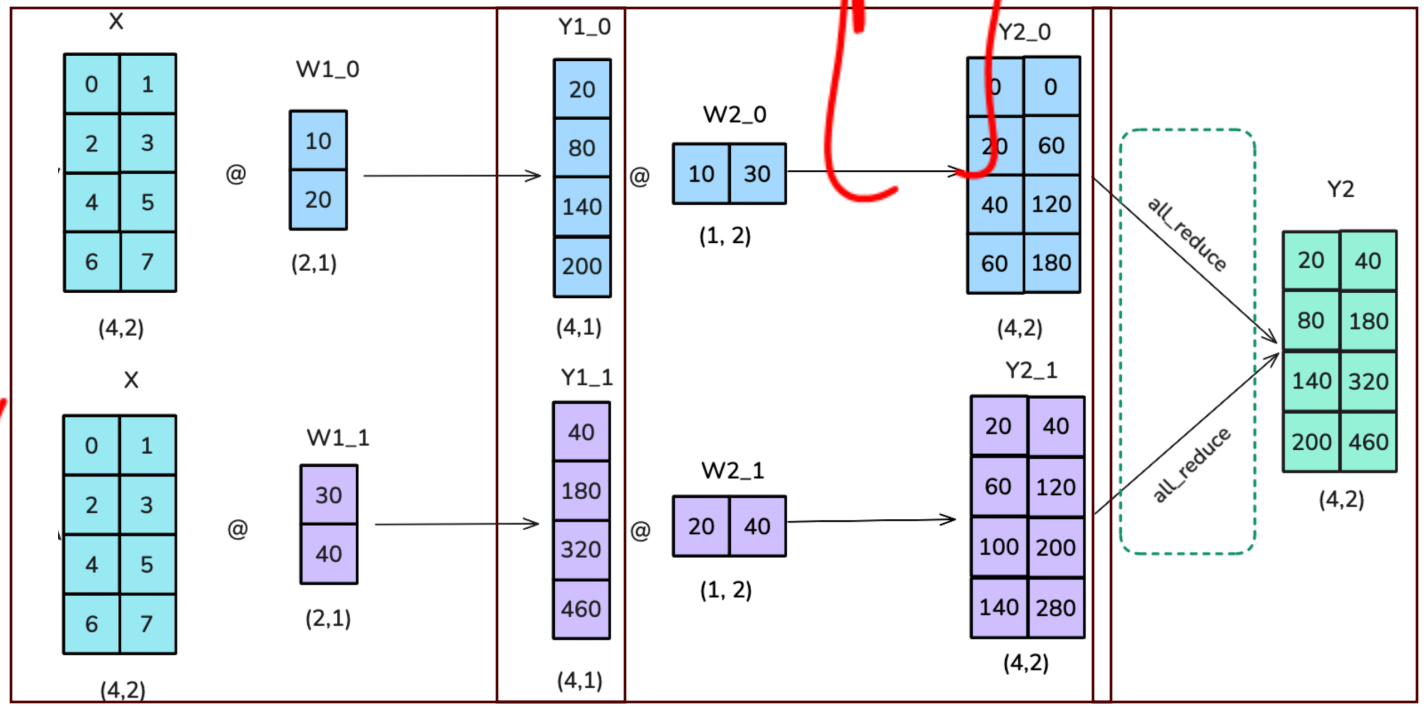


Row Linear



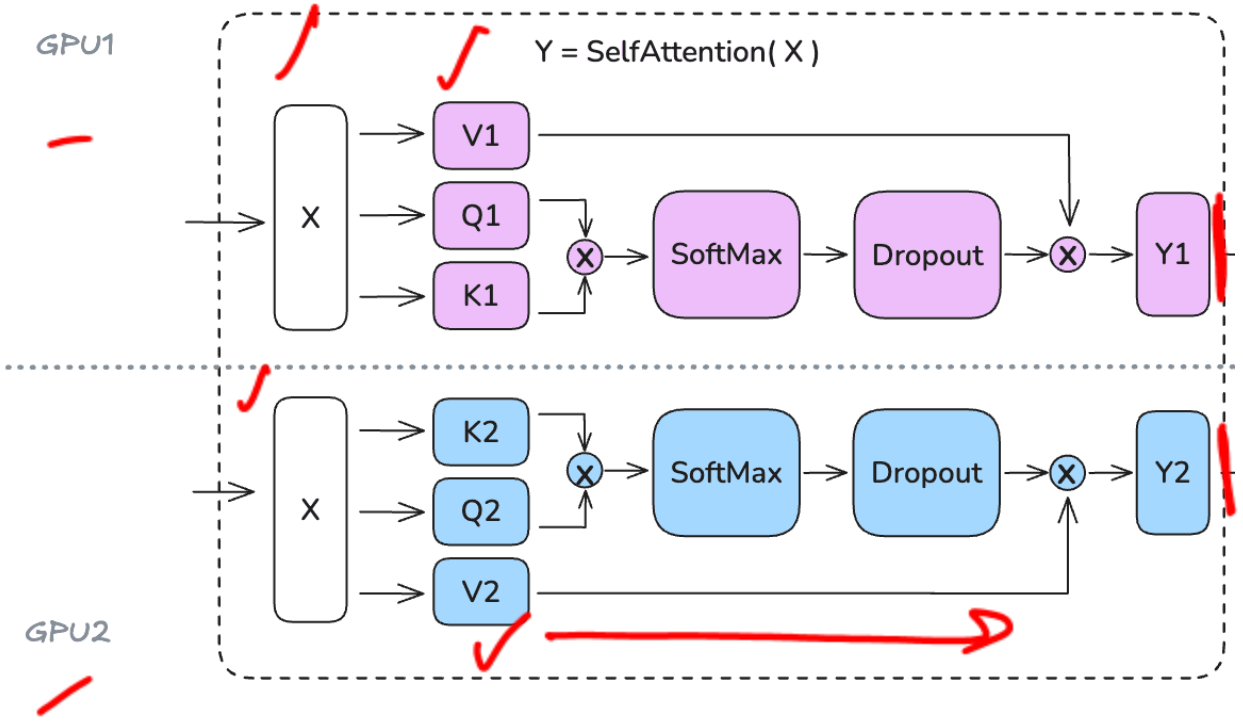
Tensor Parallelism in MLP Block

- Use *column-linear* to split the 1st layer:
  - compute different neurons on different GPUs
  - Each GPU compute $\frac{4h}{TP}$ activations
- Use *row-linear* to split the 2nd layer:
  - Each GPU acts on different neurons and computes partial output
  - No need to communicate the intermediate activations across GPUs → reduction in activation memory!
- Use *all_reduce* to communicate the partial outputs



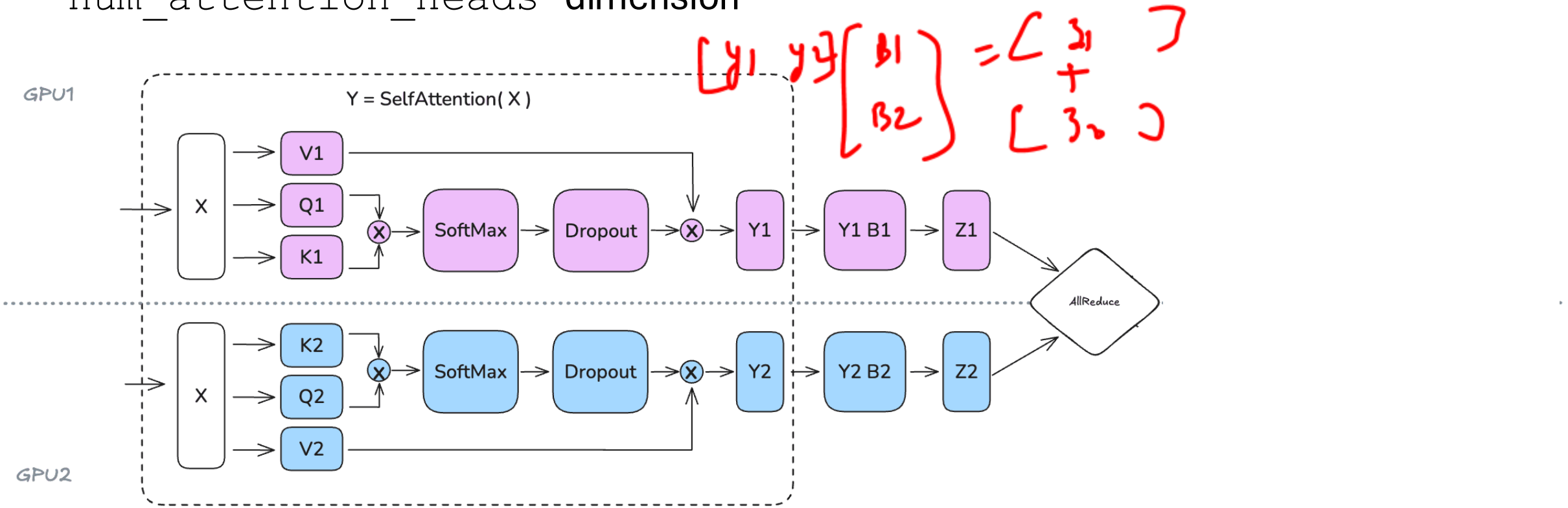
Tensor Parallelism in MHA Block

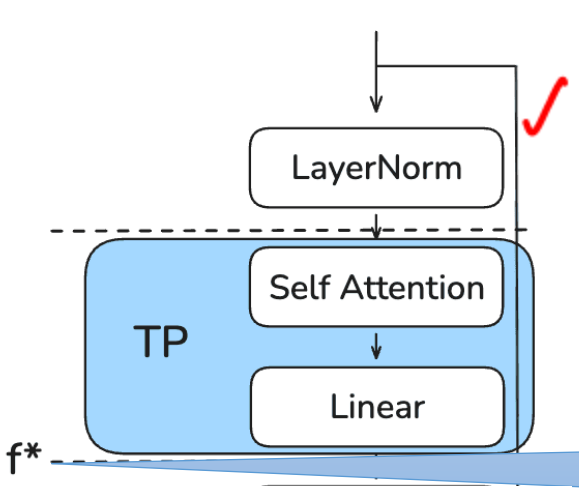
- Parallelize different heads on different GPUs – i.e. along `num_attention_heads` dimension
- Same as splitting *K*, *Q*, *V* matrices in column-parallel



Tensor Parallelism in Attention Block

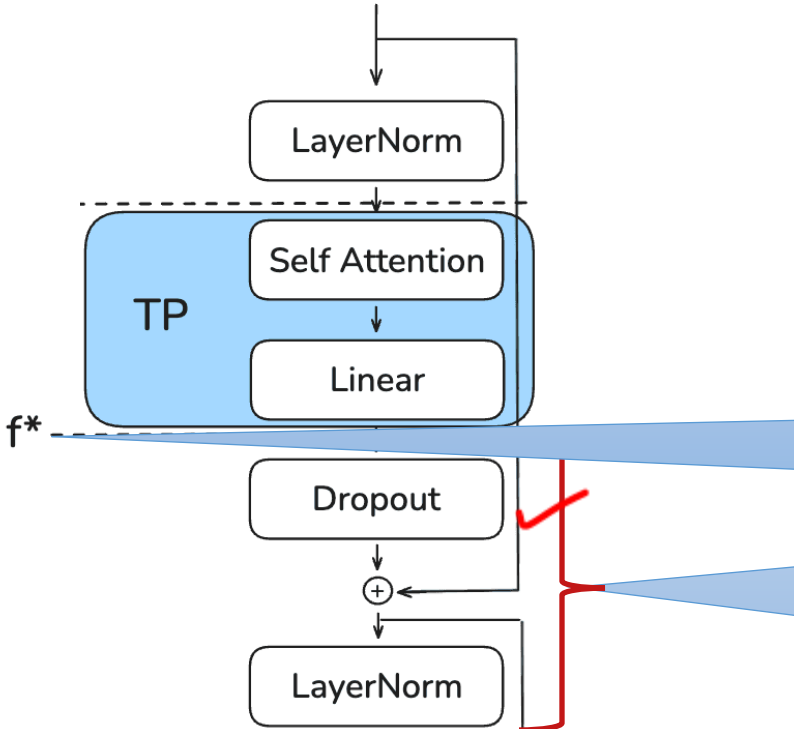
- Parallelize different heads on different GPUs – i.e. along `num_attention_heads` dimension
- Same as splitting *K*, *Q*, *V* matrices in column-parallel





*f** : all-reduce to synchronize activations

1. Synchronization not overlapping with computation
2. *"Exposed communication" overhead* is necessary to combine partial results across tensor-parallel ranks before the final LayerNorm can be applied.



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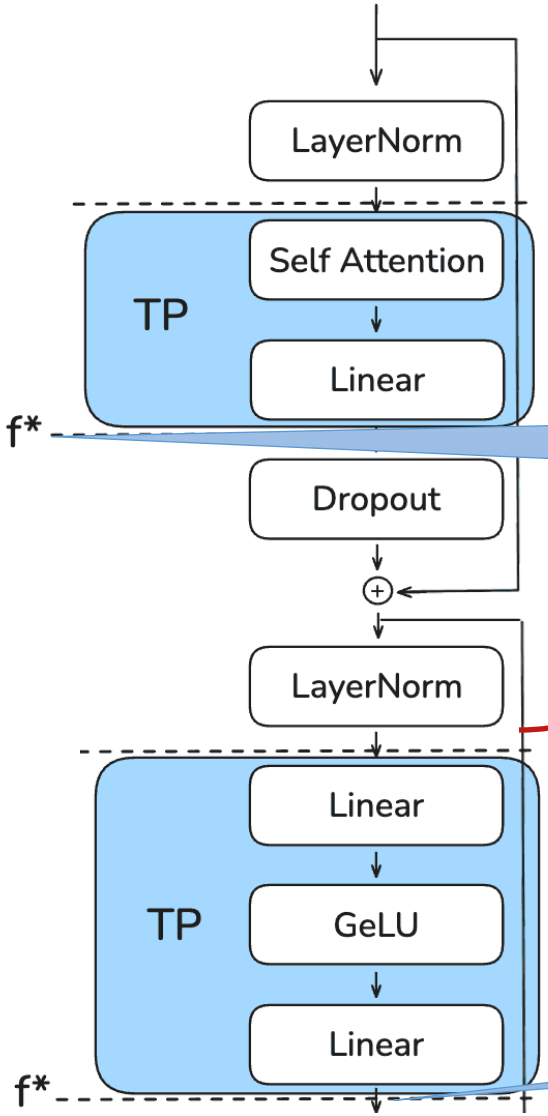
Dropout & LayerNorm: exactly same operations replicated on exactly same data



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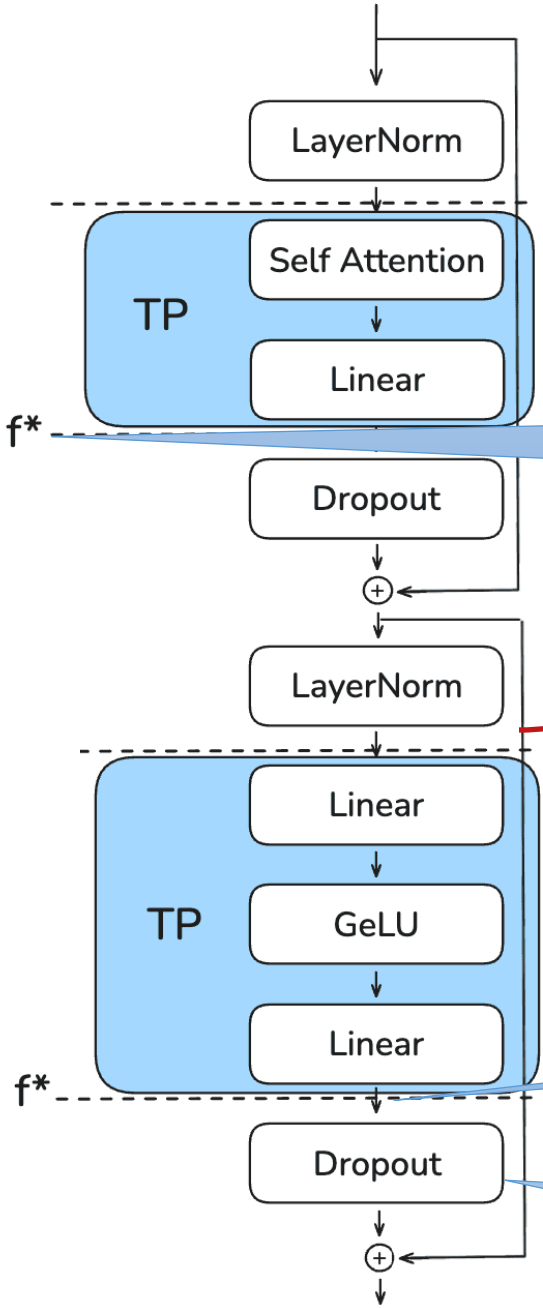

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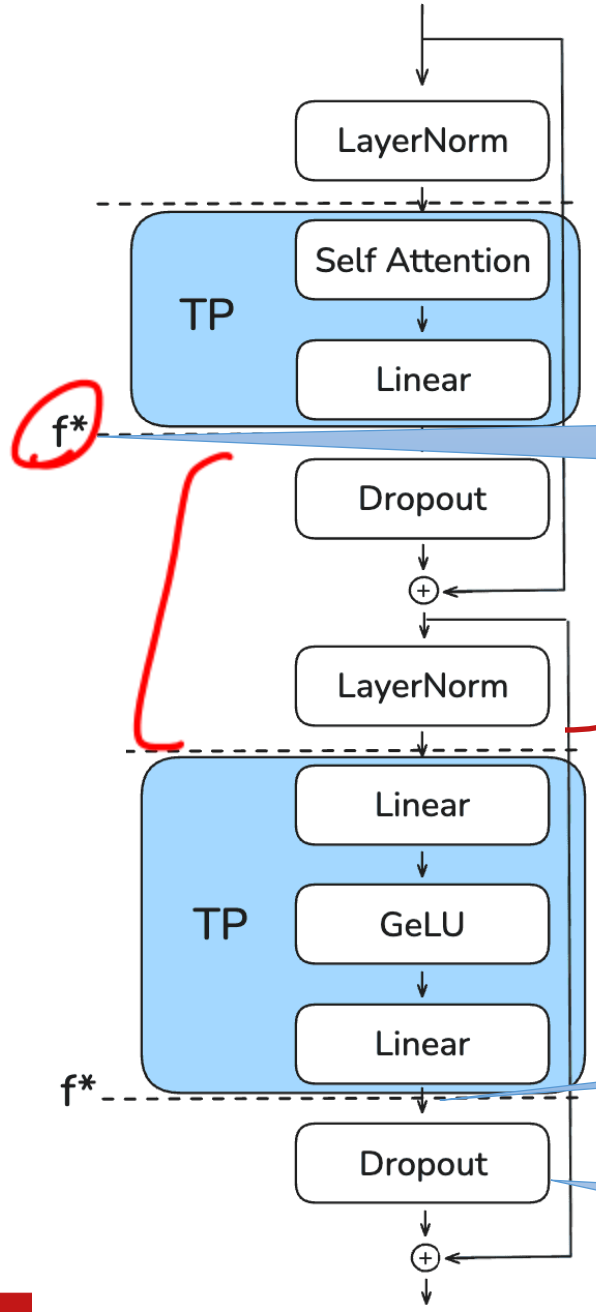
Dropout: same operation on same data!



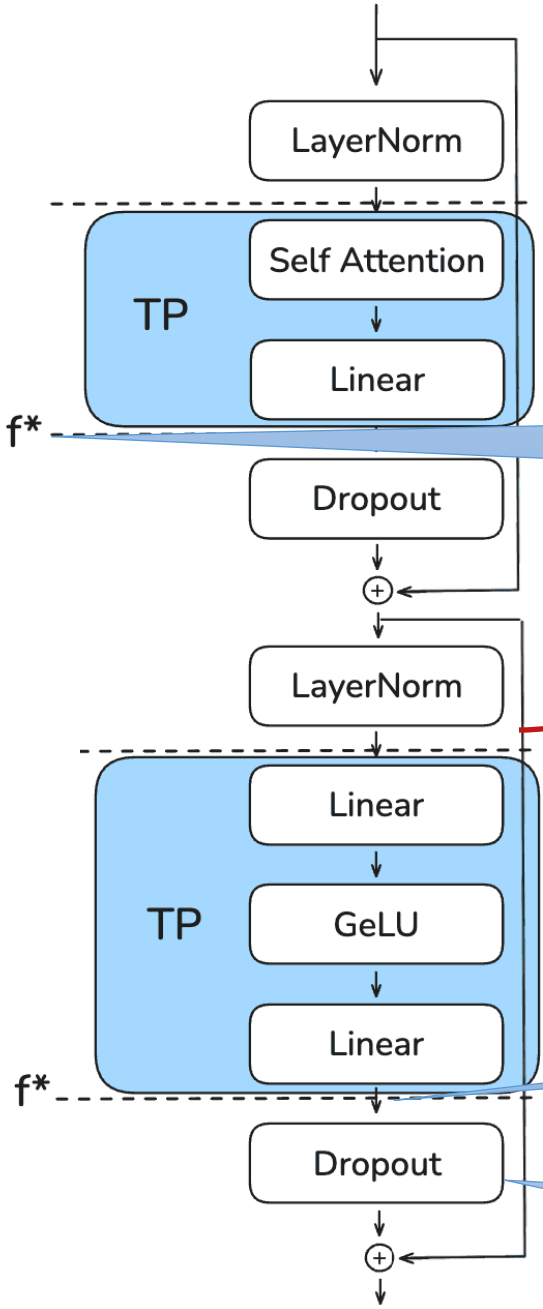
Dropout and LayerNorm – doing same operation on same data on all TP GPUs!

*f** : all-reduce to synchronize activations

Dropout & LayerNorm: exactly same operations replicated on exactly same data

*f** : all-reduce to synchronize activations

Dropout: same operation on same data!



Can we parallelize dropout and LayerNorm?

*f** : all-reduce to synchronize activations

Dropout & LayerNorm: exactly same operations replicated on exactly same data

*f** : all-reduce to synchronize activations

Dropout: same operation on same data!

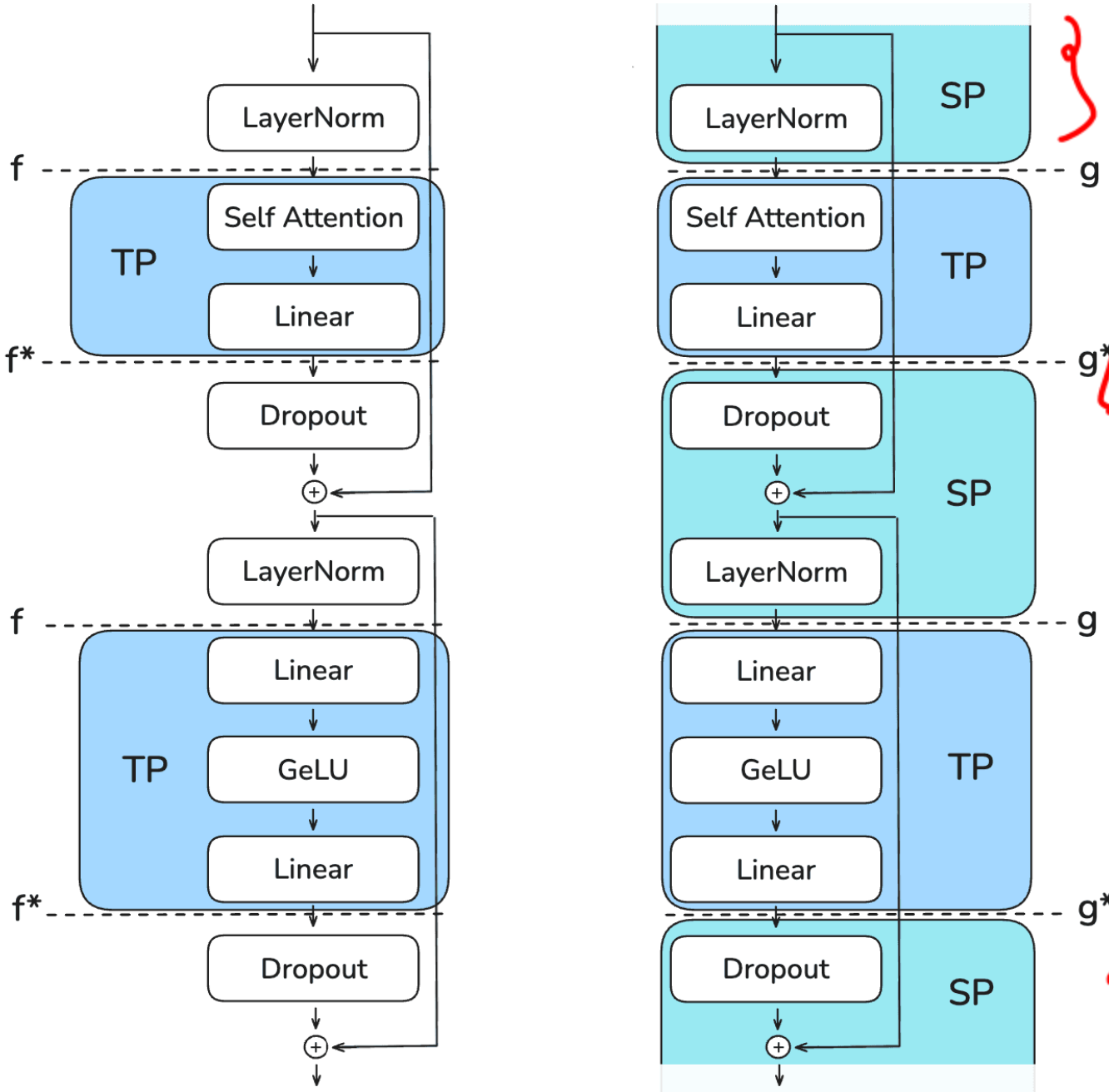
Sequence Parallel – parallelizing dropout & LayerNorm

Total	$\mathbf{34 * seq * bs * h + 5 * n_{heads} * seq^2 * bs}$
MLP Block	$\mathbf{19 * seq * bs * h}$
D/o mask	$1 * seq * bs * h$
Linear *(4h -> h)*	$8 * seq * bs * h$
GELU	$8 * seq * bs * h$
Linear *(h -> 4h)*	$2 * seq * bs * h$
Layer Norm	$\mathbf{2 * seq * bs * h}$

Attention Block	$\mathbf{11 * seq * bs * h + 5 * n_{heads} * seq^2 * bs}$

Layer Norm	$\mathbf{2 * seq * bs * h}$

- In DP, we parallelize along the "batch dim" ($\boldsymbol{bs}$)
- In TP, we parallelize along the "hidden dim" ($\boldsymbol{h}$)
- In SP, we parallelize along the input sequence dimension ($\boldsymbol{seq}$)


LayerNorm
f
Self Attention
TP
Linear
f*
Dropout
LayerNorm
f
Linear
TP
GeLU
Linear
f*
Dropout
SP
LayerNorm
g
Self Attention
TP
Linear
g*
Dropout
SP
LayerNorm
g
Linear
TP
GeLU
Linear
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SP
(all-gather)
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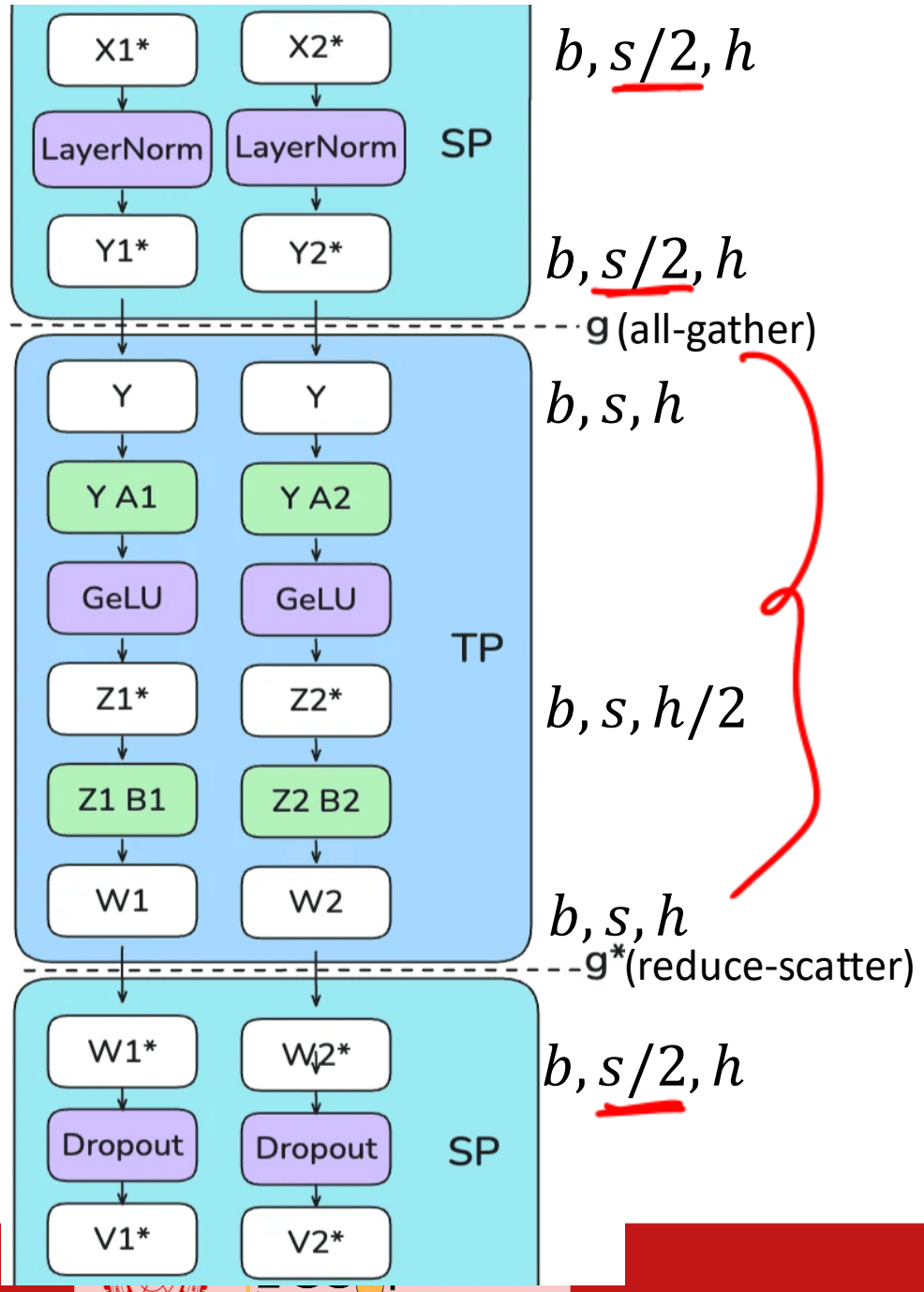
(all-gather)
(reduce-scatter)



Initial LayerNorm layer (SP region)

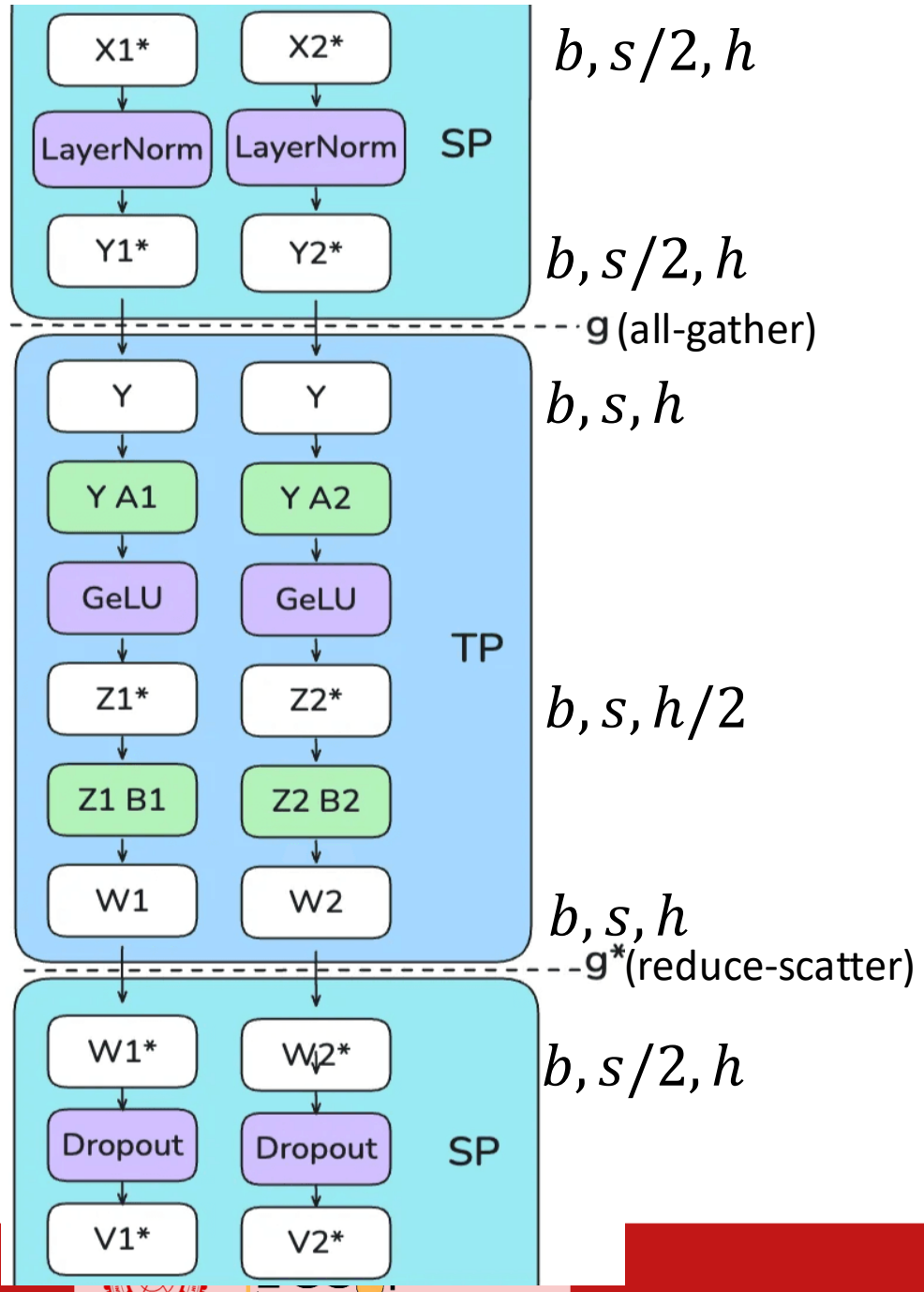
- Input tensors *X1** and *X2** $(b, s, /2h)$ enter, already split across the sequence dimension.
- Each GPU computes LayerNorm independently on its sequence chunk, giving *Y1** and *Y2**.

First transition (SP → TP)

- g operation (all-gather) combines *Y1* and *Y2* back to full sequence length.
- Restores *Y* (b, s, h) since column-linear layers need the full hidden dimension h.

First linear layer (TP region)

- *A1* and *A2* are column-linear layers, so they split *Y* along the hidden dimension.
- GELU is applied independently on each GPU.
- *Z1** and *Z2** are $(b, s, h/2)$.



$b, s/2, h$

$b, s/2, h$

b, s, h

$b, s, h/2$

b, s, h

$b, s/2, h$

Initial LayerNorm layer (SP region)

- Input tensors *X1** and *X2** $(b, s, /2h)$ enter, already split across the sequence dimension.
- Each GPU computes LayerNorm independently on its sequence chunk, giving *Y1** and *Y2**.

First transition (SP → TP)

- g operation (all-gather) combines *Y1* and *Y2* back to full sequence length.
- Restores *Y* (b, s, h) since column-linear layers need the full hidden dimension h.

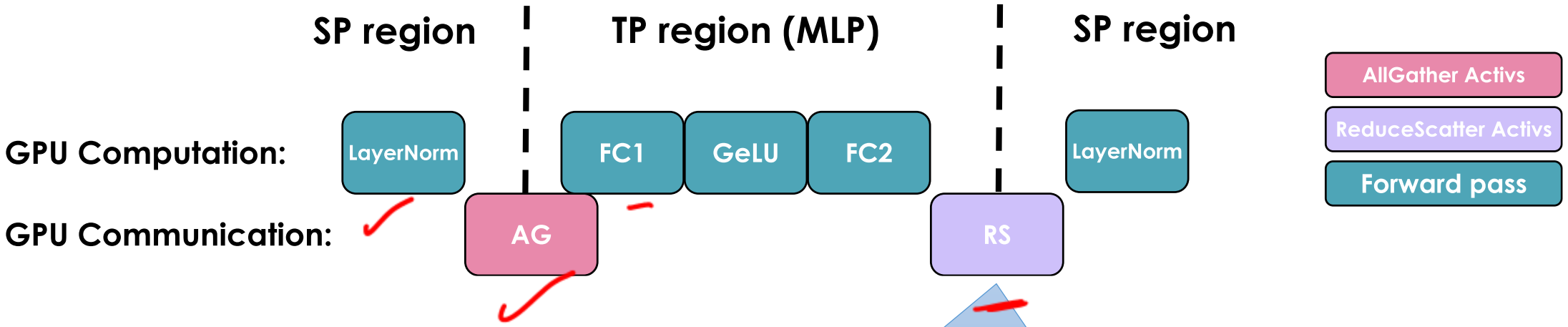
Second linear layer (TP region)

- *B1* and *B2* are row-linear layers, so they restore the hidden dimension.
- *W1* and *W2* are (b, s, h) that need to be summed together.

Final transition (TP → SP)

- g^* operation (reduce-scatter) reduces for previous row-linear correctness while scattering along the sequence dimension.
- *W1** and *W2** are $(b, s, /2h)$

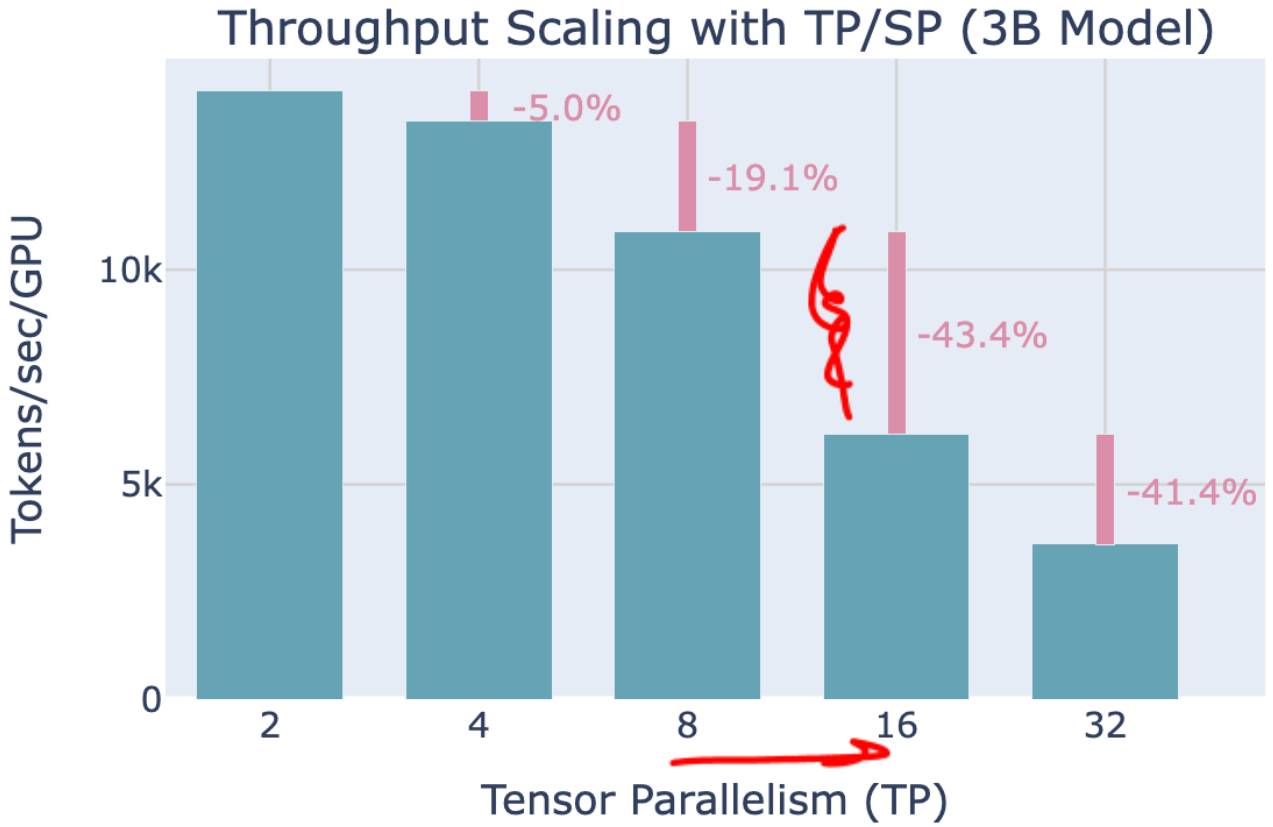
Computation-communication timeline for MLP Layer



1. Synchronization not overlapping with computation
2. *"Exposed communication" overhead* is necessary to combine partial results across tensor-parallel ranks before the LayerNorm can be applied.

Tensor+Sequence Parallelism - Tradeoffs

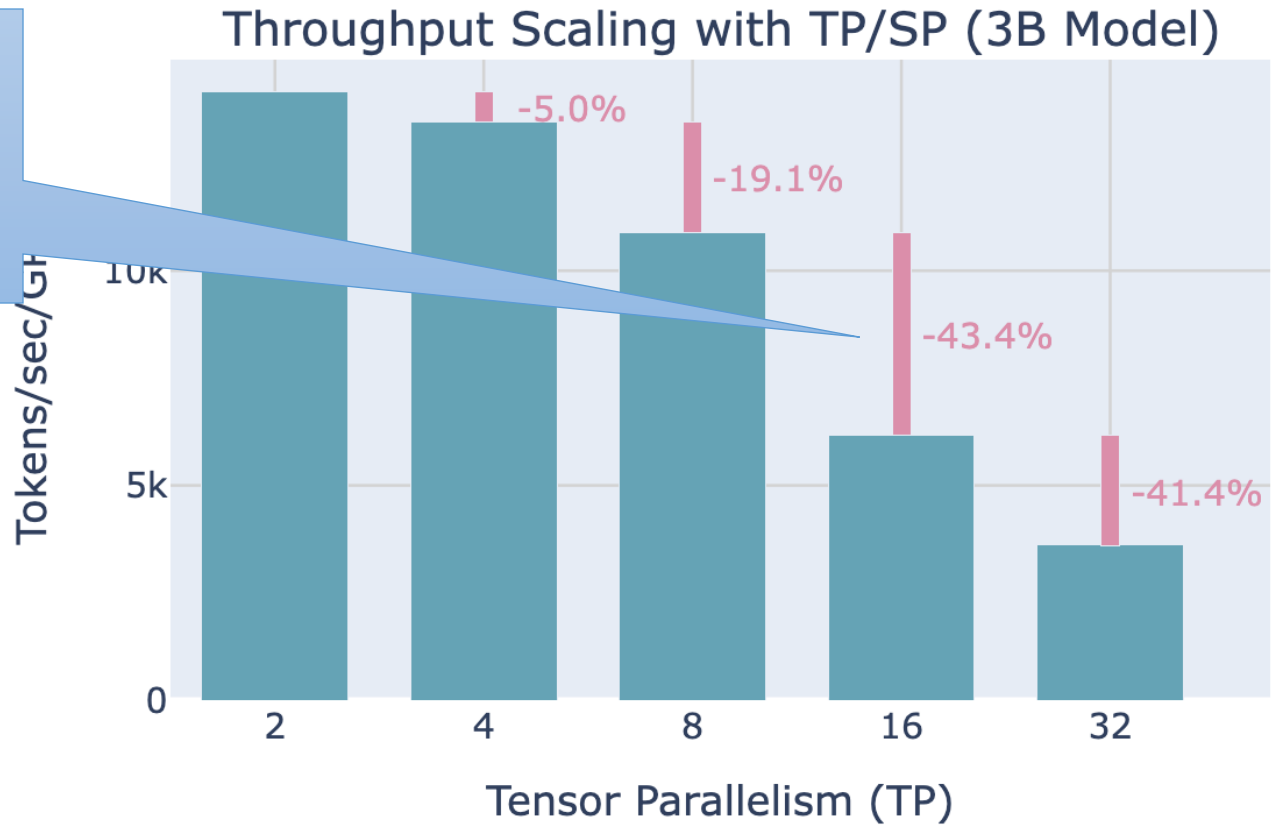
- Intermediate activations sharded across GPUs.
- **TP**: Reduces activation memory for matrix multiplication
- **SP**: Reduces activation memory for LayerNorm & dropout
- Need to gather full activations for LayerNorm
- Introduces significant communication overhead
- Introduces "*exposed communication*"



For Sequence Length 4096

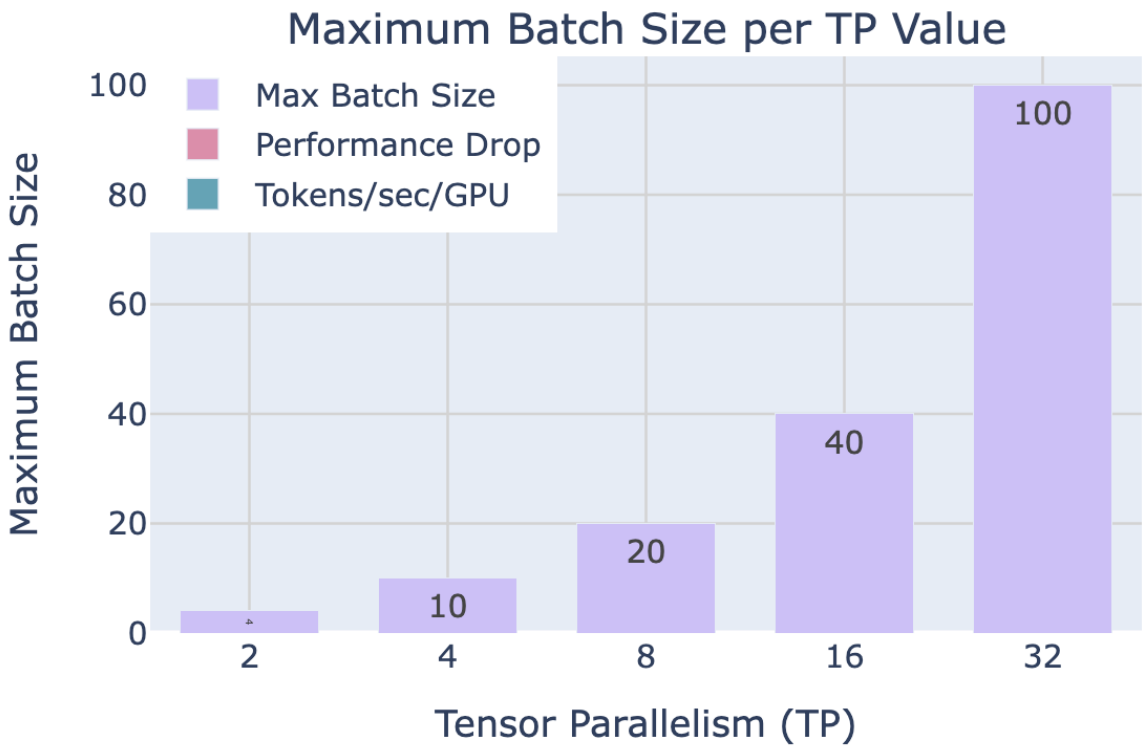
Tensor+Sequence Parallelism - Tradeoffs

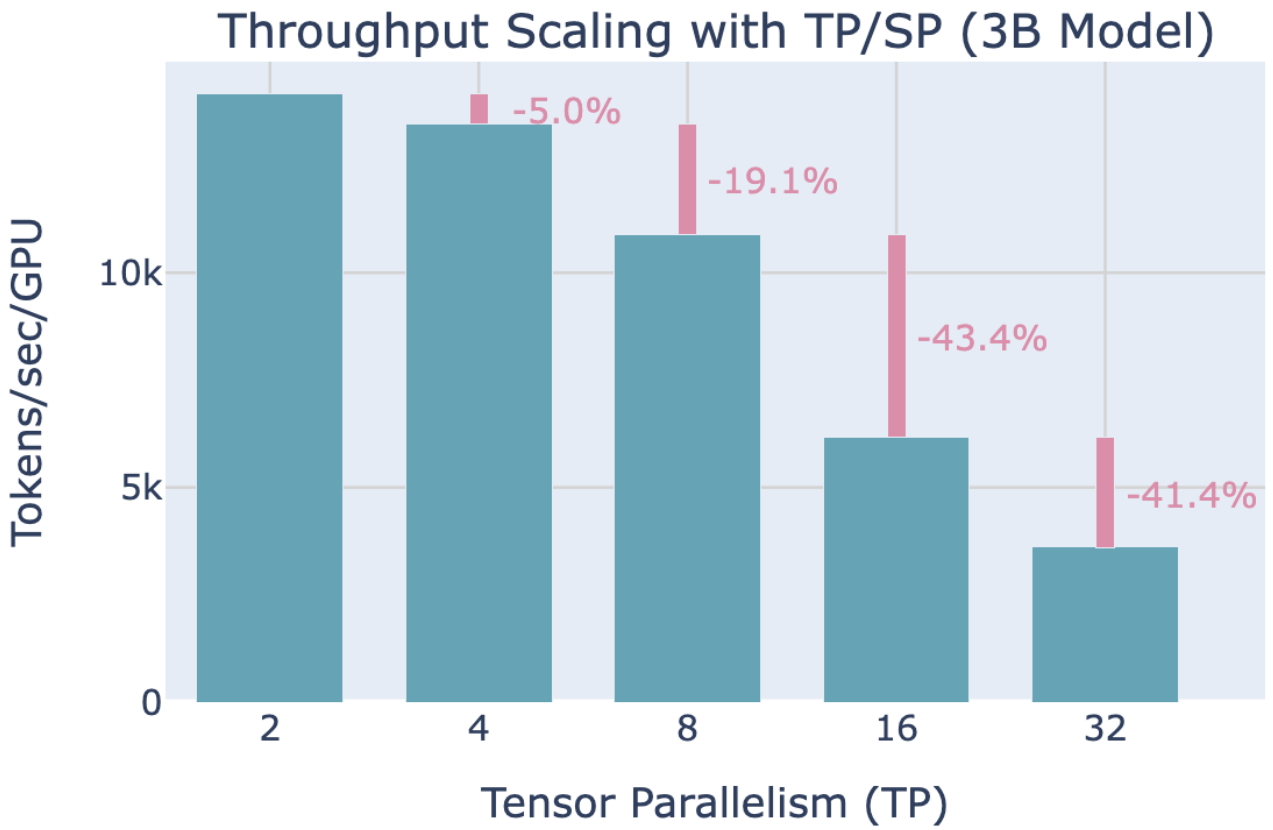
- TP leverages fast NVLink interconnects within a node.
- Slower network connections across nodes results in huge throughput drop.



For Sequence Length 4096

Tensor+Sequence Parallelism - Tradeoffs



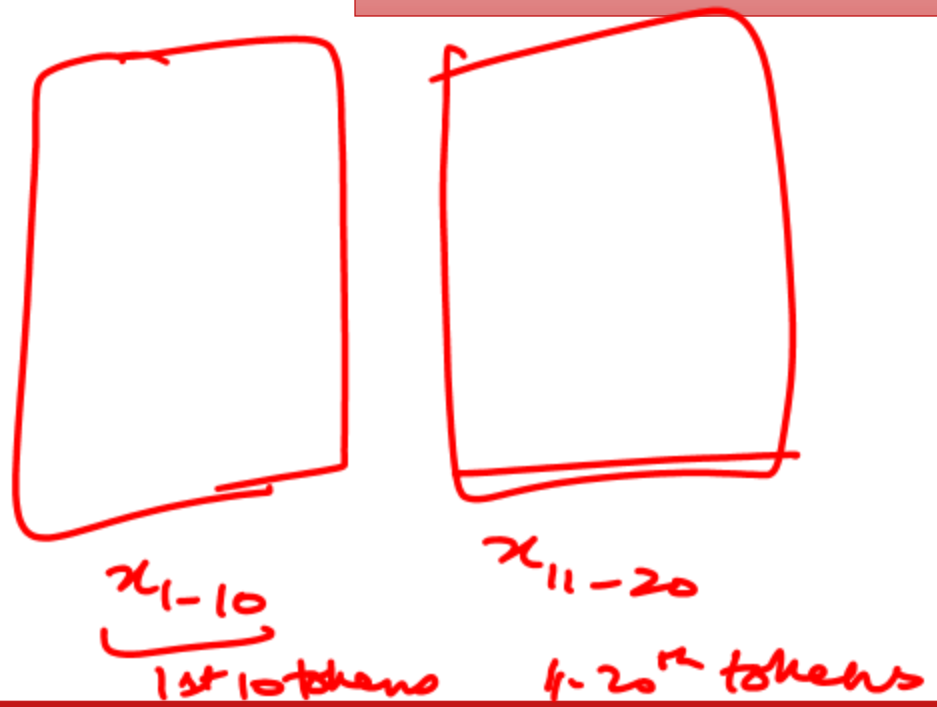


For Sequence Length 4096

Tensor+Sequence Parallelism - Limitations

1. If we scale the sequence length the activation memory will still blow up in the TP region

- In SP, we split one sequence into chunks and process each chunk in parallel.
- Can we do the same for MLP Layer?
- How about Attention Layer?



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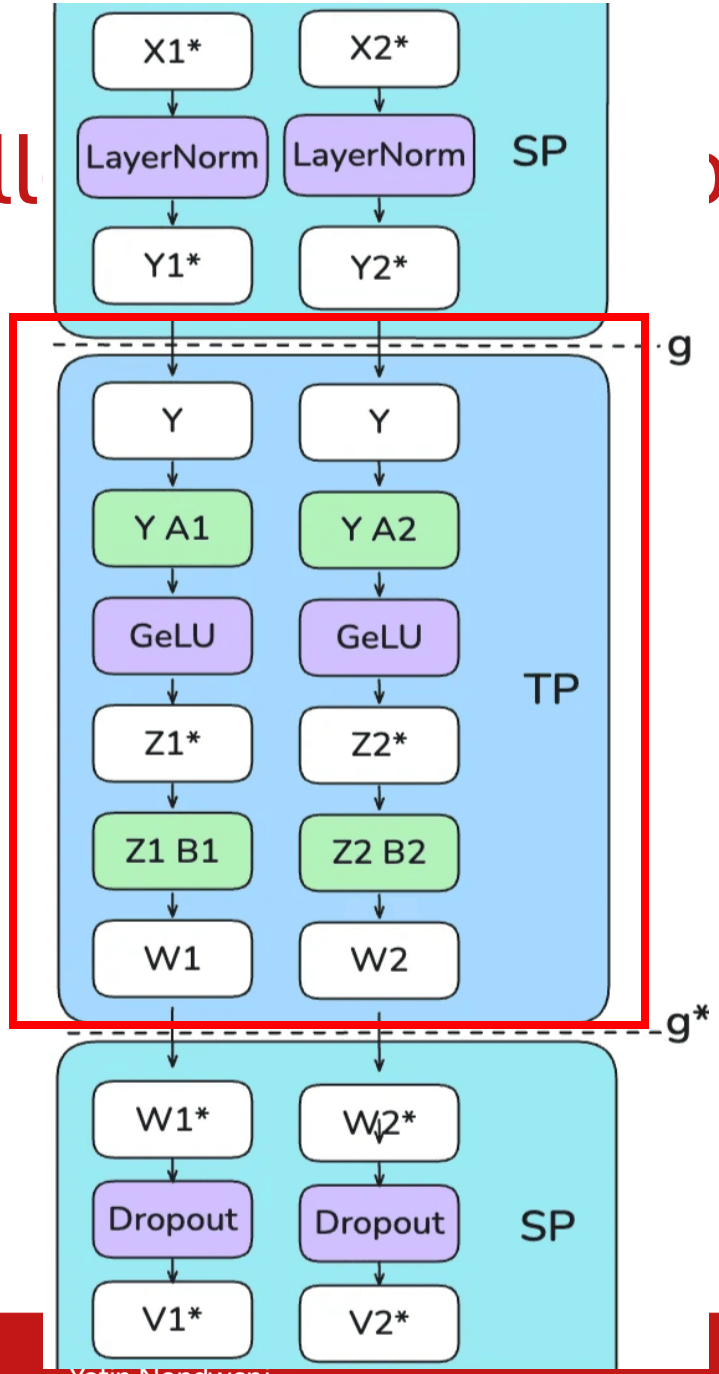


Context Parallelism

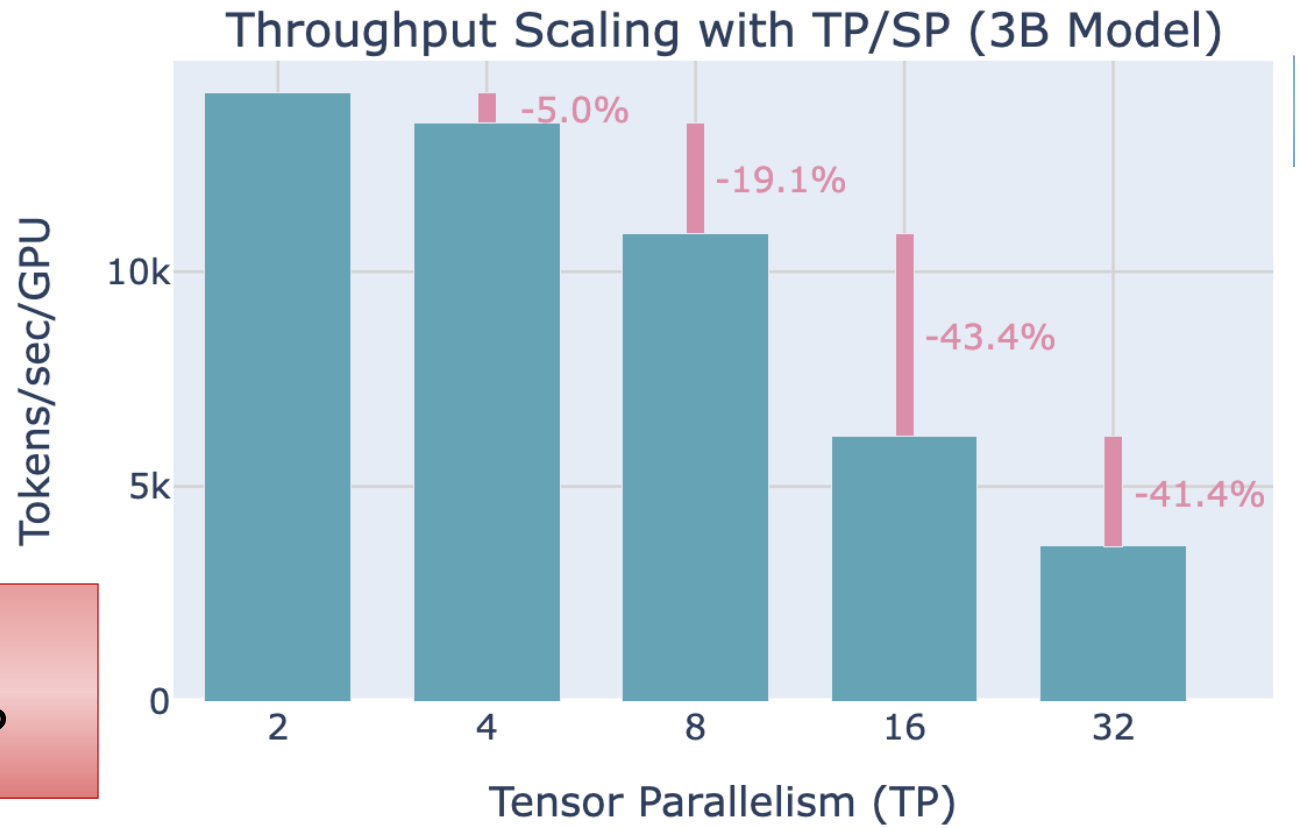
Tensor+Sequence Parallelism - Limitations

1. If we scale the sequence length the activation memory will still blow up in the TP region

2. If the model is too big to fit with TP=8 we will see a massive slowdown due to the inter-node connectivity.

- In TP, we split a “Tensor” across GPUs.
- How about splitting layers across GPUs?

Pipeline Parallelism



Tensor+Sequence Parallelism - Limitations

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Context Parallelism

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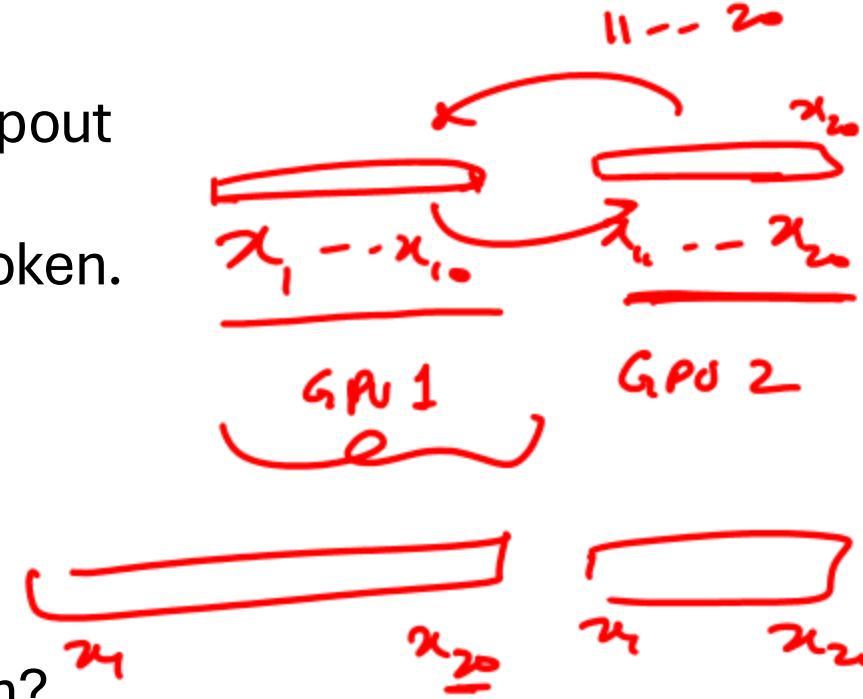
Pipeline Parallelism

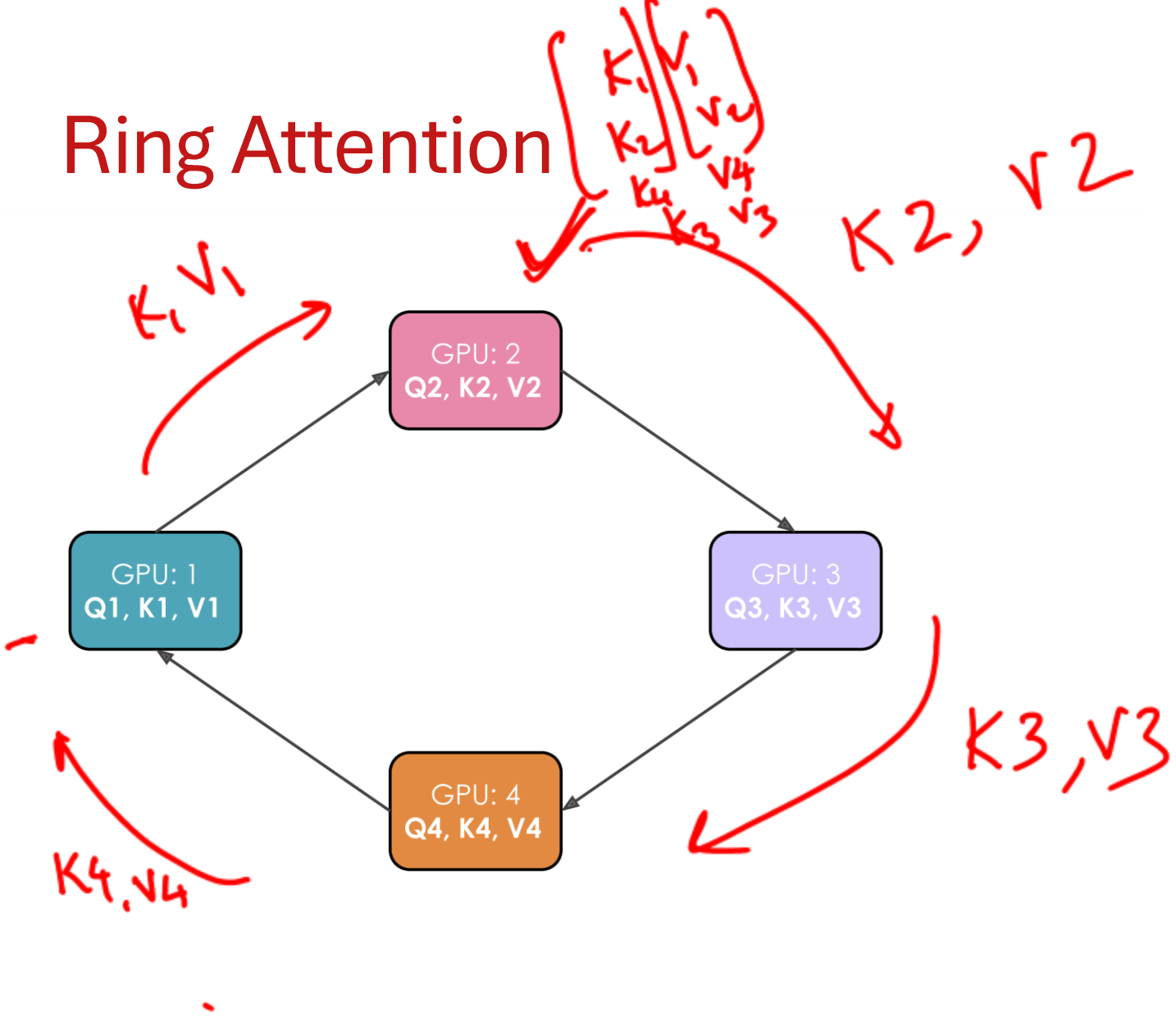
Context Parallelism – partition along sequence length

- For MLP layers, its exactly same as SP for LayerNorm & Dropout
- In Attention Layer, each token has to attend on every other token.
- But tokens in a different chunk are on a different GPU!
- Full communication b/w GPUs?
- Can we somehow overlap computation with communication?

Ring Attention - online softmax computation + overlapped computation

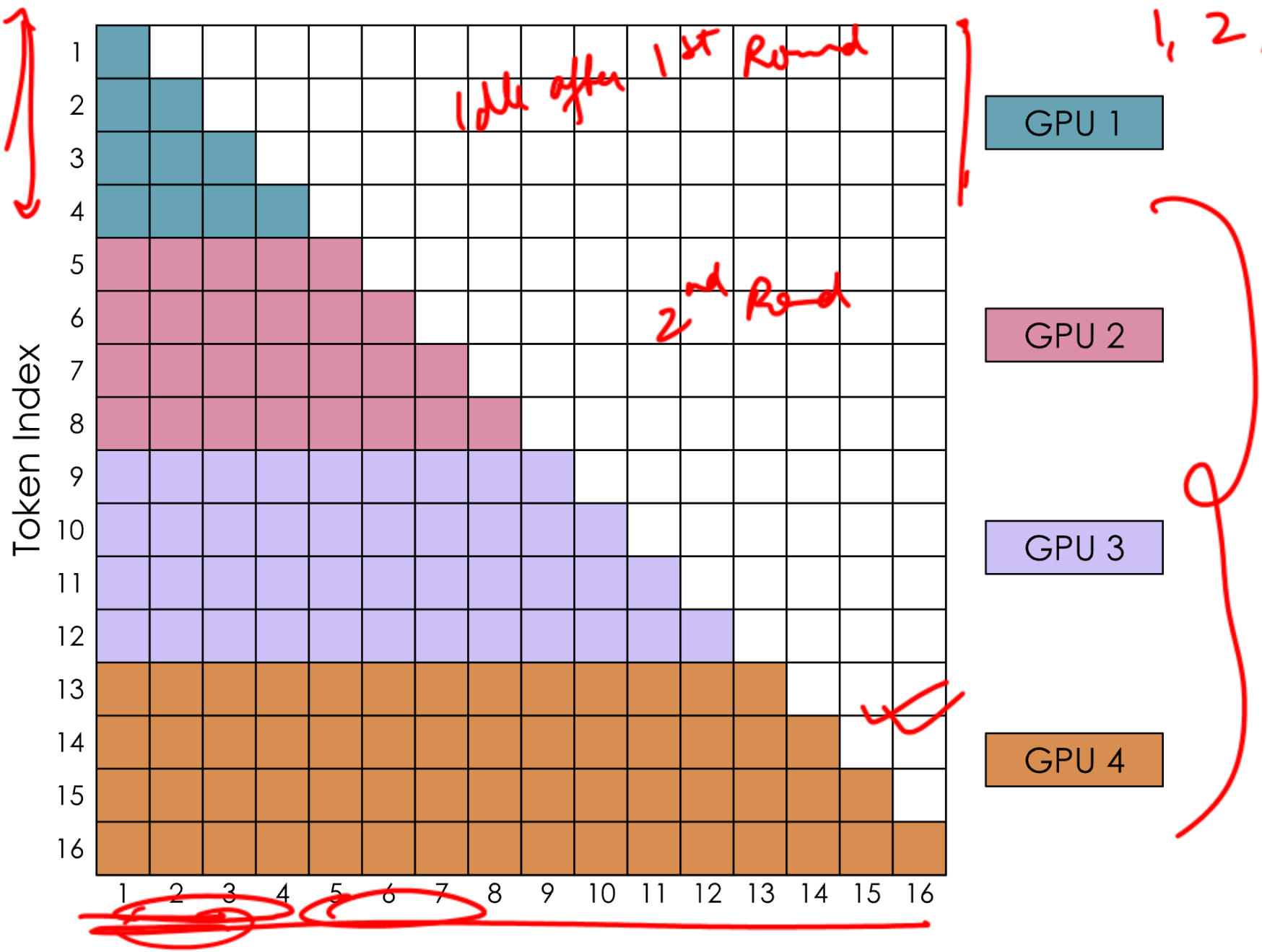


Ring Attention

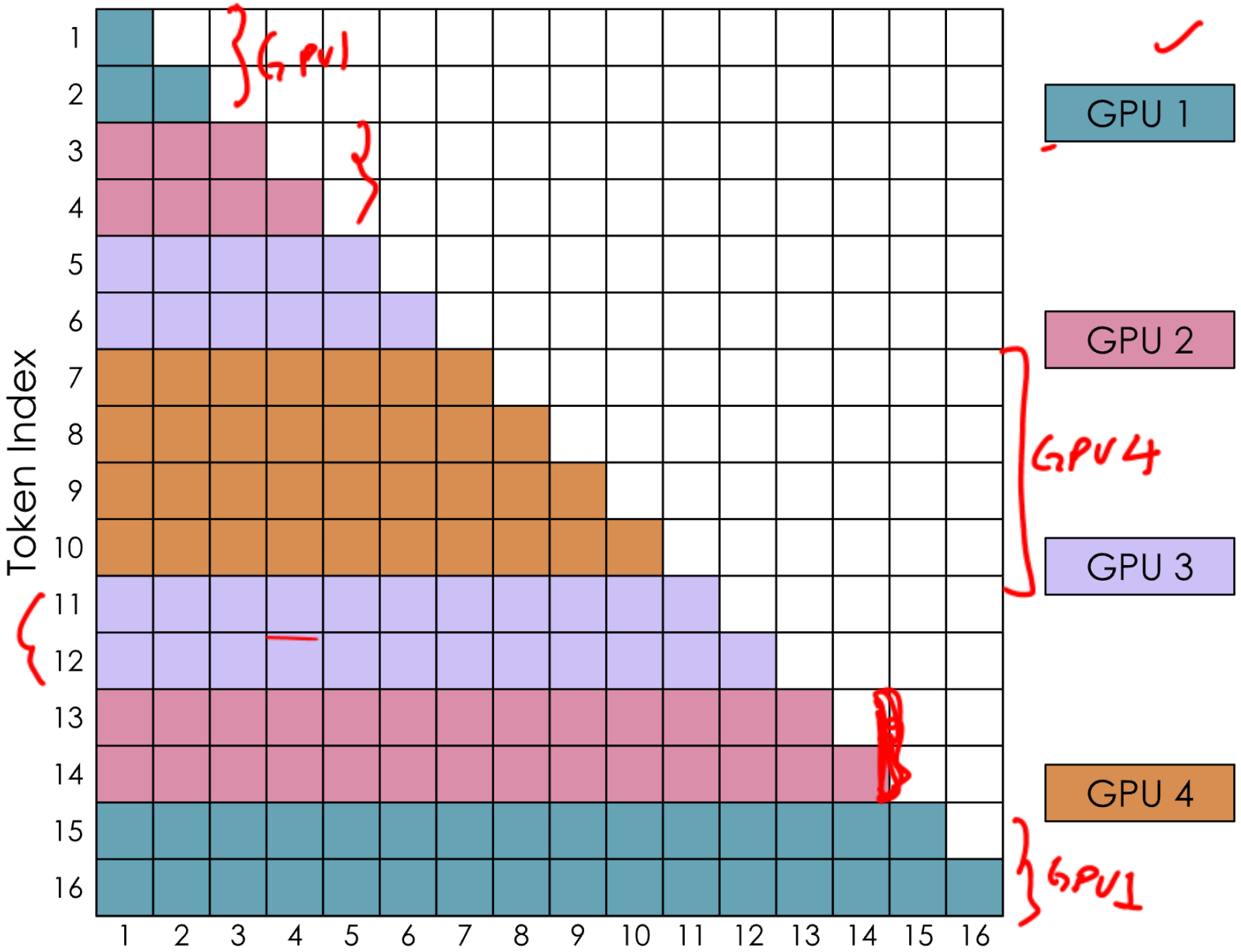


Ring Attention with Blockwise Transformers for Near-Infinite Context H. Liu, M. Zaharia, P. Abbeel. 2023 [PDF]

Ring Attention



Ring Attention

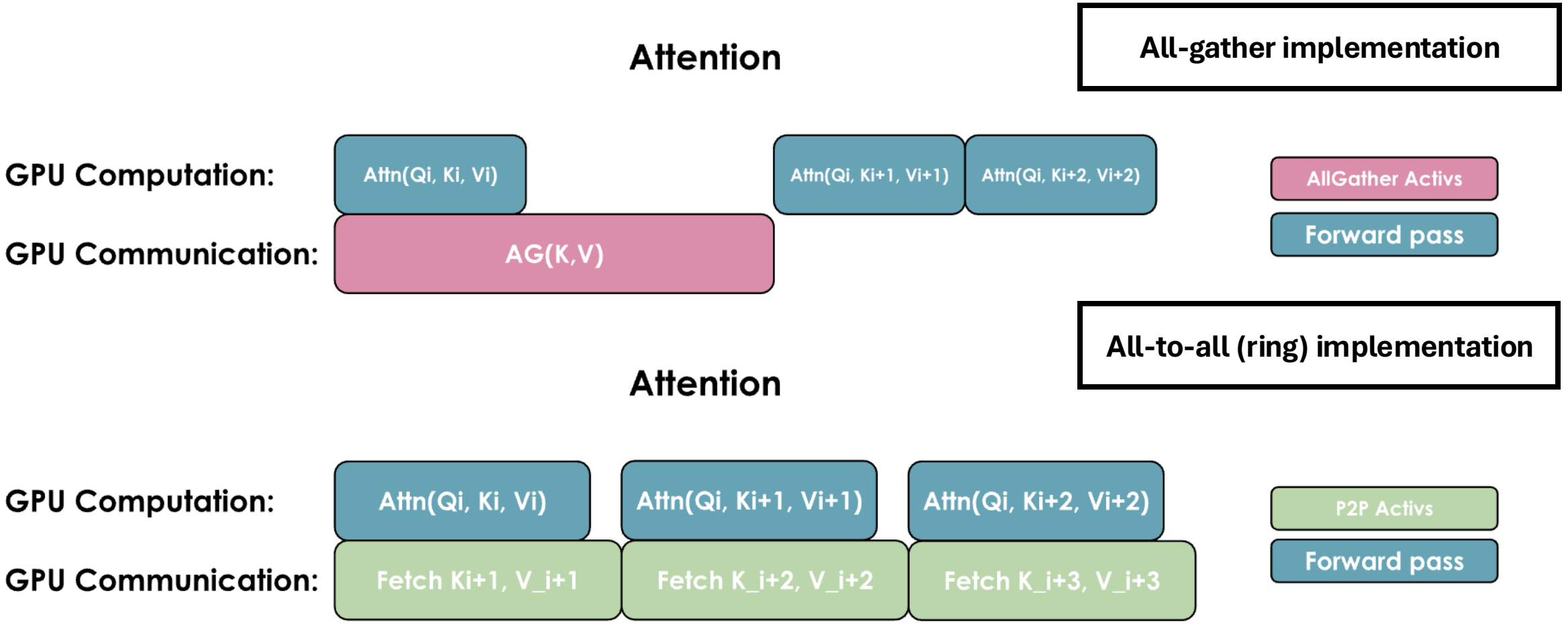


Computation-communication timeline

All-to-all (ring) implementation:

- GPUs exchange K/V pairs in a ring-like pattern, one chunk at a time.
- More memory-efficient, as each GPU only needs to store one additional chunk temporarily.
- Communication is spread out and overlapped with computation, though with some additional base latency overhead from multiple communication steps.

Comparing with Naïve *all-gather* Implementation



Tensor+Sequence Parallelism - Limitations

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Context Parallelism

- TP: Split a model across one node to tame large models
- CP: Tame the activation explosion with long sequences.

- TP: doesn't scale well across nodes

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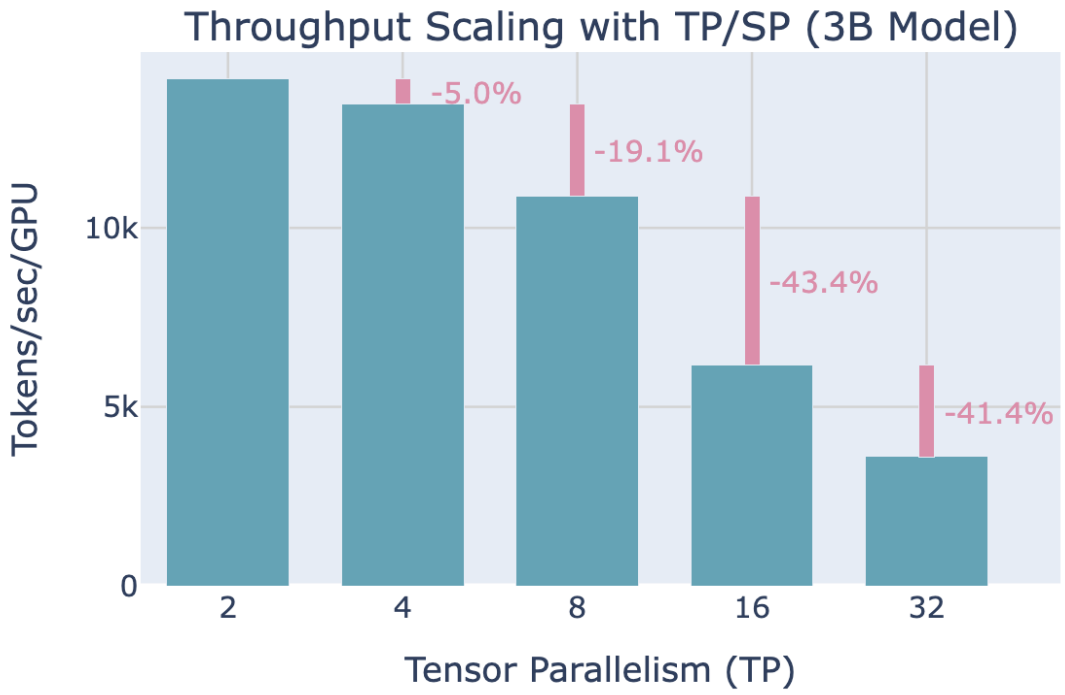

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