# Training Large Language Models

## How to reduce memory and compute

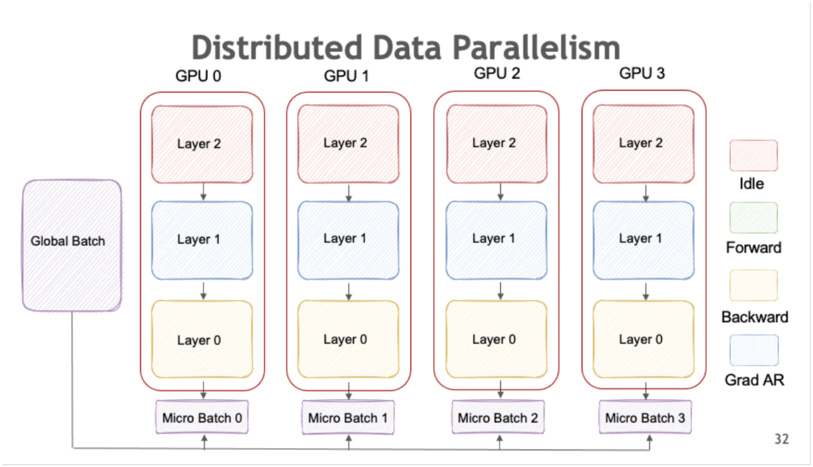
### Learning goals

- Learn about different techniques to reduce compute and memory
- Learn about distributed training with data/tensor parallelism
- Learn about FlashAttention

## DISTRIBUTED TRAINING

- Training LLMs faster on many GPUs
- Avoiding OOM issues
- **Data parallelism:** split the data on different model replicas
- **Tensor parallellism:** split model parameters accross GPUs

# DATA PARALLELISM (1) (ANIMATED GIF!)



Source: Nvidia

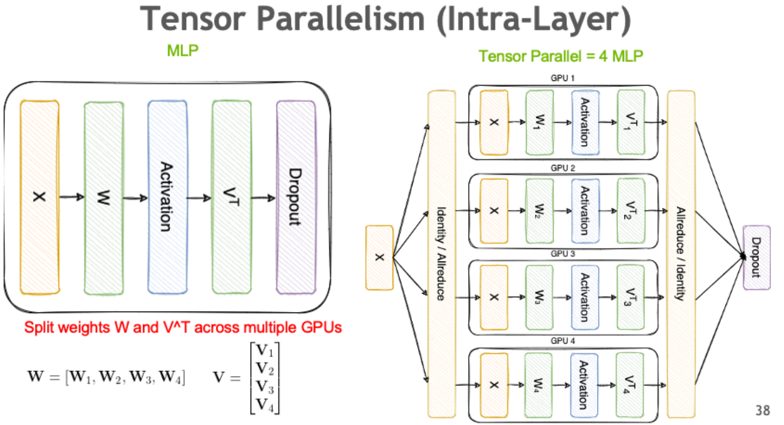
## DATA PARALLELISM (2)

- **Data Splitting:**
  - The dataset is divided into smaller chunks, and each chunk is assigned to a different processing unit (e.g., GPU or CPU) on different nodes
  - Each node processes a different subset of the data in parallel, reducing the overall training time
- **Model Replication:**
  - Each processing unit has a replica of the neural network model
  - These replicas are trained independently on their respective data subsets
- **Gradient Aggregation:**
  - After each forward and backward pass, gradients are computed locally on each node

## DATA PARALLELISM (2)

    - The gradients are then averaged (or summed) across all nodes to ensure that each model replica receives the same gradient update
- **Parameter Synchronization:**
    - The model parameters (weights and biases) are updated synchronously across all nodes
    - This ensures that all model replicas remain consistent with each other after each update step

# TENSOR PARALLELISM (1) (ANIMATED GIF!)



Split weights W and V^T across multiple GPUs

$$\mathbf{W} = [\mathbf{W}_1, \mathbf{W}_2, \mathbf{W}_3, \mathbf{W}_4] \qquad \mathbf{V} = \begin{bmatrix} \mathbf{V}_1 \\ \mathbf{V}_2 \\ \mathbf{V}_3 \\ \mathbf{V}_4 \end{bmatrix}$$

Source: Nvidia

## TENSOR PARALLELISM (2)

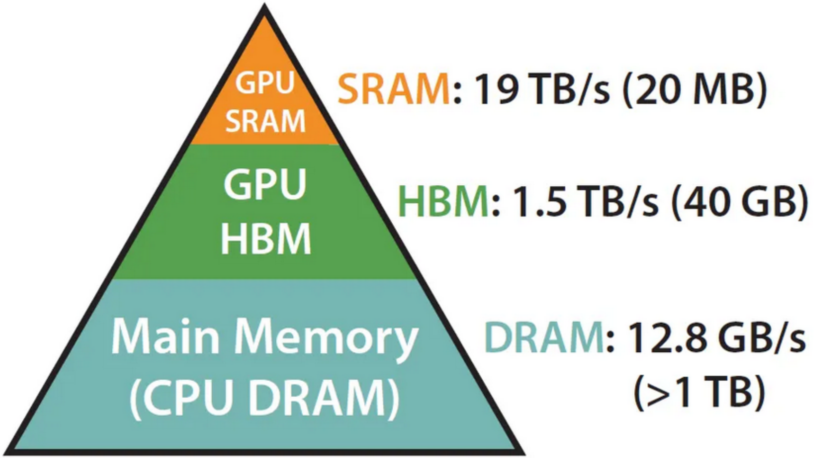
- **Model Partitioning:**
  - The model's layers or tensors are split across multiple devices
  - Different parts of the model are assigned to different devices, enabling them to work on separate portions of the computations simultaneously
- **Forward and Backward Passes:**
  - During the forward pass, each device processes its portion of the tensors with intermediate results passed between devices
  - In the backward pass, gradients are computed in the reverse order, again with necessary data transfers between devices
- **Parameter Updates:**
  - Parameter updates can be performed independently on each device for the parameters they own
  - After each update step, the devices synchronize to ensure consistency across the distributed model

## FlashAttention

Fast and Memory-Efficient Exact Attention with IO-Awareness

- Fast
  - 15 % faster than BERT
  - 3x faster than GPT-2
  - 2.4x faster than Megatron-LM
- Memory-efficient
  - Reducing from $O(n^2)$ to $O(n)$
- Exact
  - Same as “vanilla attention”, not an approximation
- IO aware
  - Reducing memory load/store operations

## GPU MEMORY HIERARCHY

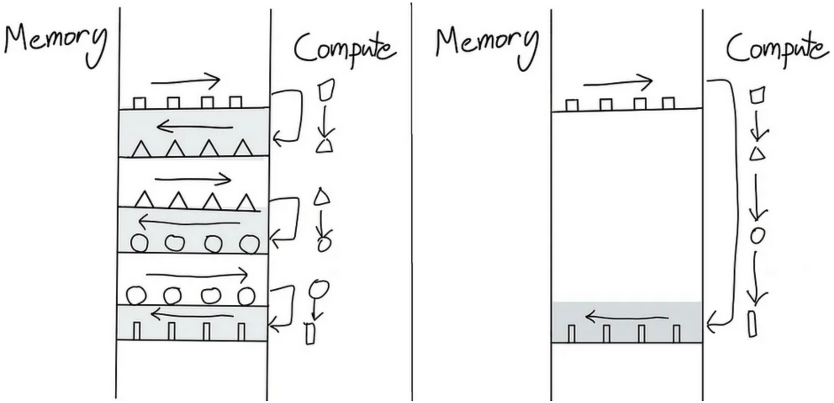


Source: Dao et al. (2022)

## COMPUTING CONSIDERATIONS

- GPU compute has been growing faster than memory bandwidth
  - GPU has to wait for data
- Transformer operations are memory-bound
  - Elementwise operations with high memory access
- IO aware means reducing memory load/store operations
- FlashAttention implements the following:
  - Operation fusion to reduce memory access
  - Tiling or chunking the softmax matrix into blocks
  - Recomputation for better memory utilization

# OPERATION FUSION



Source: `https://horace.io/brrr_intro.html`

## LIMITATIONS AND PROSPECTS

- FlashAttention requires writing attention to CUDA language
    - A new CUDA kernel for each new attention implementation
    - CUDA is lower-level than PyTorch
    - Implementation may not be transferable accross GPUs
- Towards IO-Aware Deep Learning
    - Extending beyonde attention
- Multi-GPU IO-Aware Methods
    - FlashAttention computation may be parallelizable accross multiple GPUs