UNIVERSITY OF ILLINOIS URBANA-CHAMPAIGN

CS 498: Machine Learning System
Spring 2026

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Today

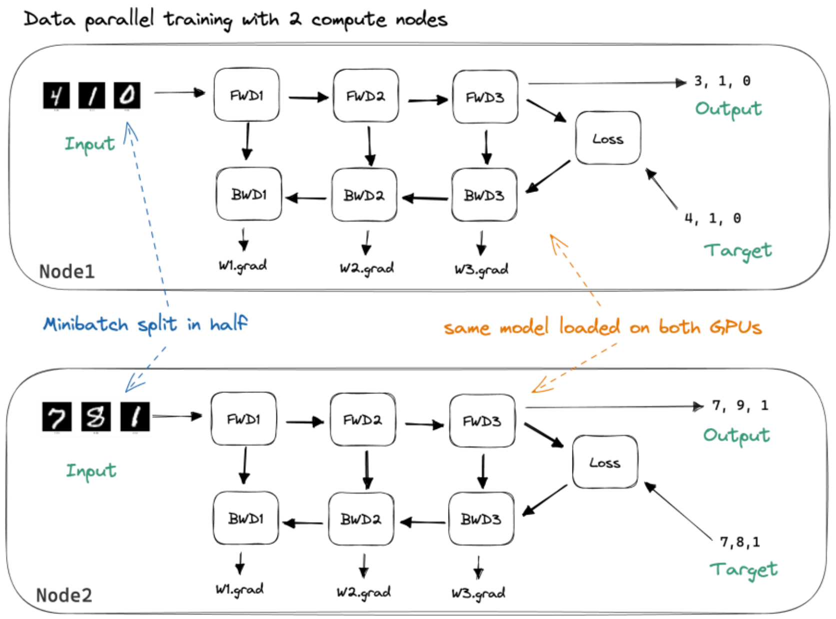
Tensor Slicing Model Parallelism

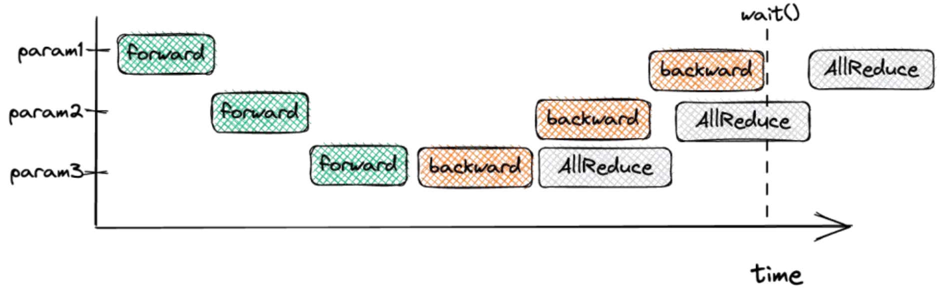
Learning Objectives

- **Explain why data parallelism alone is insufficient for training LLMs**
- **Understand the difference between tensor vs. pipeline parallelism**

Data Parallelism

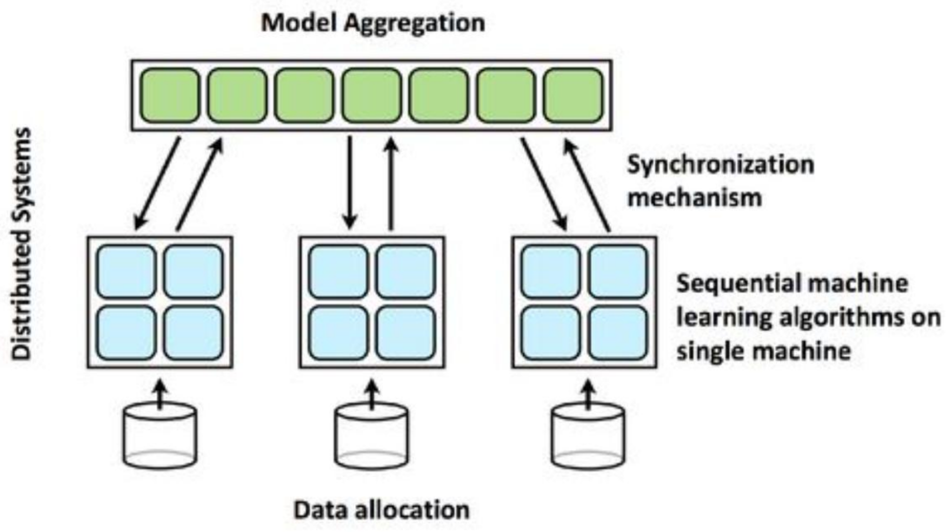
- Partitions a training minibatch across multiple devices
- Linearly scalable
- Slicing activation only
- Does not help with excessive model size



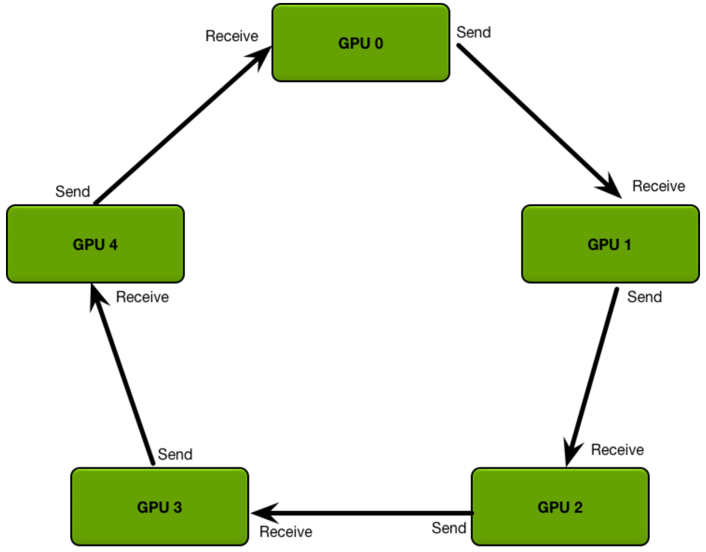


Recall: Data Parallelism

Parameter Server



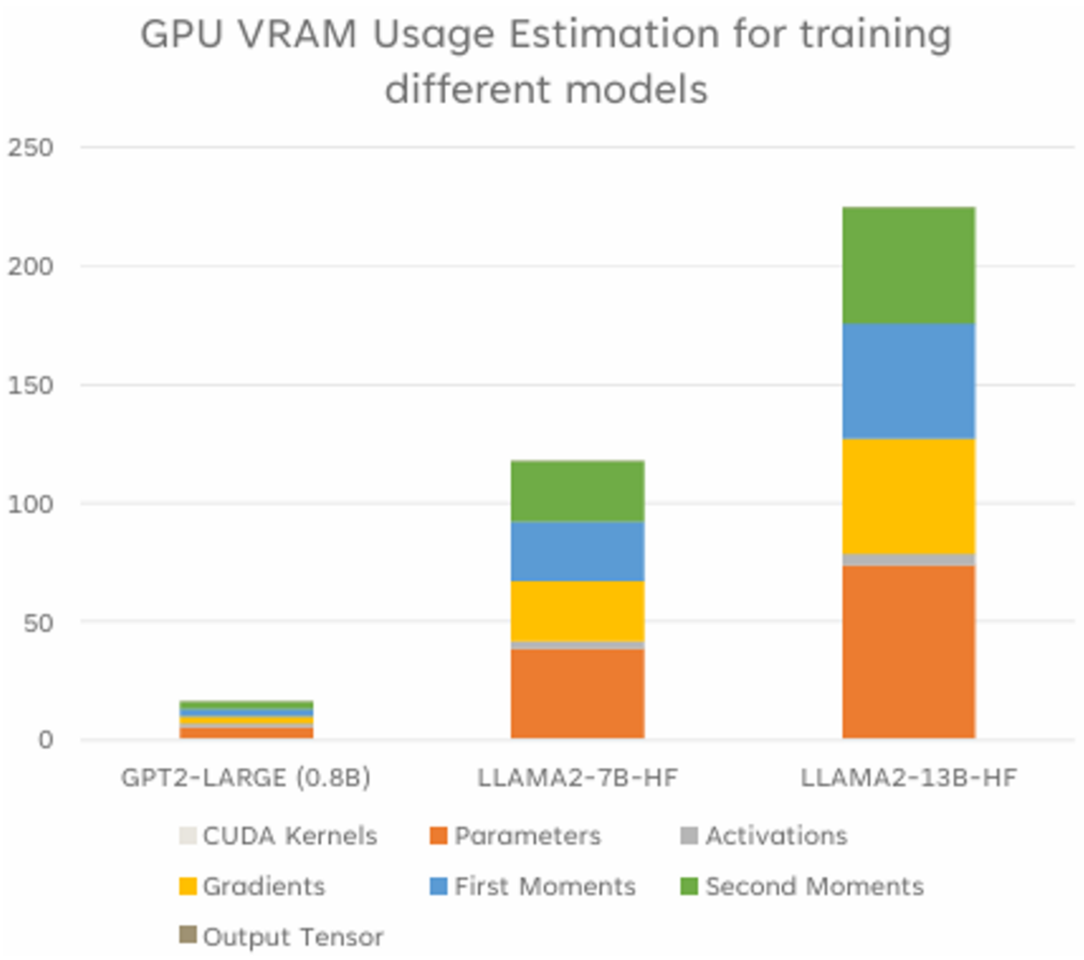
AllReduce



Data parallelism does not help with excessive model size

Large Models Require Large Memory

- Training >> Inference
- Adam >> SGD *(due to optimizer state)*
- Larger minibatch
- Scaling law => More parameters
- …



Question: How do we speed up training or simply enable training?

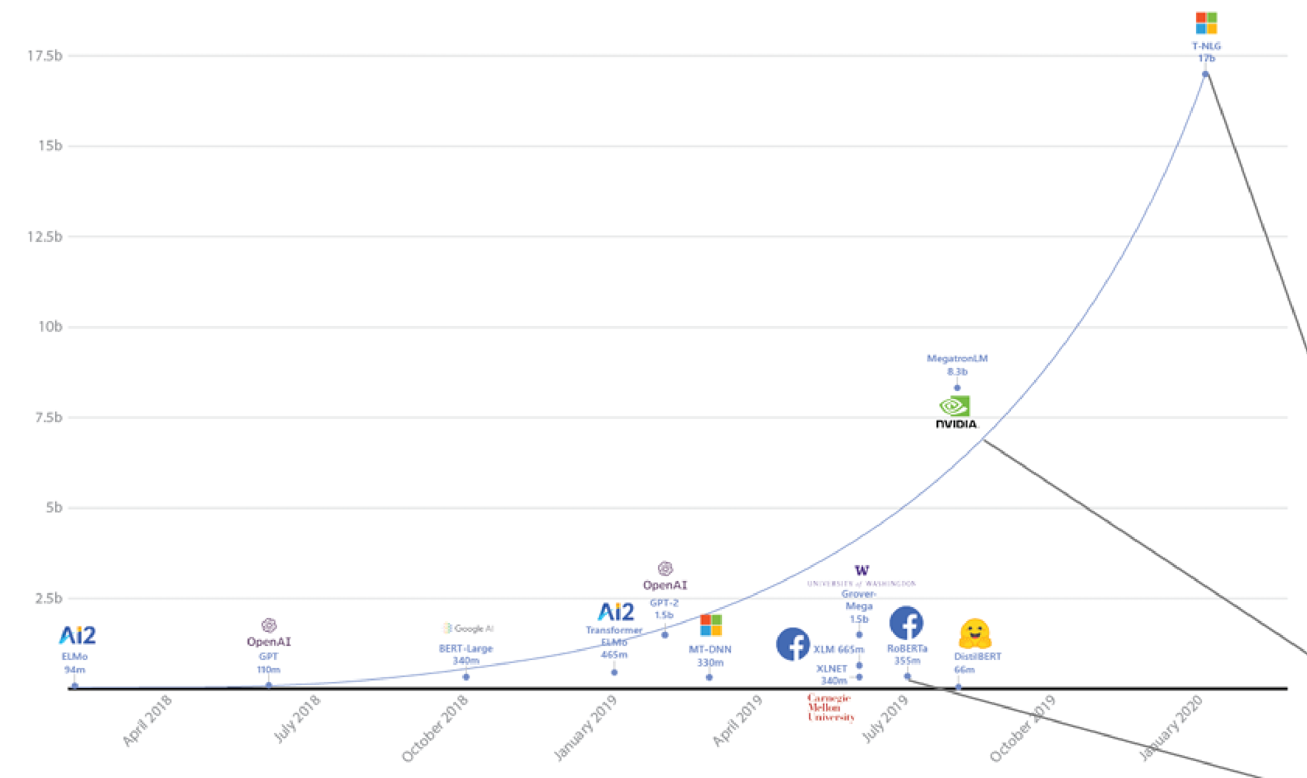
Megatron-LM

- Paper: https://arxiv.org/abs/1909.08053
- Repo: https://github.com/NVIDIA/Megatron-LM

- NVIDIA's framework, released in 2019, for efficiently training large-scale language models

Motivation

Computational Needs of NLP



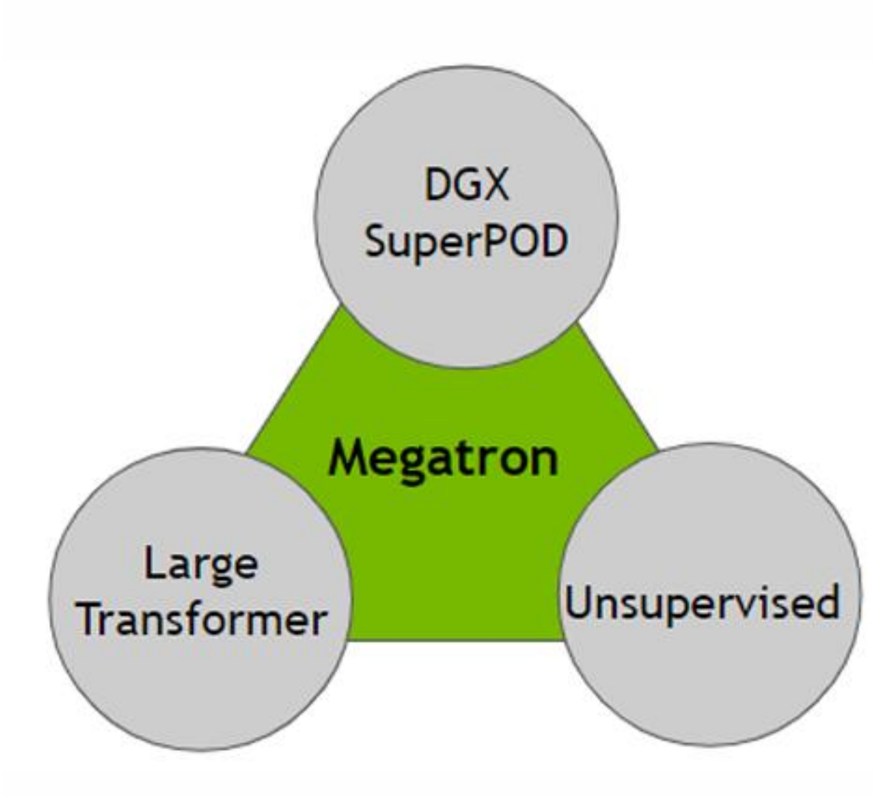
Model	# of Parameters	# of Iterations	# of GPUs	Training Time
T-NLG (MS + NV)	17.2 B	300 K	400	60 days
Megatron-GPT2 (NV)	8.3 B	300 K	512	10 days
Megatron-BERT (NV)	3.9 B	2 M	512	25 days
RoBERTa (FB)	345M	4 M	1024	1 day

Motivation: Why Megatron?

Training larger transformer-based language models became an important way to advance SoTA NLP applications.

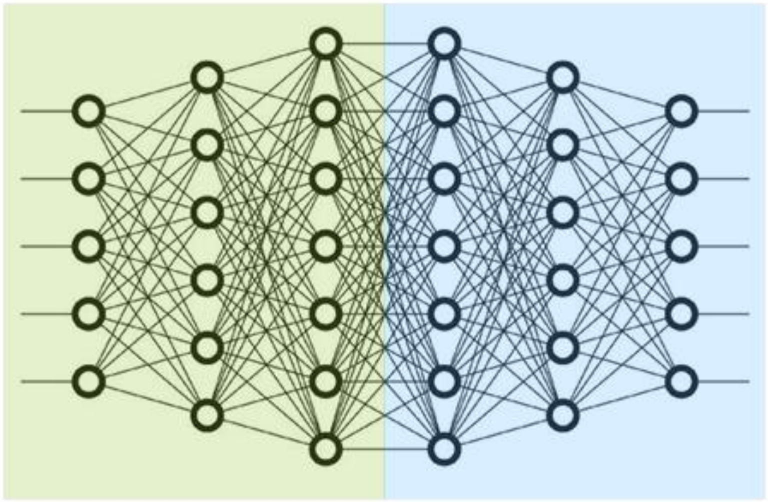
Unsupervised language models such as GPT-2, BERT, and XLNet demonstrate the power of scaling language models trained on a huge corpus.

Nvidia DGX boxes optimized for deep learning provides a unique opportunity for training very large models.

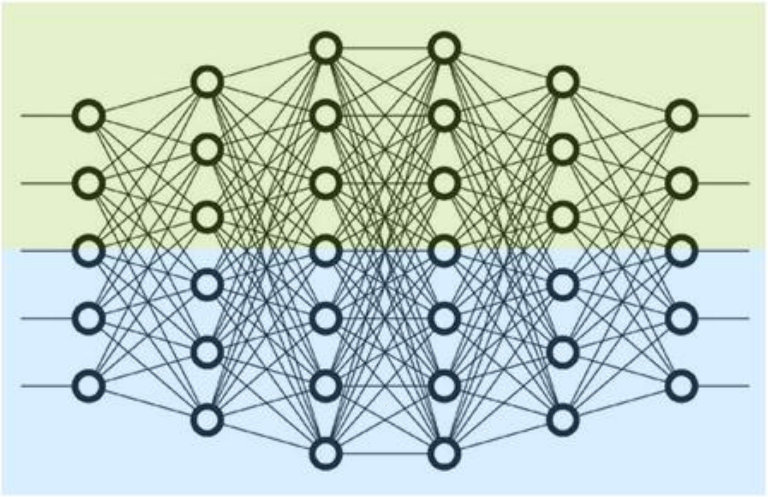


Model Parallelism

Inter-layer (Pipeline) parallelism
- Split sets of layers across multiple devices
- Layer 0, 1, 2 and layer 3, 4, 5 are on different devices



Intra-layer (Tensor) parallelism
- Split individual layers across multiple devices
- Both devices compute different parts of layer 0, 1, 2, 3, 4, 5



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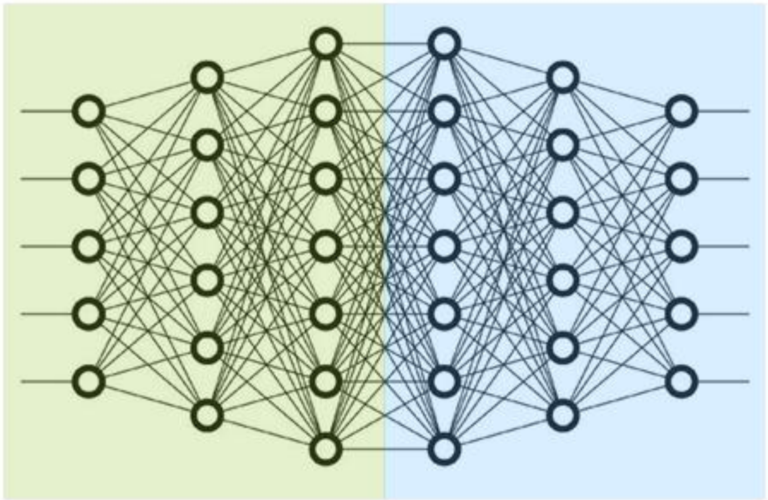

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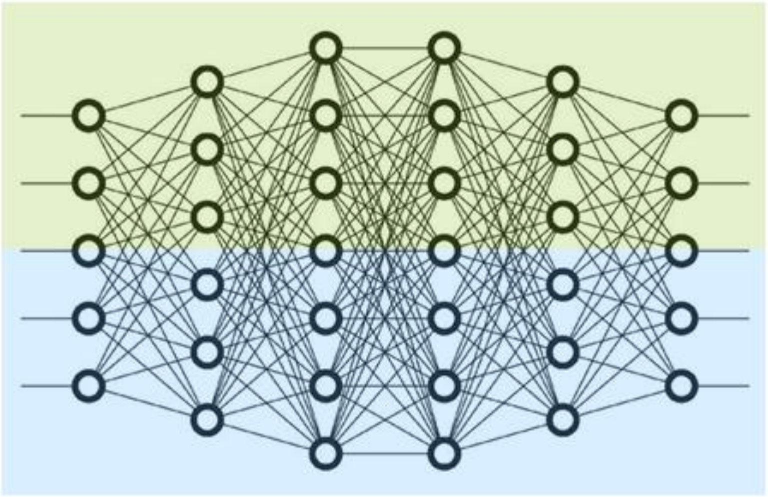
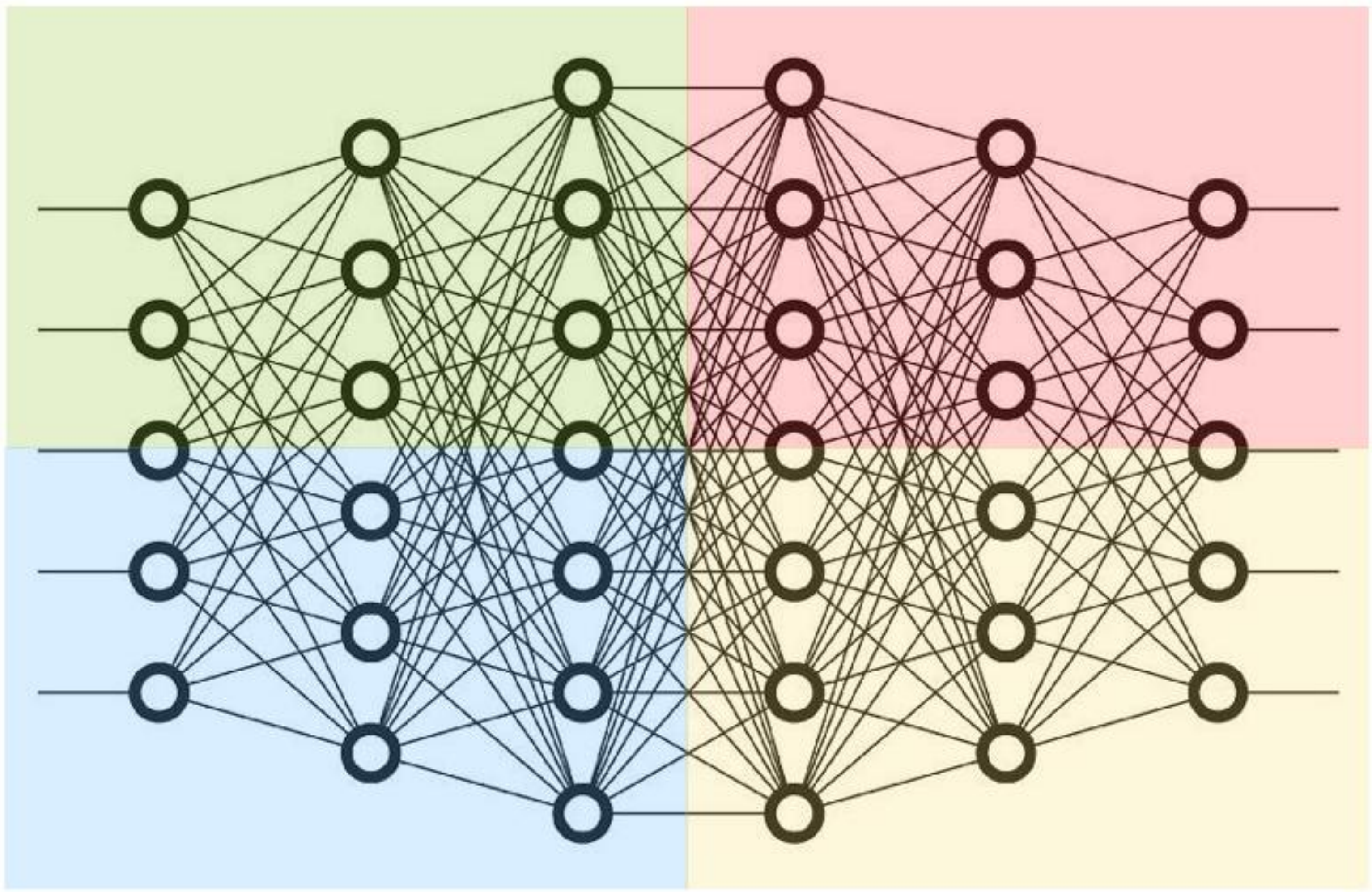


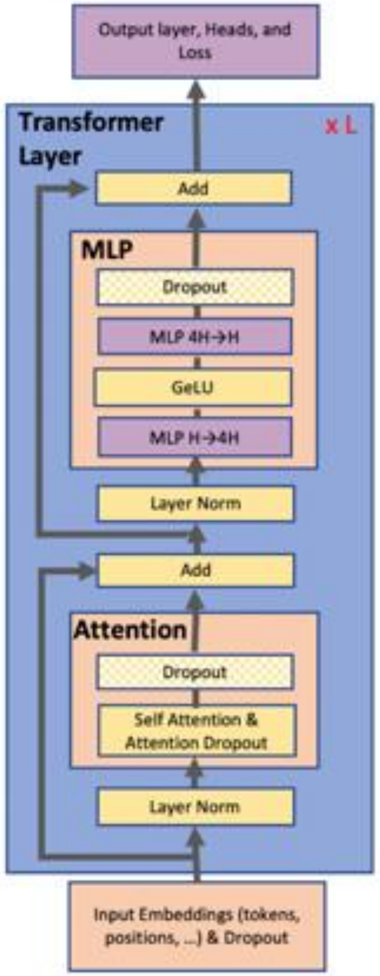
Complementary Types of Model Parallelism



Inter + Intra Parallelism

Goals and Approach

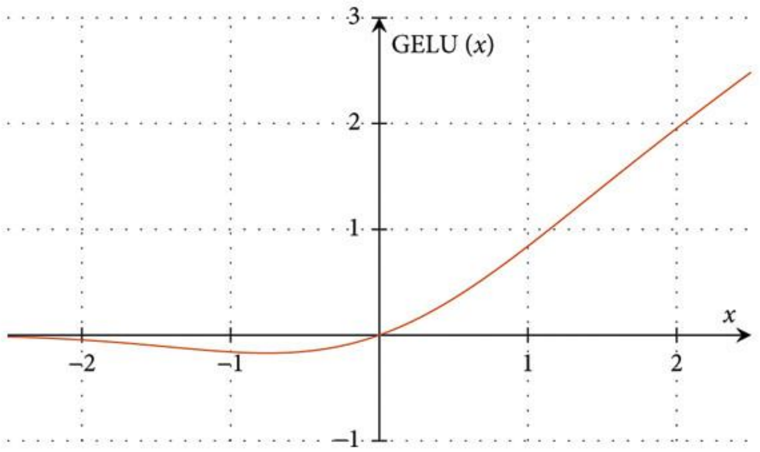
- Tailored for transformer networks
- Transformer layer
  - Self-attention block
  - Two-layer MLP
- Targets:
  - Reduce synchronization cost
  - Simple to implement with a few highly optimized collectives NCCL provides



Tensor Parallelism: MLP

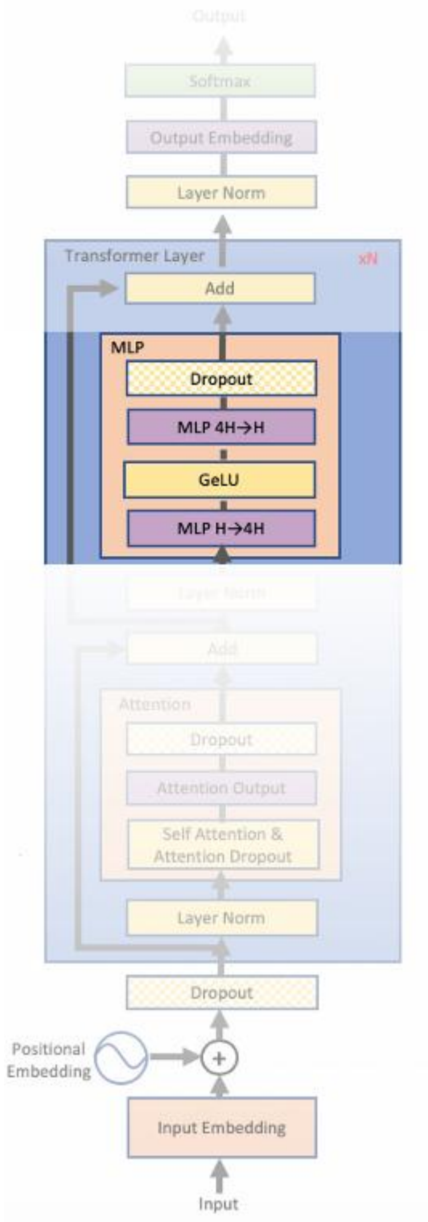
- MLP:

$$Y = \mathrm{GeLU}(XA)$$
$$Z = \mathrm{Dropout}(YB)$$

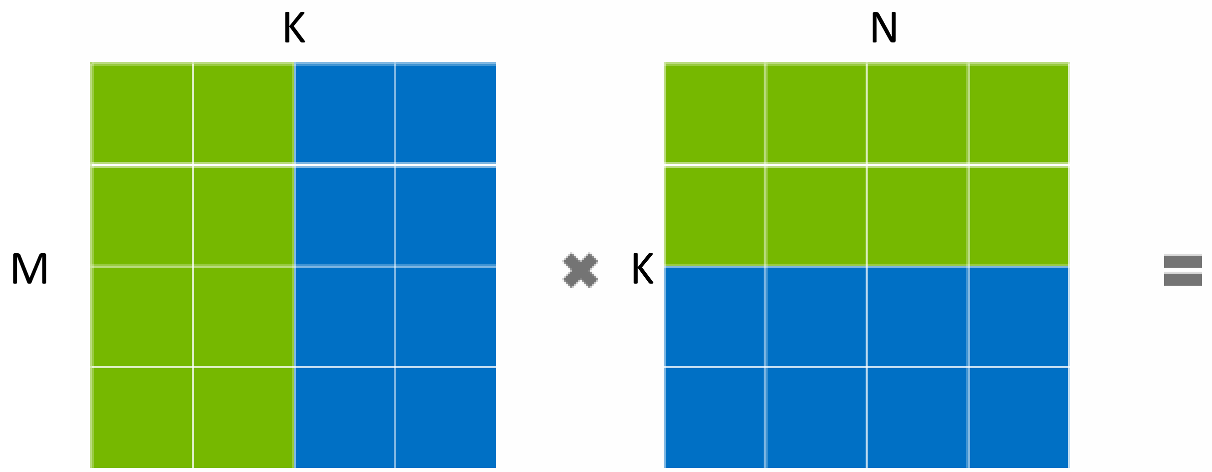


Dropout (YB):

Randomly drop a certain percentage of values to prevent overfitting



Tensor Parallel: Parallel GeMM (General Matrix Multiplications)



$$X = [X_1, X_2]$$

$$A = \begin{bmatrix} A_1 \\ A_2 \end{bmatrix}$$

$$Y = Y_1 + Y_2$$

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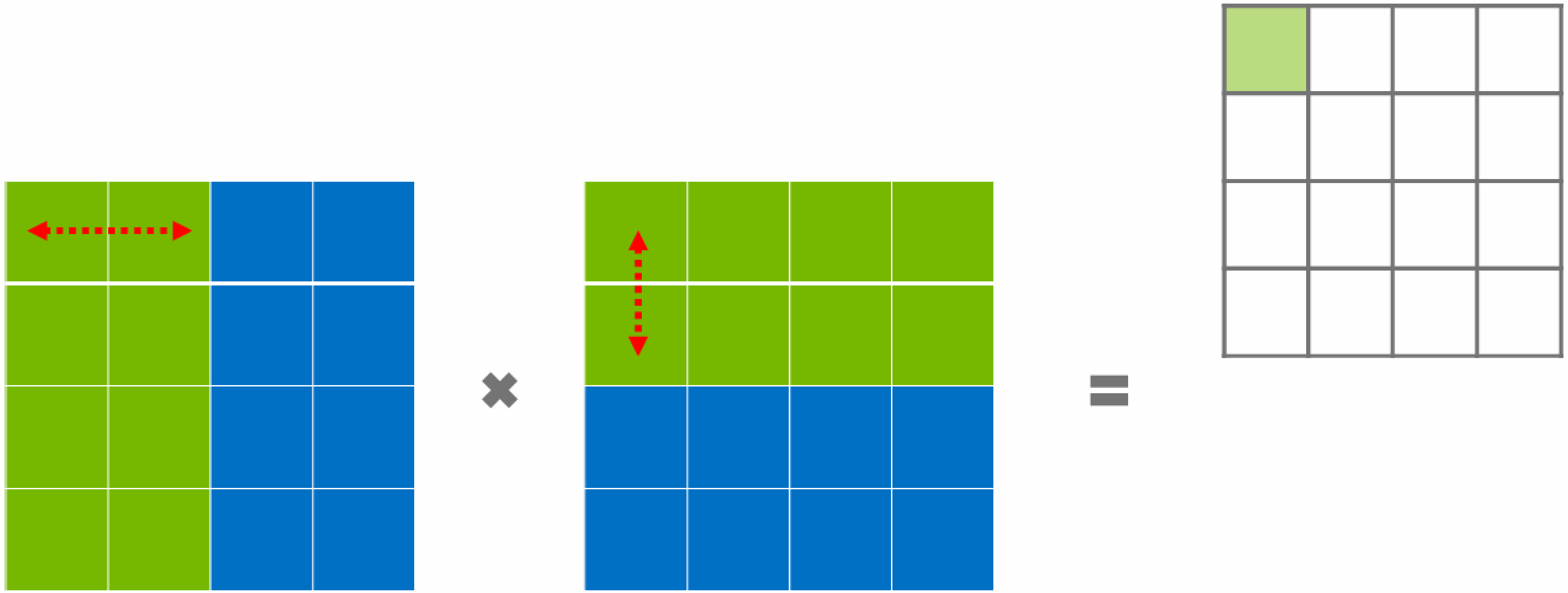

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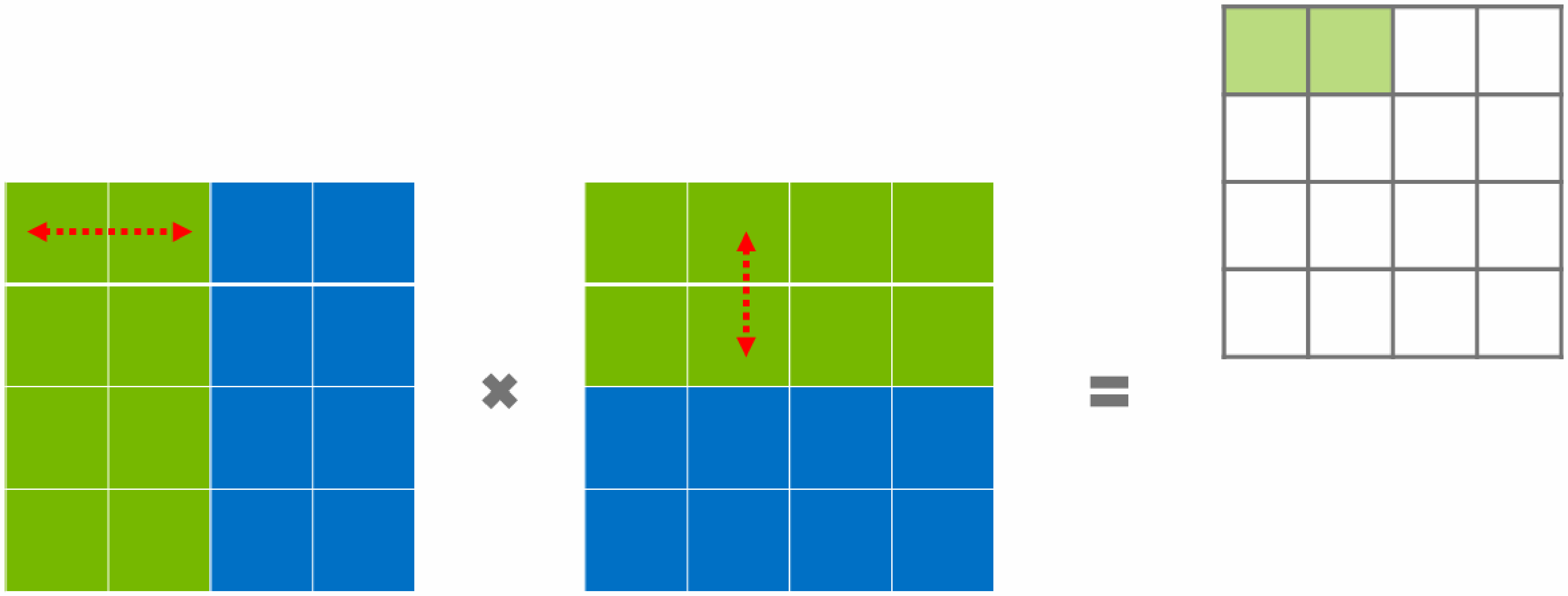

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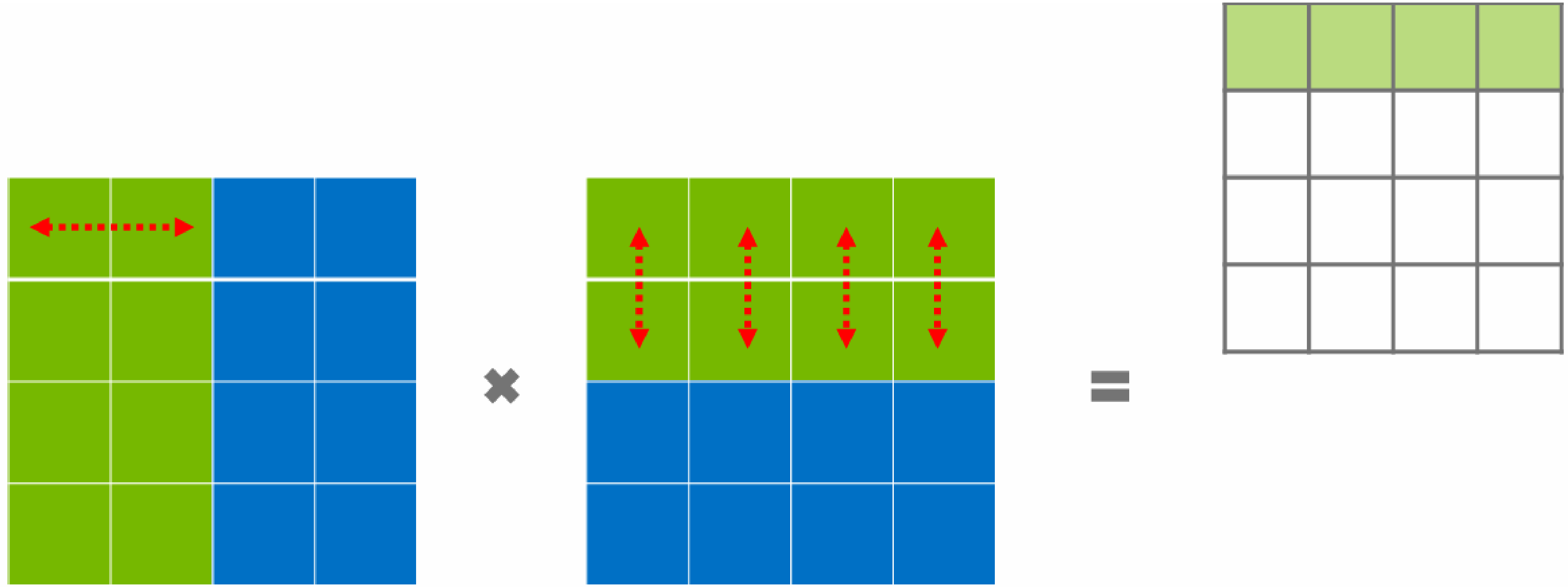

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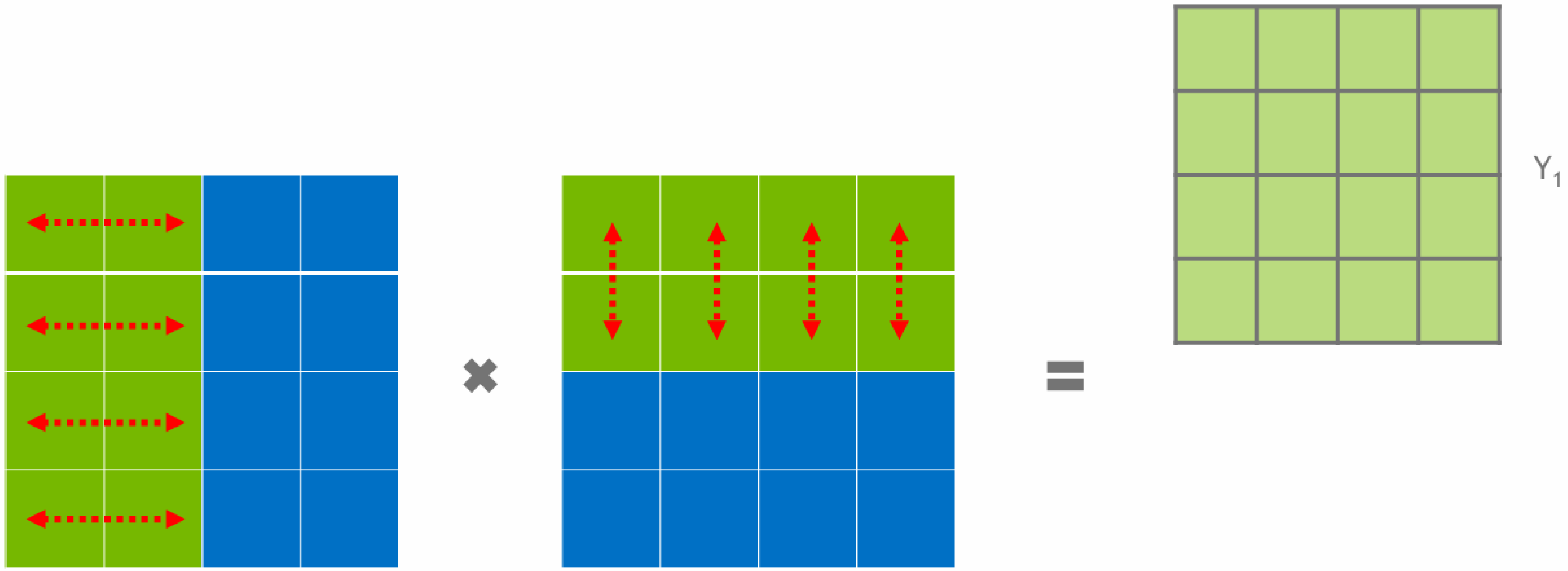

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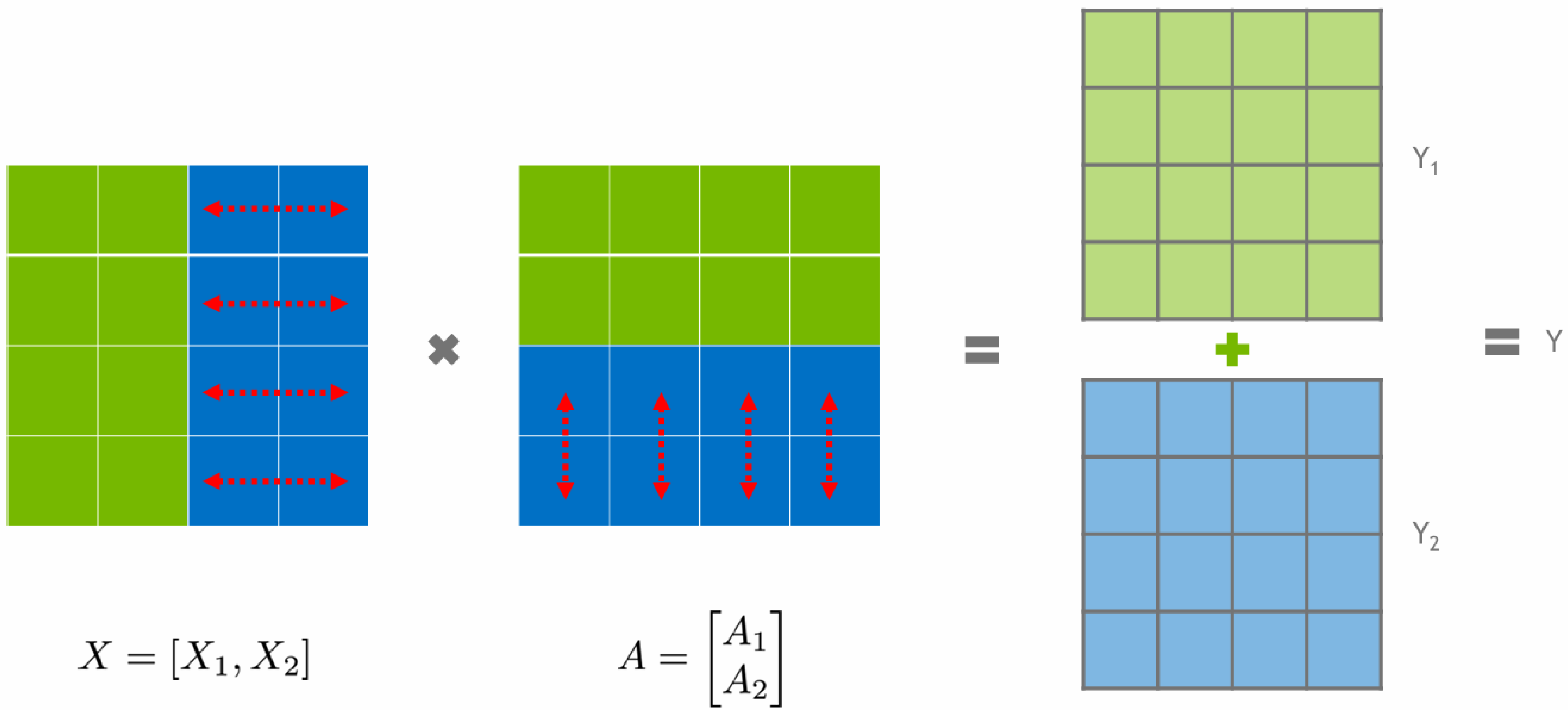

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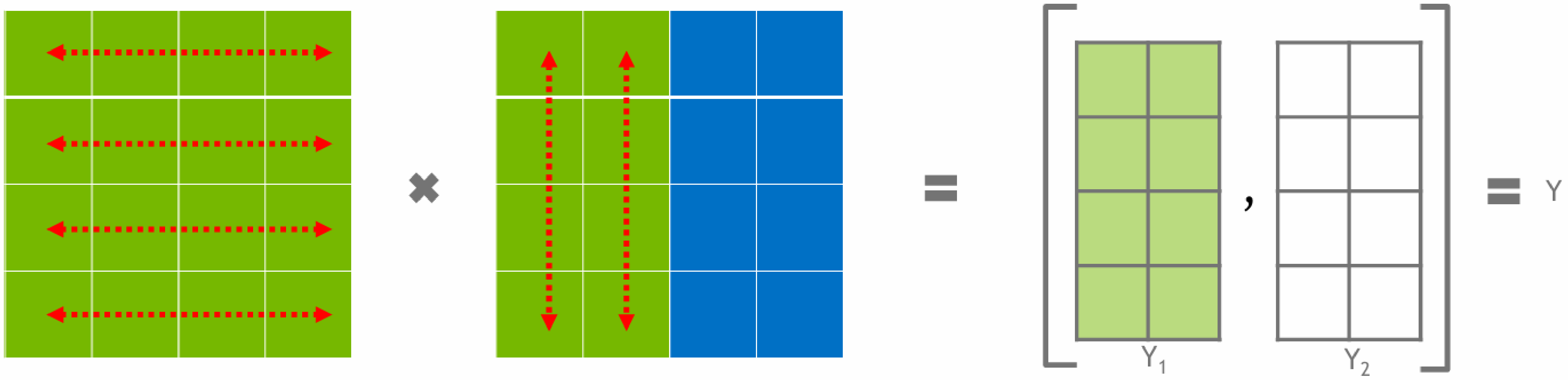

X $\quad A = [A_1, A_2] \quad$ $Y = [Y_1, Y_2]$

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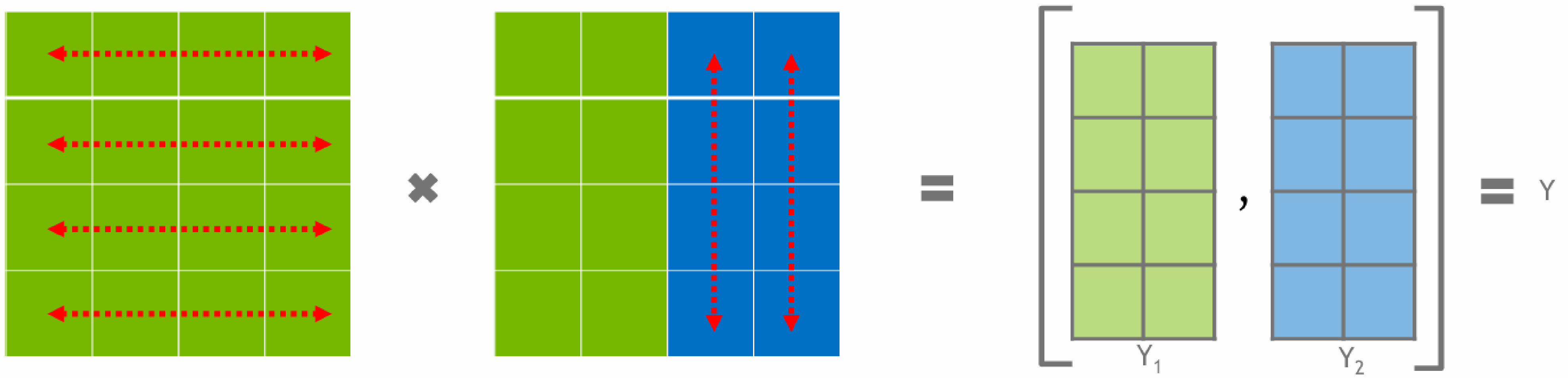

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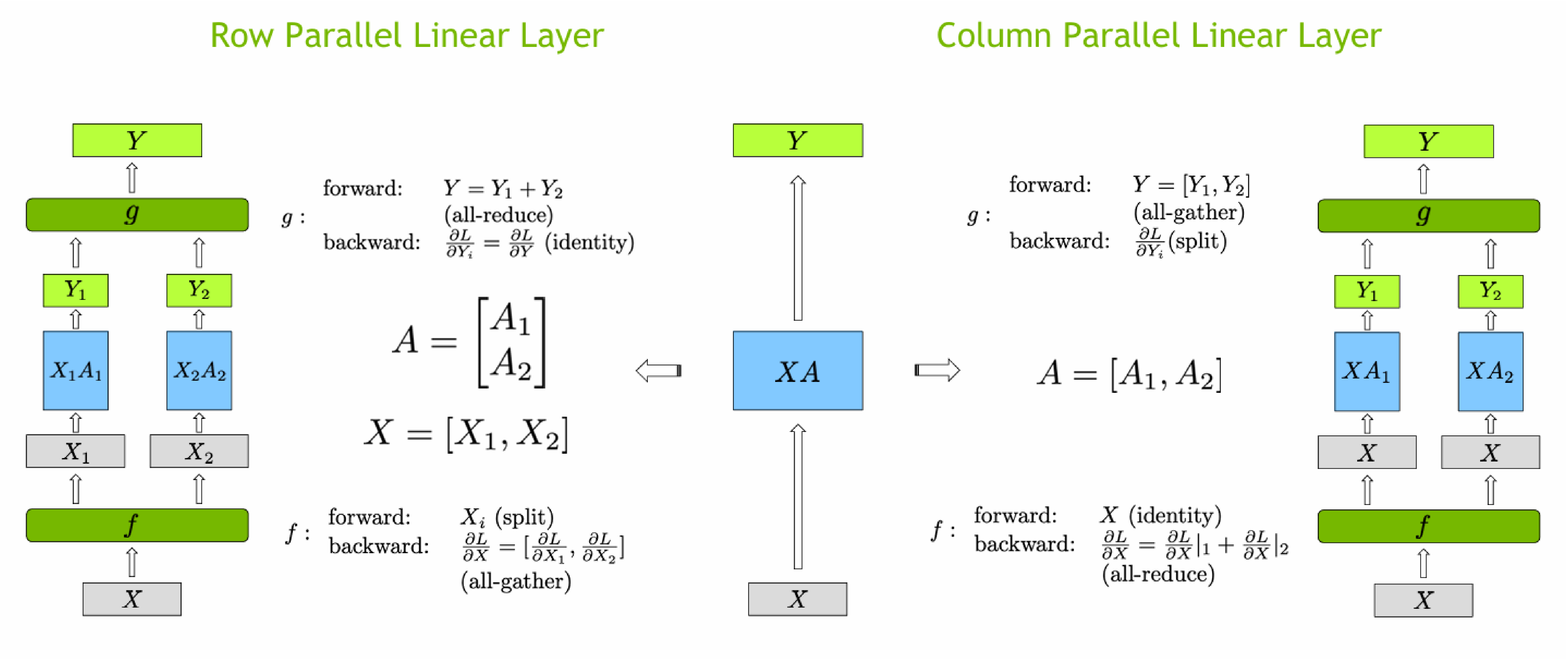
Tensor Parallelism



Tensor Parallelism

Normal

Operation: $Y_{n\times n} = X_{n\times n}A_{n\times n}$

Flops: $2n^3$

Bandwidth: $6n^2$

Intensity: $\frac{1}{3}n$

Parallel

Operation: $Y_{n\times(n/p)} = X_{n\times n}A_{n\times(n/p)}$

Flops: $2n^3/p$

Bandwidth: $2n^2(1+2/p)$

Intensity: $\frac{1}{2+p}n$

Ratio between serial and parallel

Flops: $1/p$

Bandwidth: $\frac{1+2/p}{3}$

Intensity: $\frac{3}{2+p}$

Tensor Parallelism: MLP

- MLP:

$$Y = \text{GeLU}(XA)$$
$$Z = \text{Dropout}(YB)$$

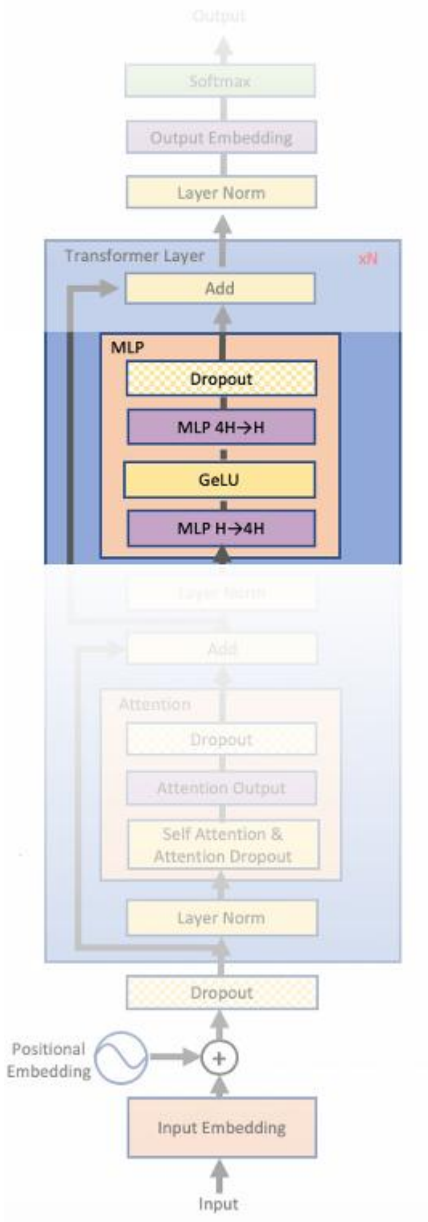
- Approach 1: split X column-wise and A row-wise

$$X = [X_1, X_2] \quad A = \begin{bmatrix} A_1 \\ A_2 \end{bmatrix} \longrightarrow Y = \text{GeLU}(X_1A_1 + X_2A_2)$$

GeLU of sums != sum of GeLUs

$$\begin{pmatrix} X_0 & X_1 \\ X_2 & X_3 \end{pmatrix} \begin{pmatrix} A_0 & A_1 \\ A_2 & A_3 \end{pmatrix} = \begin{pmatrix} X_0 \\ X_2 \end{pmatrix} \begin{pmatrix} A_0 & A_1 \end{pmatrix} + \begin{pmatrix} X_1 \\ X_3 \end{pmatrix} \begin{pmatrix} A_2 & A_3 \end{pmatrix}$$

$$= \underbrace{X_A A_A + X_B A_B}_{\text{Summation}}$$



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Requires AllReduce before GeLU

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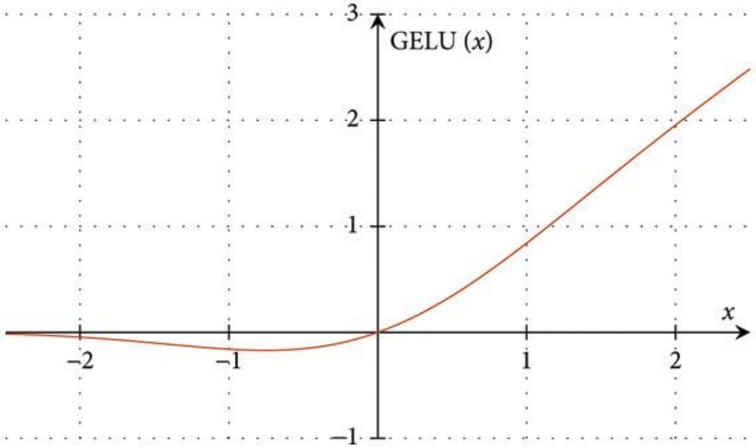

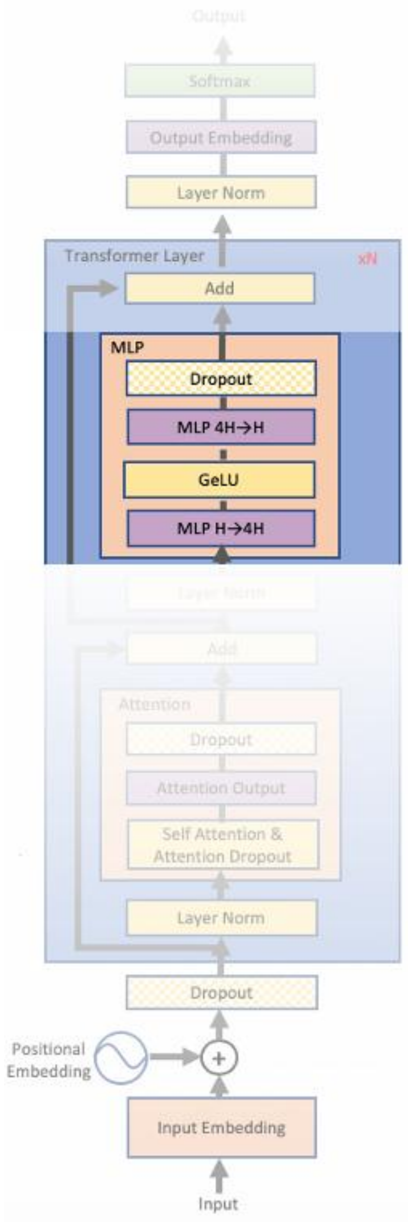

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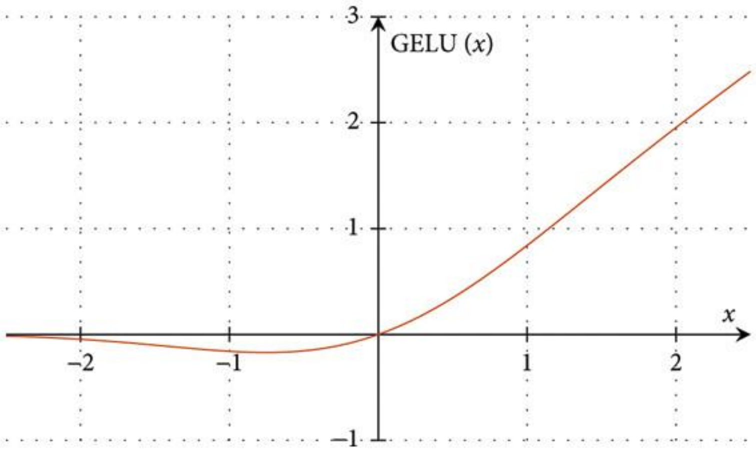
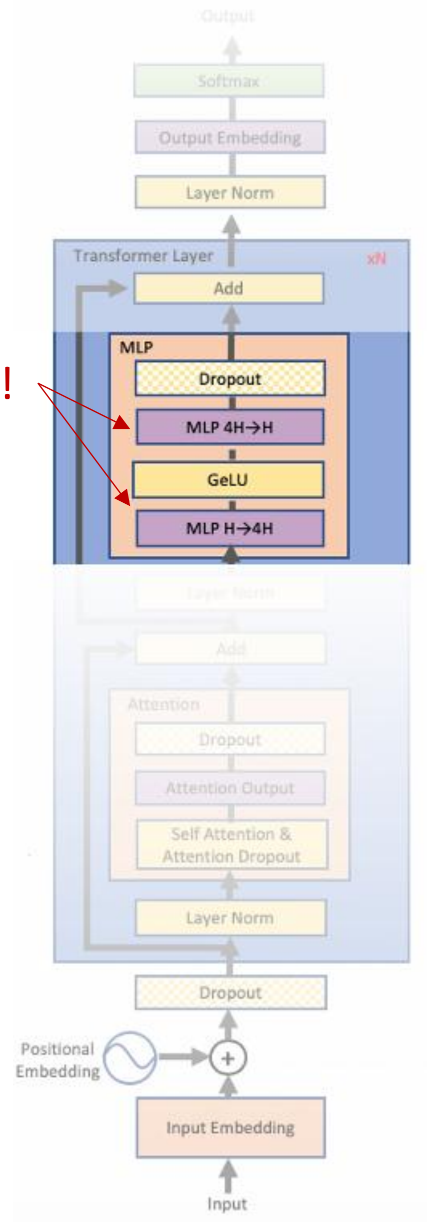
GeLU of sums != sum of GeLUs

Shape(Y) = [B, S, 4H]!





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  - Requires synchronization before GeLU

GeLU of sums != sum of GeLUs

- Approach 2: split A column-wise

$$A = [A_1, A_2] \longrightarrow [Y_1, Y_2] = [\mathrm{GeLU}(XA_1), \mathrm{GeLU}(XA_2)]$$

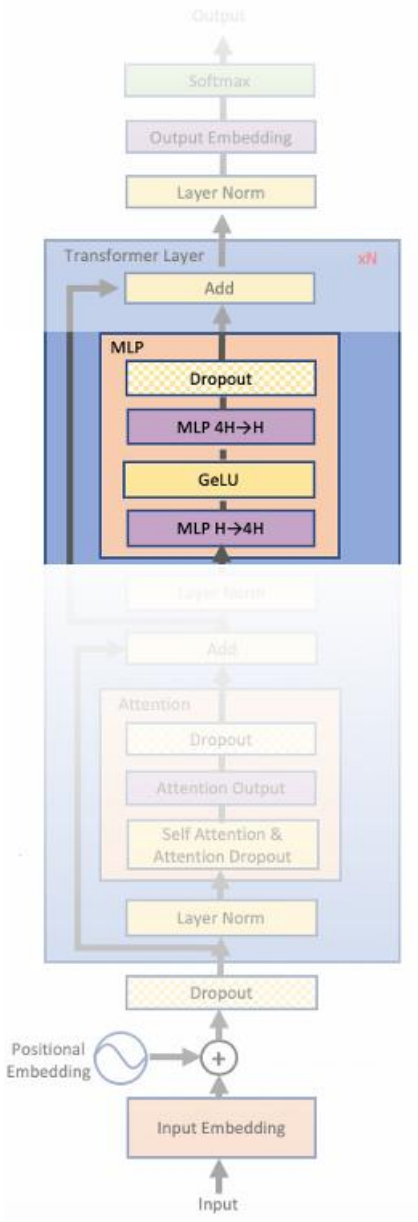
  - No synchronization necessary

Can run in parallel now!

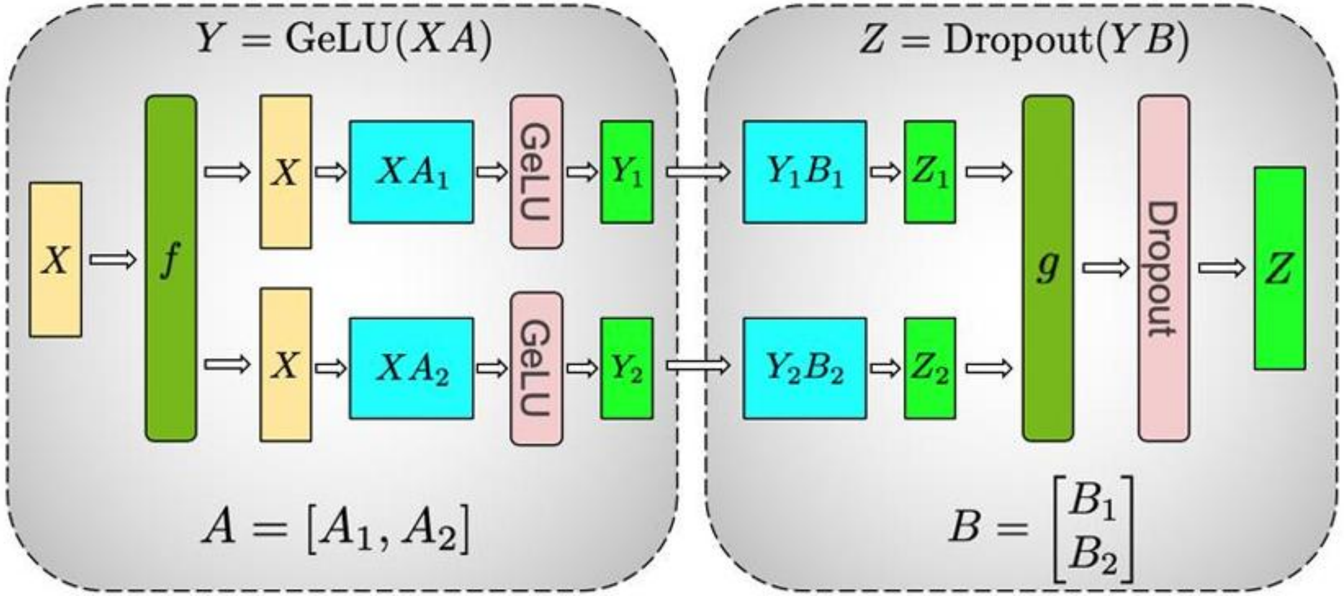
$$\begin{pmatrix} X_0 & X_1 \\ X_2 & X_3 \end{pmatrix}\begin{pmatrix} A_0 & A_1 \\ A_2 & A_3 \end{pmatrix} = \left(\begin{pmatrix} X_0 & X_1 \\ X_2 & X_3 \end{pmatrix}\begin{pmatrix} A_0 \\ A_2 \end{pmatrix} \quad \begin{pmatrix} X_0 & X_1 \\ X_2 & X_3 \end{pmatrix}\begin{pmatrix} A_1 \\ A_3 \end{pmatrix}\right)$$

$$= (XA_A \quad XA_B)$$

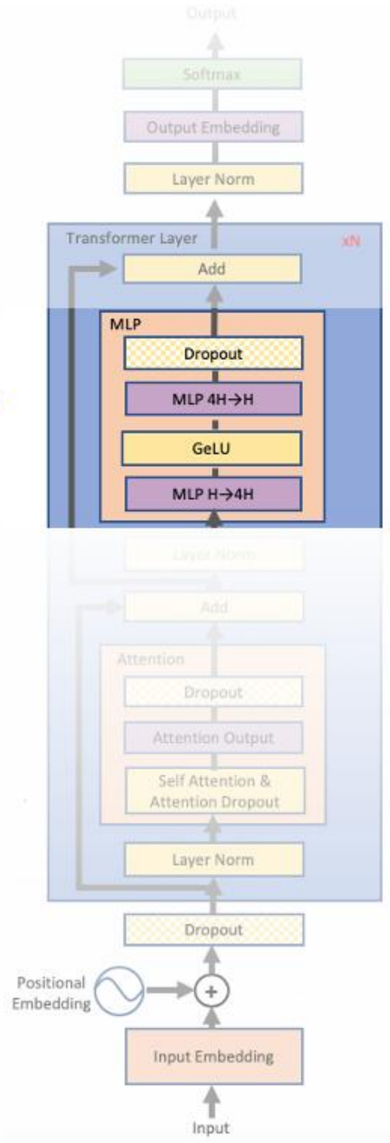
Concatenation



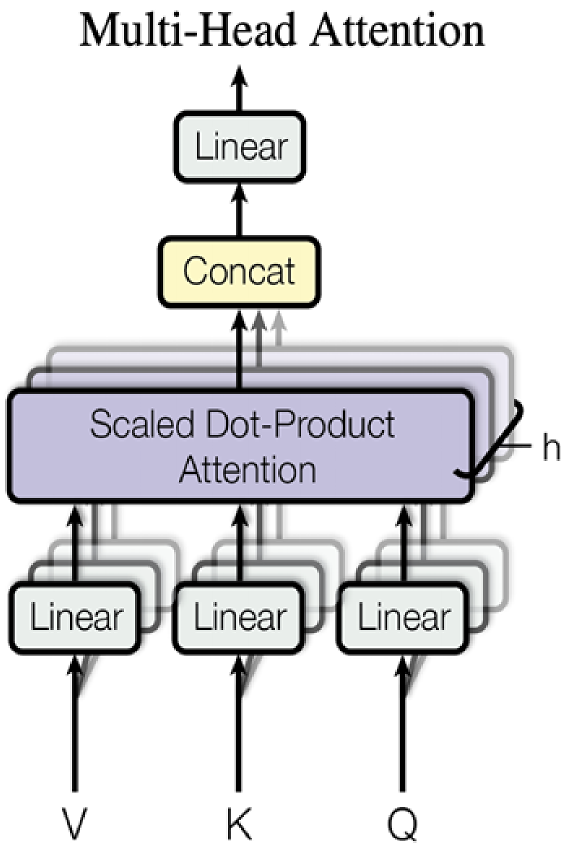
Tensor Parallelism: MLP

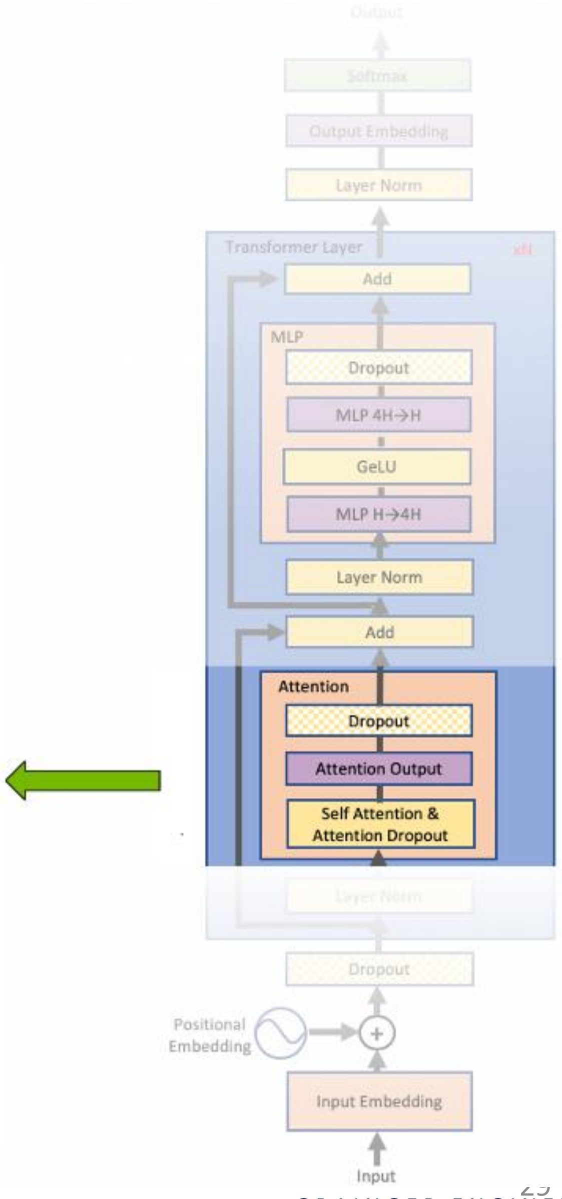


f and ***g*** are **conjugate**, ***f*** is **identity** operator in the forward pass and **all-reduce** in the backward pass while ***g*** is **all-reduce** in forward and **identity** in backward.



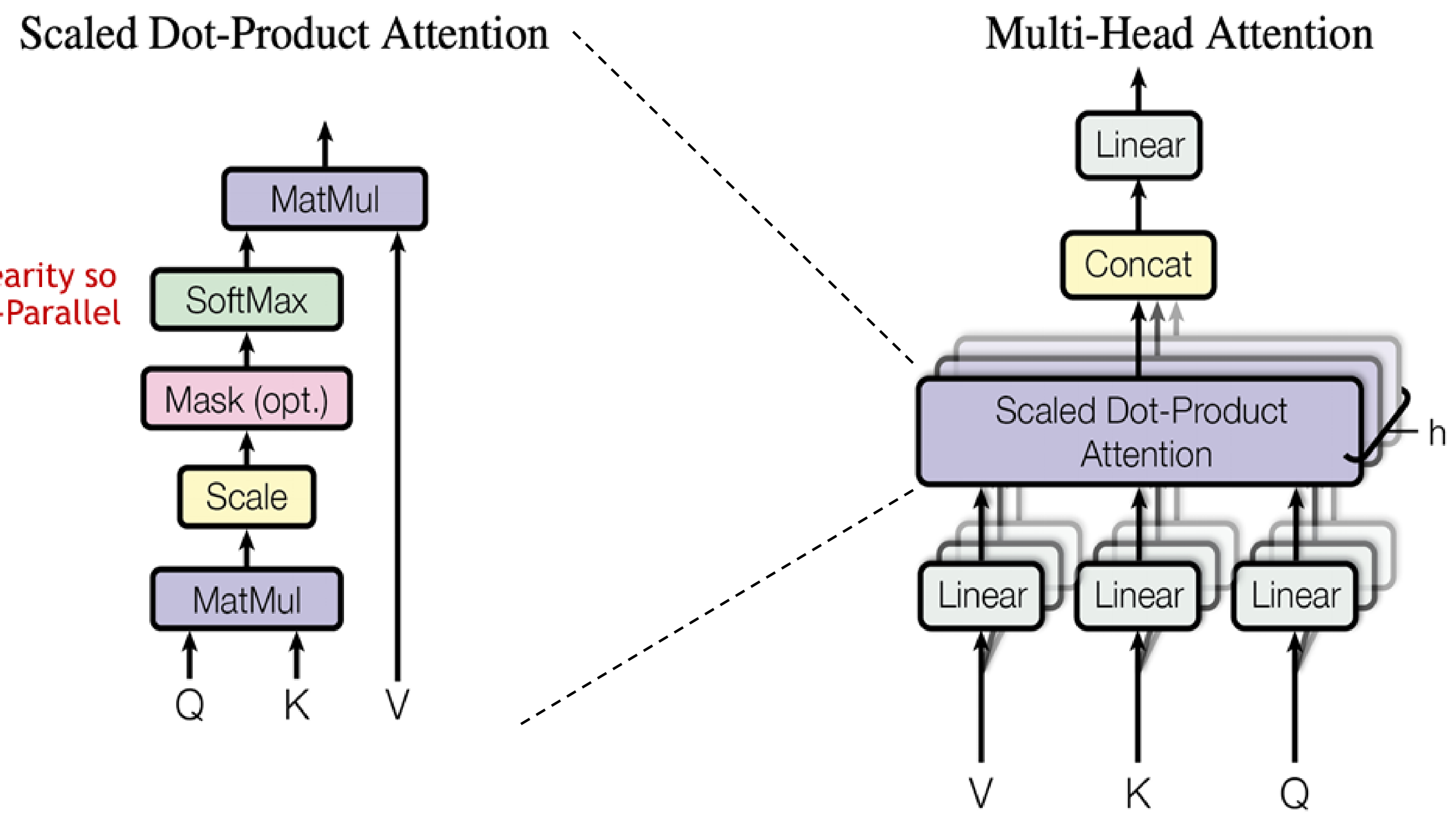
Tensor Parallelism: Self-Attention

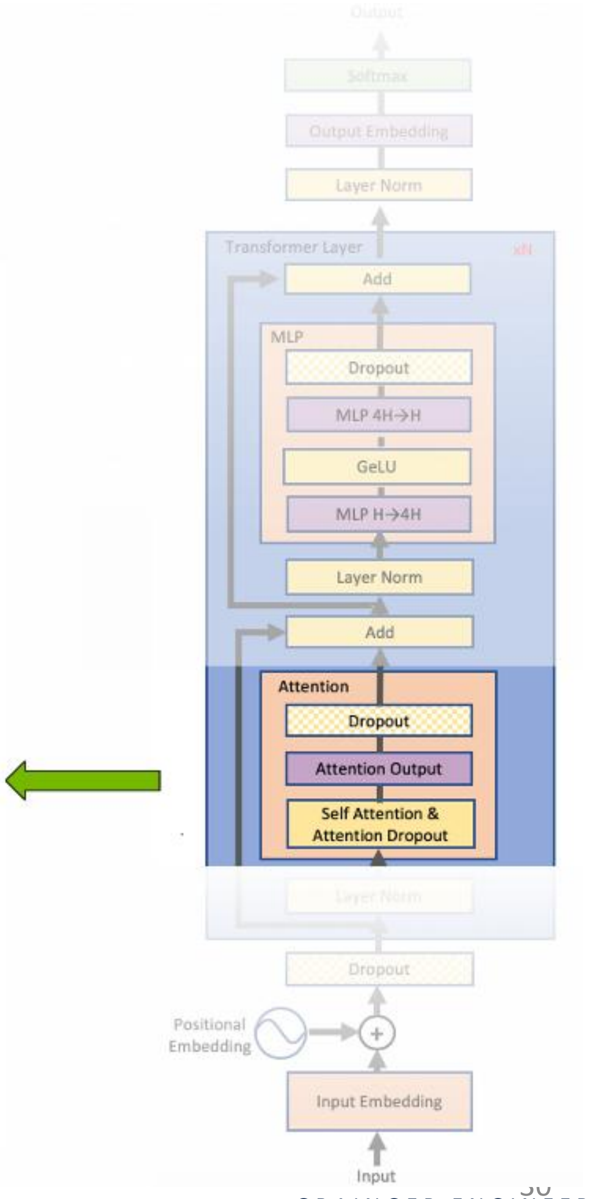




Tensor Parallelism: Self-Attention

Nonlinearity so no Row-Parallel





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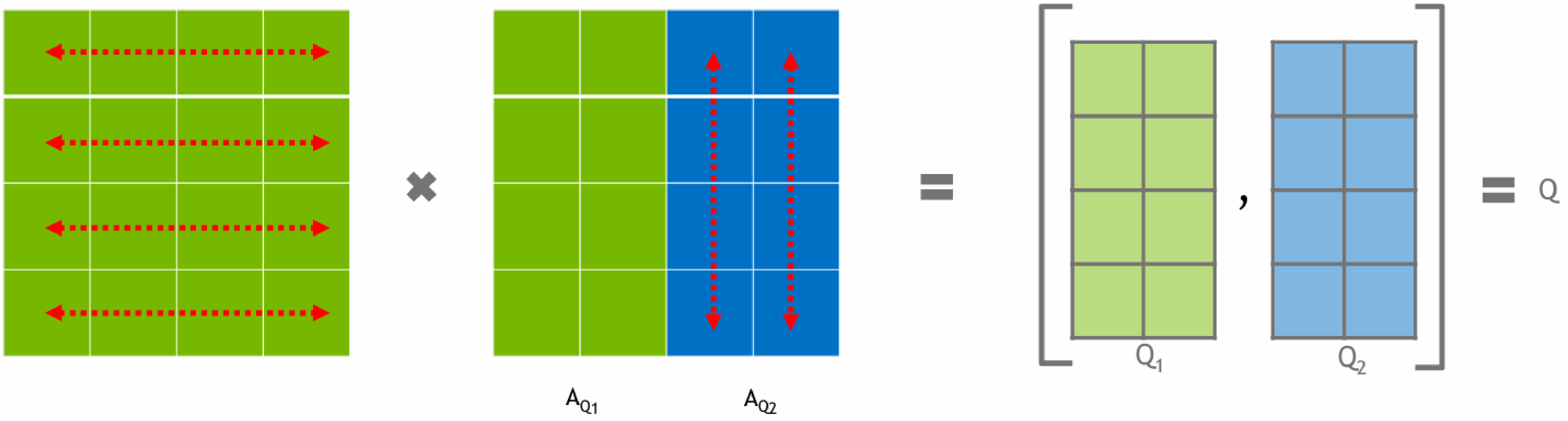
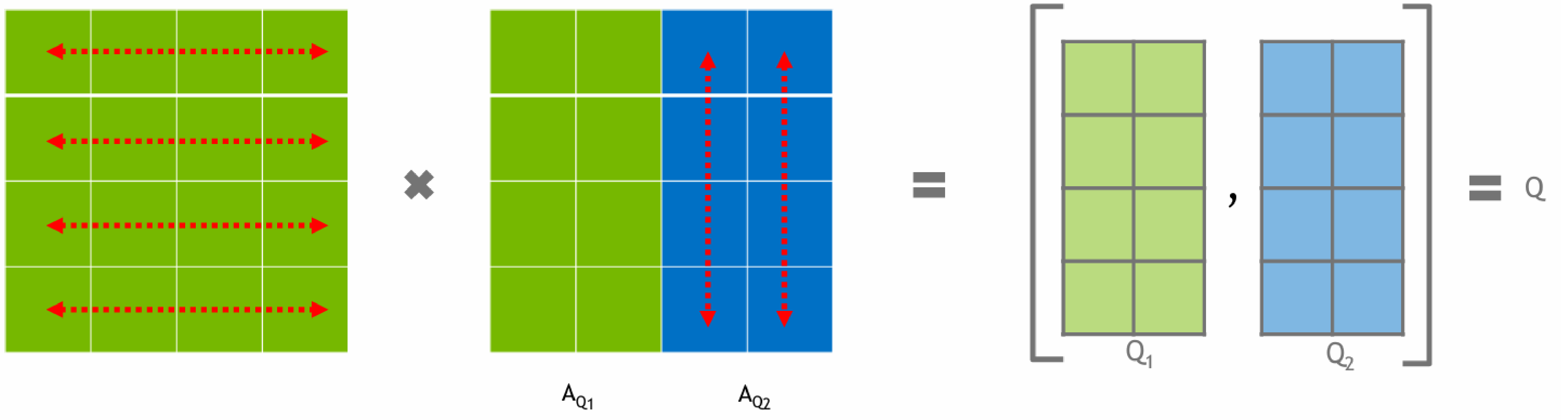


X $\quad$ $A = [A_1, A_2]$ $\quad$ $Y = [Y_1, Y_2]$

Attention heads can be parallelized with Column Parallel GEMMs (ex. Query head 1 (Q_1) and Query head 2 (Q_2))

Tensor Parallelism: Self-Attention



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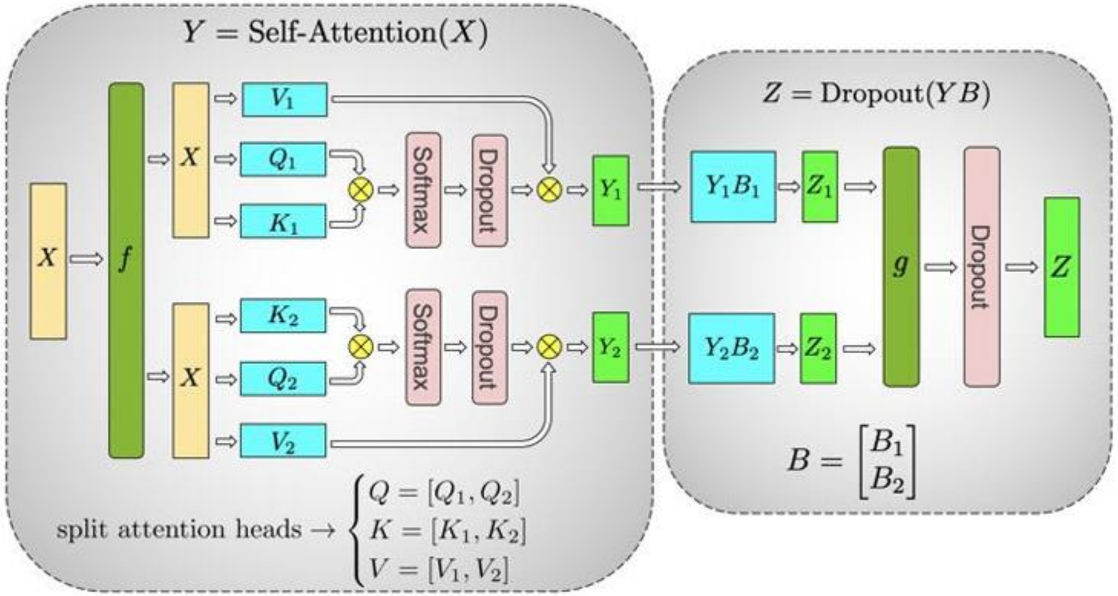
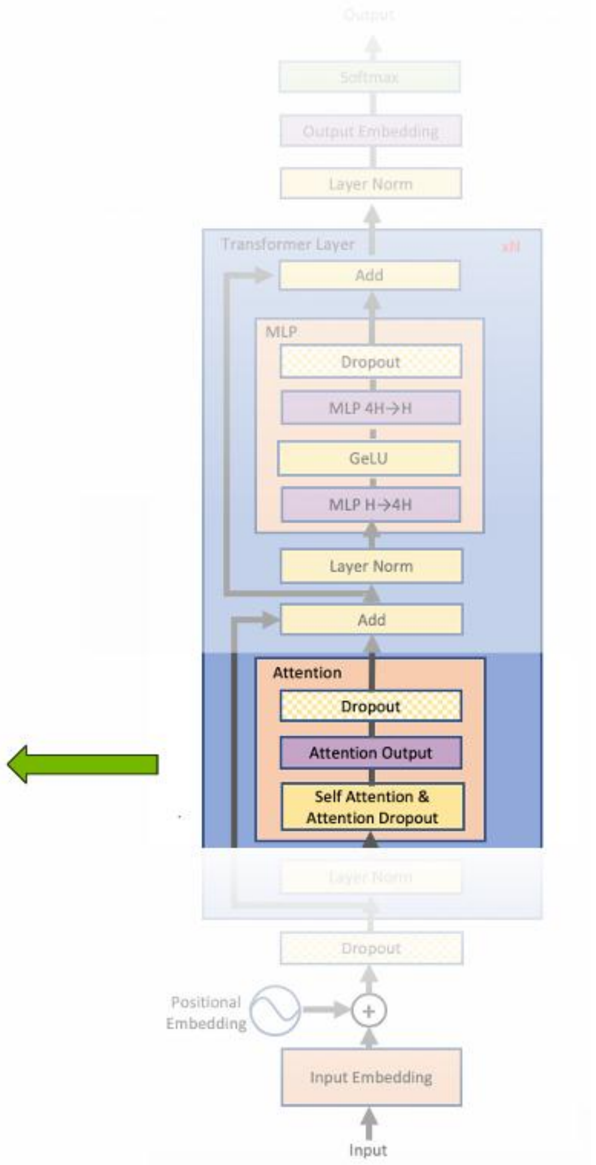
Attention heads can be parallelized with Column Parallel GEMMs (ex. Query head 1 (Q_1) and Query head 2 (Q_2))

Question: What if we have more GPUs than the number of heads?

Tensor Parallelism: Self-Attention

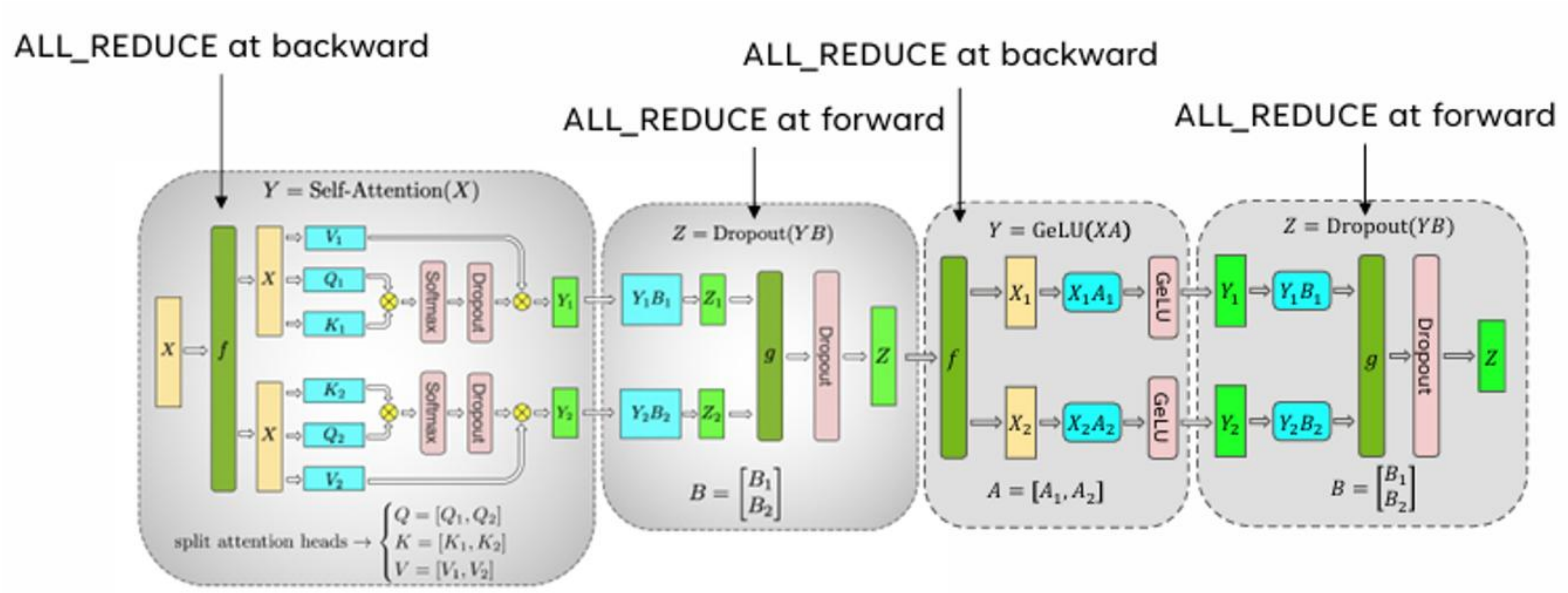




f and ***g*** are **conjugate**, ***f*** is **identity** operator in the forward pass and **all-reduce** in the backward pass while ***g*** is **all-reduce** in forward and **identity** in backward.

Tensor Parallelism: Communication Cost

- 4 total communication operations in 1 forward + backward pass



Experiments

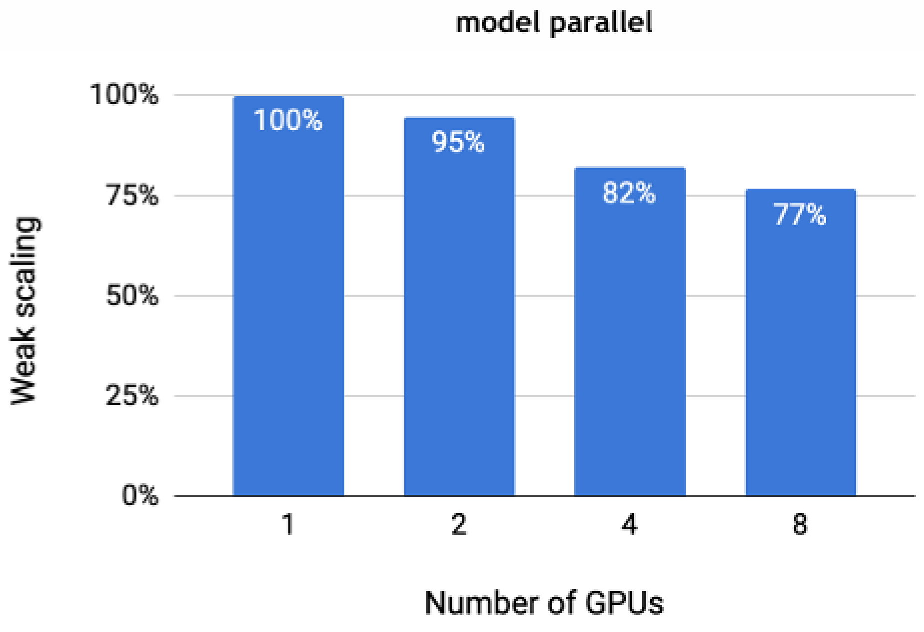
- 32 DGX-2H servers
  - 512 V100 SXM3 32GB GPUs
- Intra-server connection
  - 300 GB/s NVSwitch
- Inter-server connection
  - 100 GB/s InfiniBand (8 per server)

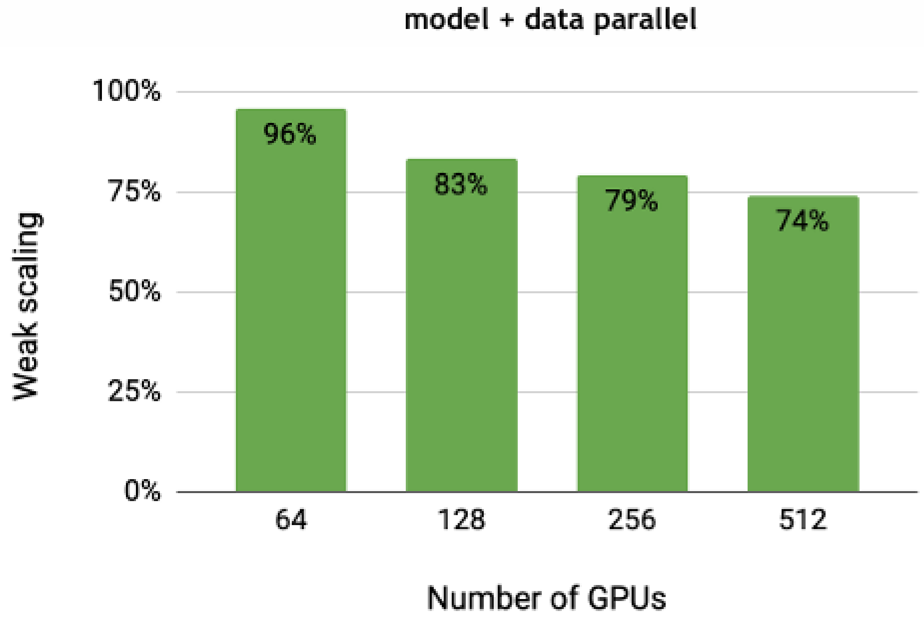
- GPT-2 & BERT Models
- TP (+ DP)
- Mixture of datasets

Experiments: Scalability

- GPT-2: 1B-8B
- Hidden size: 1536-3072
- Parameters/GPU: ~1.B
- Weak scaling@512 GPUs: 74%

Config	Hidden size	Attention heads	Number of layers	Number of parameters (billions)	Model parallel GPUs	Model+data parallel GPUs
1	1536	16	40	1.2	1	64
2	1920	20	54	2.5	2	128
3	2304	24	64	4.2	4	256
4	3072	32	72	8.3	8	512

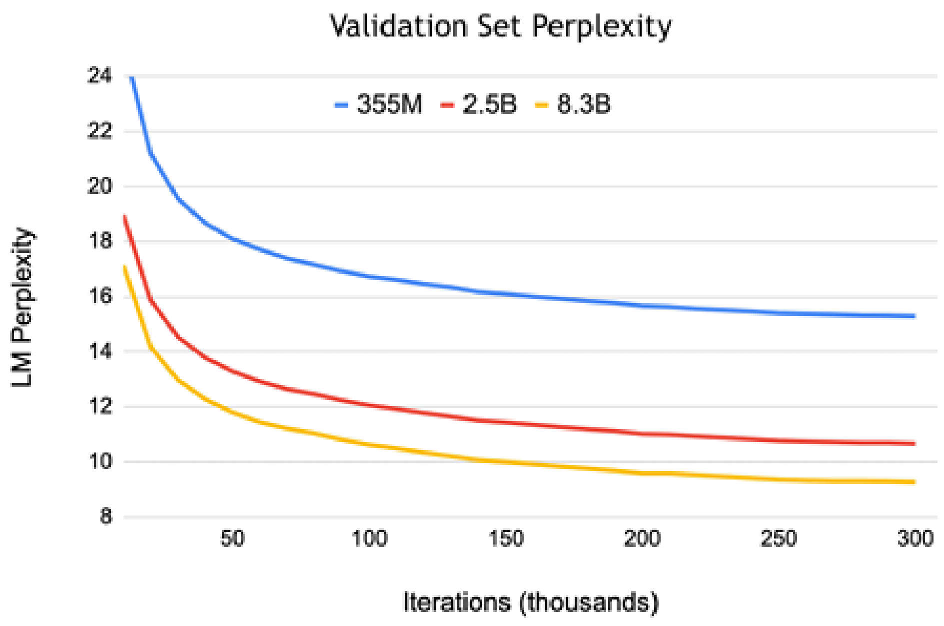




Baseline (1.2B parameters on a single GPU) achieves 39 TeraFLOPs per second, i.e. 30% of the theoretical peak during the entire training process

Experiments: GPT-2

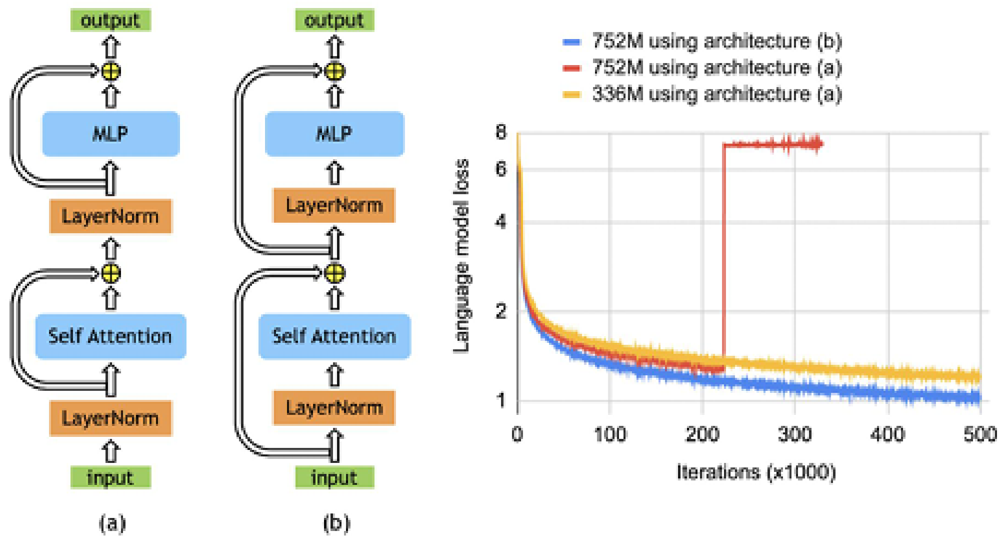
- Training data: 174 GB WebText/CC-Stories/Wikipedia/RealNews
- 3 model sizes: 355 million, 2.5 billion, and 8.3 billion
- Zero-shot evaluation results for Wikitext-103 perplexity and Lambada cloze accuracy



Model Size	Wikitext-103 (Perplexity ↓)	Lambada (Accuracy ↑)
355 M	19.22	46.26
2.5 B	12.68	61.52
8.3 B	**10.81**	**66.51**
Previous SOTA	16.43*	63.24**

Experiments: Megatron-BERT

- Scaling BERT to larger sizes is also possible
- Reordering residual connections to stabilize training
- Megatron-BERT 3.9B, 12x larger than BERT-Large, over 2 million iterations @ batch size 1024



Parameter Count	Parameter Multipler	Hidden Size	Attention Heads	Layers	Model Parallel GPUs	Model + Data Parallel GPUs
334M	1x	1024	16	24	1	128
1.3B	4x	2048	32	24	1	256
3.9B	12x	2506	40	48	4	512

Experiments: SQUAD & RACE

Model	Trained tokens (ratio)	MNLI† m/mm accuracy	QQP† accuracy	SQuAD 1.1† F1/EM	SQuAD 2.0† F1/EM	RACE m/h* accuracy
RoBERTa	2	90.2 / 90.2	92.2	94.6 / 88.9	89.4 / 86.5	86.5 / 81.3
ALBERT	3	90.8	92.2	94.8 / 89.3	90.2 / 87.4	89.0 / 85.5
XLNet	2	90.8 / 90.8	92.3	95.1 / 89.7	90.6 / 87.9	88.6 / 84.0
Megatron-334M	1	89.7 / 90.0	92.3	94.2 / 88.0	88.1 / 84.8	86.9 / 81.5
Megatron-1.3B	1	90.9 / 91.0	92.6	94.9 / 89.1	90.2 / 87.1	90.4 / 86.1
Megatron-3.9B	**1**	**91.4 / 91.4**	**92.7**	**95.5 / 90.0**	**91.2 / 88.5**	**91.8 / 88.6**

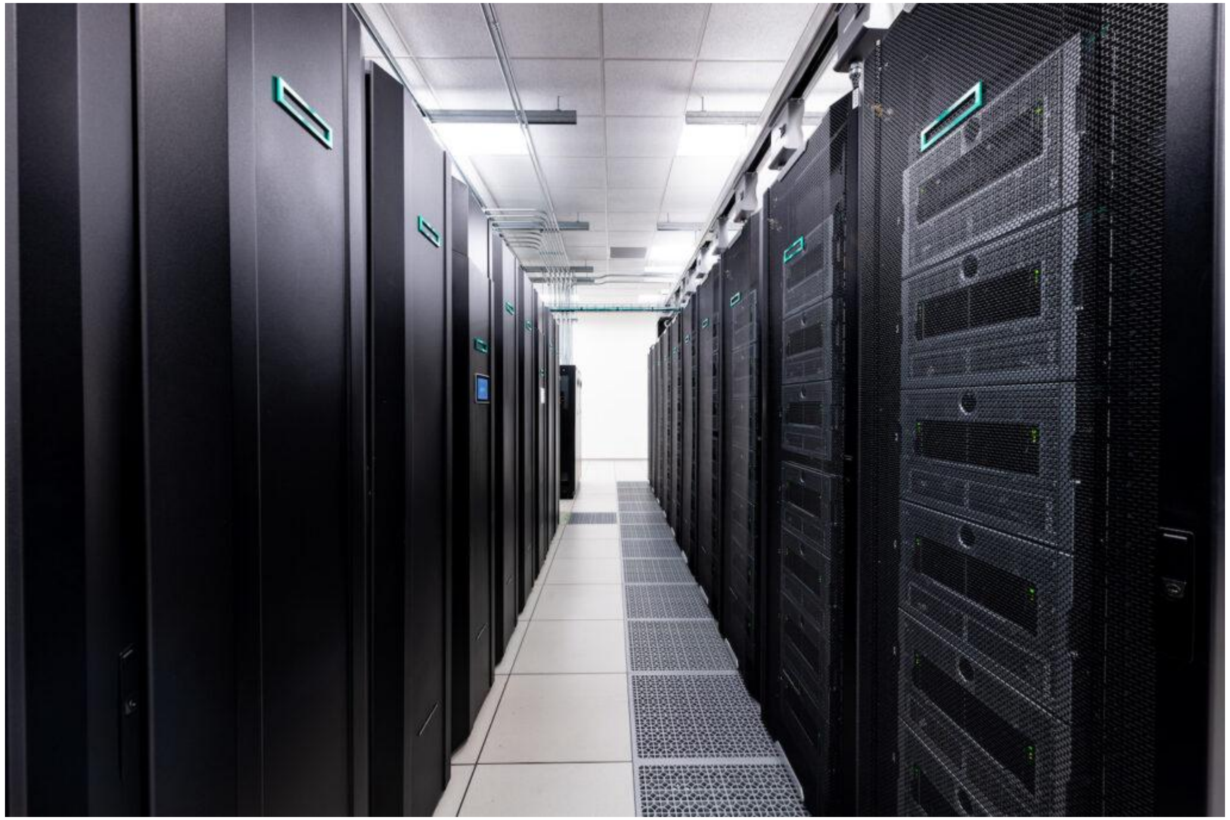
Median single model downstream results on Dev† and Test* sets.
State of the art results are bolded.

Questions?

Hardware: Delta

- Home page: https://www.ncsa.illinois.edu/research/project-highlights/delta/

- 100 quad A100 GPU node, each with 4 A100
- 100 quad A40 GPU node, each with 4 A40
- 5 8-way A100 GPU, each with 8 A100
- 1 MI100 node, 8 MI100



Delta Onboarding

- https://docs.ncsa.illinois.edu/systems/delta/en/latest/user_guide/accessing.html

Delta Login Methods

Direct Access Login Nodes

Direct access to the Delta login nodes is via SSH using your NCSA username, password, and NCSA Duo MFA. See the NCSA Allocation and Account Management page for links to NCSA Identity and NCSA Duo services. The login nodes provide access to the CPU and GPU resources on Delta.

See NCSA Allocation and Account Management for the steps to change your NCSA password for direct access and set up NCSA Duo.

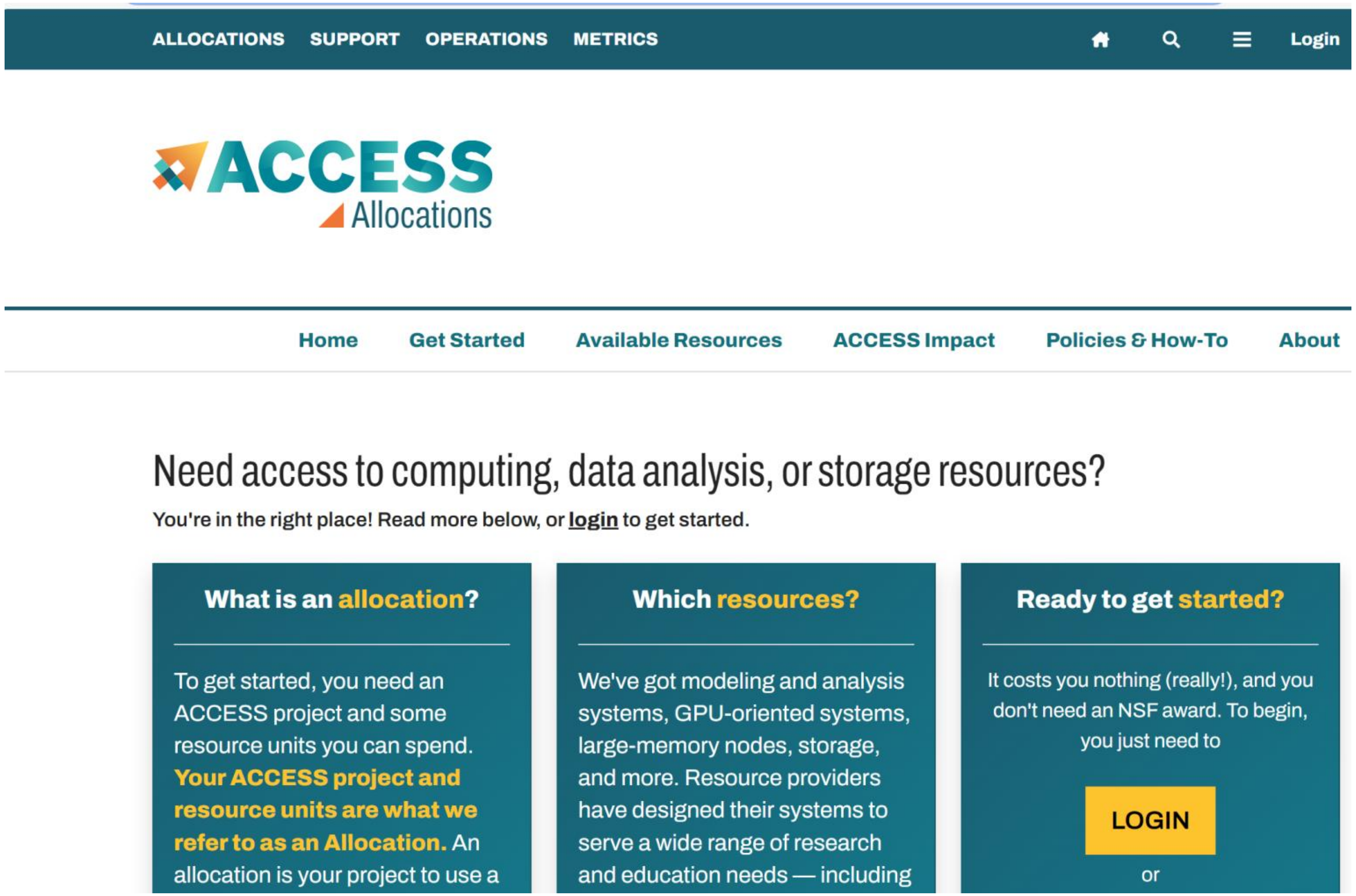
For ACCESS awarded projects, to find your local NCSA username go to your ACCESS Profile page and scroll to the bottom for the **Resource Provider Site Usernames** table. If you do not know your NCSA username, submit a support request (Getting Help) for assistance.

Login Node Hostnames

Login Node Hostname	Example Usage with SSH
dt-login01.delta.ncsa.illinois.edu	`ssh -Y username@dt-login01.delta.ncsa.illinois.e` (-Y allows X11 forwarding from Linux hosts)

Step 1: Create ACCESS ID

- Register an ACCESS id at: https://access-ci.org/ (top right-hand corner)
- After you register, send the instructor your ACCESS id. The instructor will add you to access to his GPU allocation.



Step 2: Get Started

- Delta uses Slurm to manage jobs/GPUs
- Please watch this tutorial video: Getting Started on NCSA's Delta Supercomputer.
- After that, you may want to check Delta User Documentation — UIUC NCSA Delta User Guide (illinois.edu).
- Please learn how to use slurm to get GPUs: Slurm Workload Manager - Quick Start User Guide (schedmd.com).

Step 3: SSH Login

- You shall use ssh to login to the node: Delta Login Methods — UIUC NCSA Delta User Guide (illinois.edu).
- For instance, you can use commands such as “srun -A bcjw-delta-gpu --time=00:30:00 --nodes=1 --ntasks-per-node=16 --partition=gpuA100x4,gpuA40x4 --gpus=1 --mem=32g --pty /bin/bash”
- Maintaining Persistent Sessions: tmux

Delta Login Methods

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Login Node Hostnames

Login Node Hostname	Example Usage with SSH
dt-login01.delta.ncsa.illinois.edu	`ssh -Y username@dt-login01.delta.ncsa.illinois.e` (-Y allows X11 forwarding from Linux hosts)
dt-login02.delta.ncsa.illinois.edu	`ssh -l username dt-login02.delta.ncsa.illinois.e` (-l username alt. syntax for `user@host`)
login.delta.ncsa.illinois.edu (round robin DNS name for the set of login nodes)	`ssh username@login.delta.ncsa.illinois.edu`

Additional Info

- It is the instructor's own research allocation, and it has a limit. So please be mindful when using GPU resources.
  - Avoid allocating too many GPUs at once
  - Turn off the job when you are not using the GPUs

- The allocation has 500 GB of storage in total (shared by the class and other students in the instructor's lab)
  - Please avoid downloading large data files and super large model checkpoints, e.g., one llama7b checkpoint consumes roughly 14GB.

Course Project (Reproducibility Challenge)

4-credit undergraduate students, 3-credit graduate students
Some suggestions below, but it can be any machine learning system related papers that you are interested in

GPTCache: An Open-Source Semantic Cache for LLM Applications Enabling Faster Answers and Cost Savings	https://github.com/zilliztech/GPTCache
RouteLLM: Learning to Route LLMs with Preference Data	https://github.com/lm-sys/RouteLLM
LLM-QAT: Data-Free Quantization Aware Training for Large Language Models	https://github.com/facebookresearch/LLM-QAT
Speculative decoding in vLLM	https://docs.vllm.ai/en/v0.5.5/models/spec_decode.html
REST: Retrieval-Based Speculative Decoding	https://github.com/FasterDecoding/REST
MemGPT: Towards LLMs as Operating Systems	https://github.com/letta-ai/letta
…	…

Course Project (Open-End Research Project)

4-credit graduate students

- Benchmark and analyze important DL workloads to understand their performance gap and identify important angles to optimize their performance.
- Apply and evaluate how existing solutions work in the context of emerging AI/DL workloads.
- Design and implement new algorithms that are both theoretically and practically efficient.
- Design and implement system optimizations, e.g., parallelism, cache-locality, IO-efficiency, to improve the compute/memory/communication efficiency of AI/DL workloads.
- Offer customized optimization for critical DL workloads where latency is extremely tight.
- Build library/tool/framework to improve the efficiency of a class of problems.
- Integrate important optimizations into existing frameworks (e.g., DeepSpeed), providing fast and agile inference.
- Combine system optimization with modeling optimizations.
- Combine and leverage hardware resources (e.g., GPU/CPU, on-device memory/DRAM/NVMe/SSD) in a principled way.