

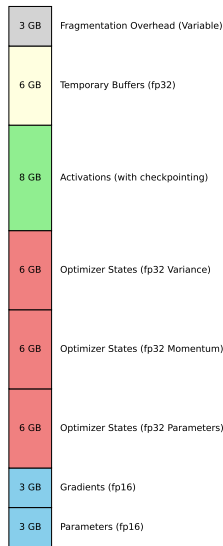
# Large models training

Daniil Merkulov

Optimization for ML. Faculty of Computer Science. HSE University



# GPT-2 training Memory footprint



Example: 1.5B parameter GPT-2 model needs 3GB for weights in 16-bit precision but can't be trained on a 32GB GPU using Tensorflow or PyTorch. Major memory usage during training includes optimizer states, gradients, parameters, activations, temporary buffers, and fragmented memory.

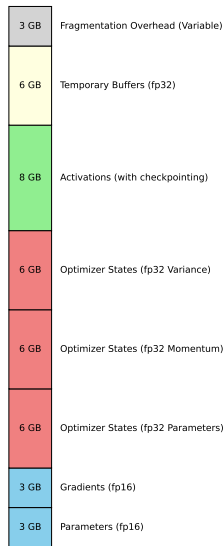
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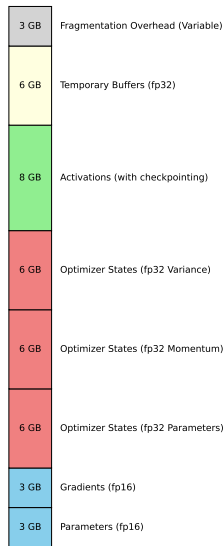
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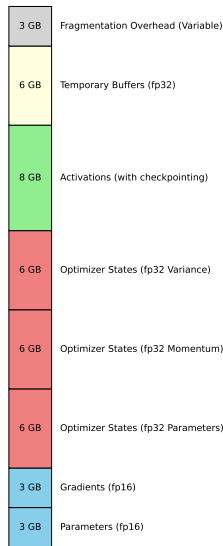
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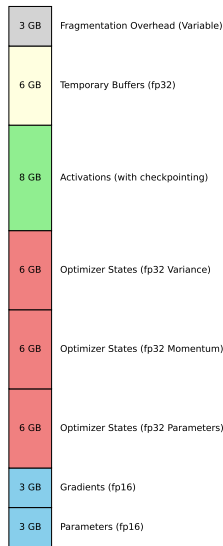
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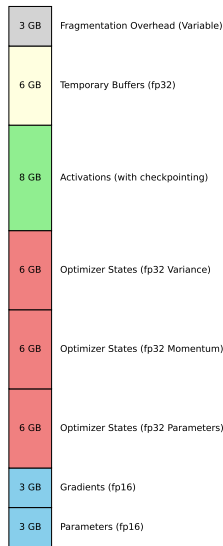
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- Activation checkpointing can reduce activation memory by about 50%, with a 33% recomputation overhead.

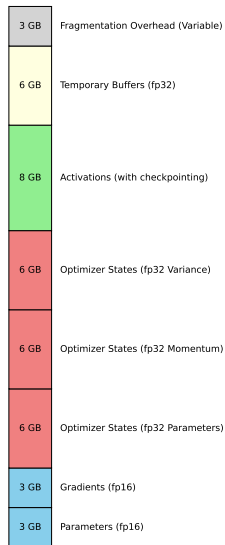
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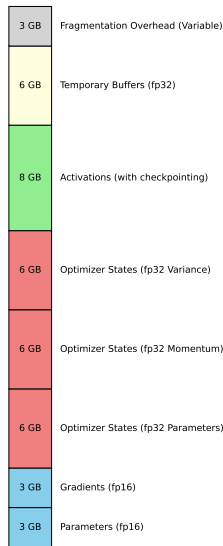
- Store intermediate results; e.g., gradient all-reduce operations fuse gradients into a single buffer.

## Memory Fragmentation:





# GPT-2 training Memory footprint



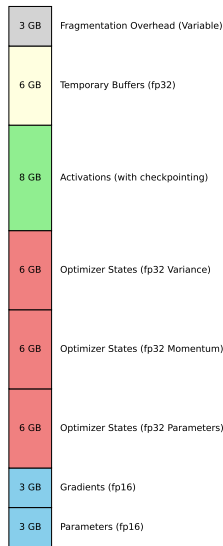
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## Temporary Buffers:

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- For large models, temporary buffers can consume substantial memory (e.g., 6GB for 1.5B parameter model with fp32 buffer).

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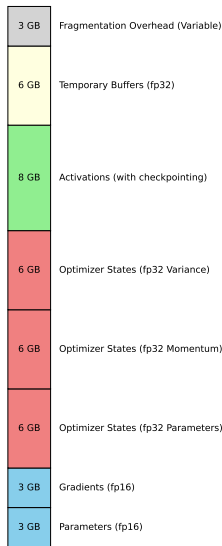
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- Memory fragmentation can cause out-of-memory issues despite available memory, as contiguous blocks are required.

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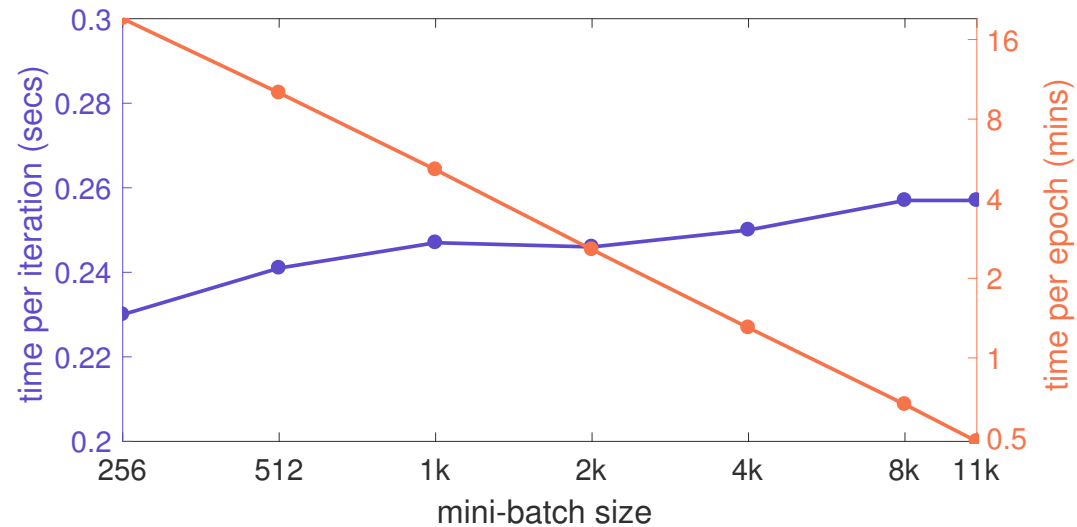
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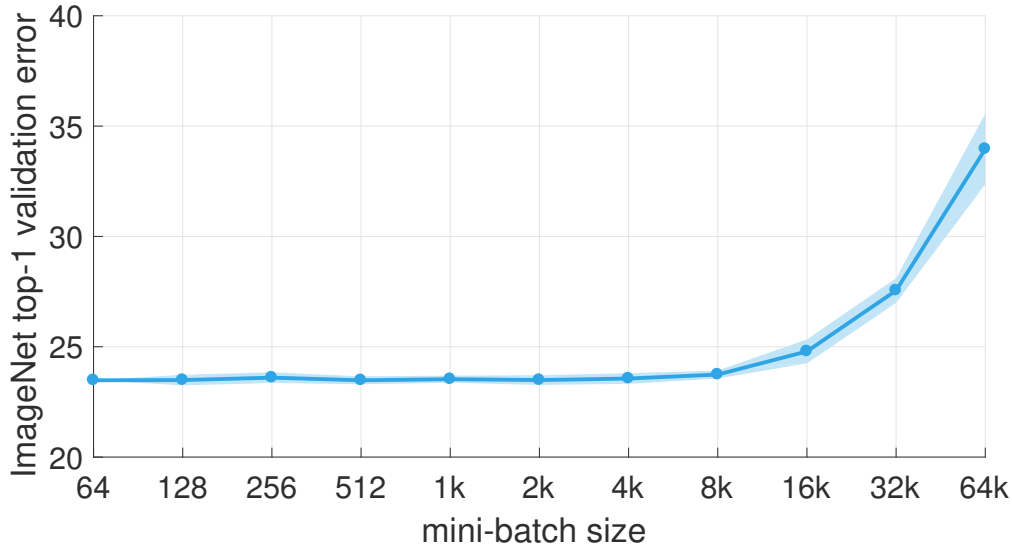
- Memory fragmentation can cause out-of-memory issues despite available memory, as contiguous blocks are required.
- In some cases, over 30% of memory remains unusable due to fragmentation.

## Large batch training <sup>1</sup>



<sup>1</sup>Accurate, Large Minibatch SGD: Training ImageNet in 1 Hour

## Large batch training <sup>2</sup>



<sup>2</sup>Accurate, Large Minibatch SGD: Training ImageNet in 1 Hour

$$f \rightarrow \min_{x,y,z}$$

Large batch training

## Large batch training <sup>3</sup>

Effective batch size ( $kn$ )	$\alpha$	top-1 error (%)
256	0.05	$23.92 \pm 0.10$
256	0.10	$23.60 \pm 0.12$
256	0.20	$23.68 \pm 0.09$
8k	$0.05 \cdot 32$	$24.27 \pm 0.08$
8k	$0.10 \cdot 32$	$23.74 \pm 0.09$
8k	$0.20 \cdot 32$	$24.05 \pm 0.18$
8k	0.10	$41.67 \pm 0.10$
8k	$0.10 \cdot \sqrt{32}$	$26.22 \pm 0.03$

Comparison of learning rate scaling rules. ResNet-50 trained on ImageNet. A reference learning rate of  $\alpha = 0.1$  works best for  $kn = 256$  (23.68% error). The linear scaling rule suggests  $\alpha = 0.1 \cdot 32$  when  $kn = 8k$ , which again gives best performance (23.74% error). Other ways of scaling  $\alpha$  give worse results.

<sup>3</sup>Accurate, Large Minibatch SGD: Training ImageNet in 1 Hour

## Linear and square root scaling rules

When training with large batches, the learning rate must be adjusted to maintain convergence speed and stability. The **linear scaling rule**<sup>4</sup> suggests multiplying the learning rate by the same factor as the increase in batch size:

$$\alpha_{\text{new}} = \alpha_{\text{base}} \cdot \frac{\text{Batch Size}_{\text{new}}}{\text{Batch Size}_{\text{base}}}$$

The **square root scaling rule**<sup>5</sup> proposes scaling the learning rate with the square root of the batch size increase:

$$\alpha_{\text{new}} = \alpha_{\text{base}} \cdot \sqrt{\frac{\text{Batch Size}_{\text{new}}}{\text{Batch Size}_{\text{base}}}}$$

Authors claimed, that it suits for adaptive optimizers like Adam, RMSProp and etc. while linear scaling rule serves well for SGD.

---

<sup>4</sup>Accurate, Large Minibatch SGD: Training ImageNet in 1 Hour

<sup>5</sup>Learning Rates as a Function of Batch Size: A Random Matrix Theory Approach to Neural Network Training

## Gradual warmup<sup>6</sup>

Gradual warmup helps to avoid instability when starting with large learning rates by slowly increasing the learning rate from a small value to the target value over a few epochs. This is defined as:

$$\alpha_t = \alpha_{\max} \cdot \frac{t}{T_w}$$

where  $t$  is the current iteration and  $T_w$  is the warmup duration in iterations. In the original paper, authors used first 5 epochs for gradual warmup.

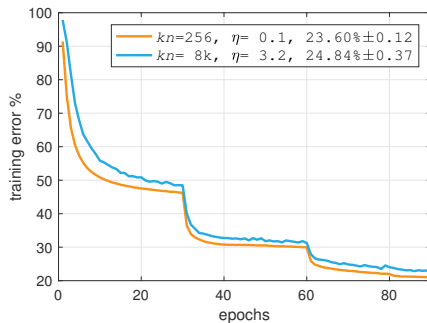


Figure 1: no warmup

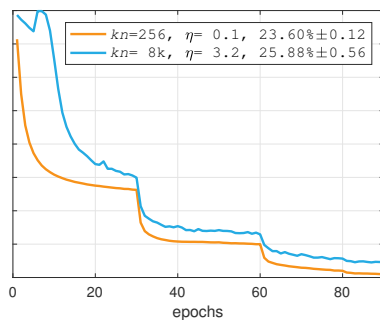


Figure 2: constant warmup

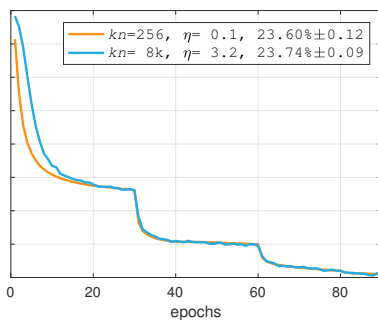


Figure 3: gradual warmup

<sup>6</sup>Accurate, Large Minibatch SGD: Training ImageNet in 1 Hour



# Gradient accumulation

Gradient accumulation allows the effective batch size to be increased without requiring larger memory by accumulating gradients over several mini-batches:

## Without gradient accumulation

```
for i, (inputs, targets) in enumerate(data):  
    outputs = model(inputs)  
    loss = criterion(outputs, targets)  
    loss.backward()  
  
    optimizer.step()  
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## With gradient accumulation

```
for i, (inputs, targets) in enumerate(data):  
    outputs = model(inputs)  
    loss = criterion(outputs, targets)  
    loss.backward()  
    if (i+1) % accumulation_steps == 0:  
        optimizer.step()  
        optimizer.zero_grad()
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# Data Parallel training

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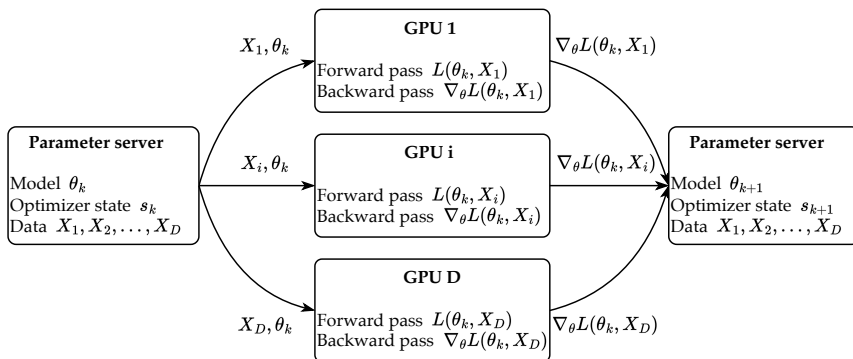
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Per device batch size:  $b$ . Overall batchsize:  $Db$ . Data parallelism involves splitting the data across multiple GPUs, each with a copy of the model. Gradients are averaged and weights updated synchronously:





# Distributed Data Parallel training

Distributed Data Parallel (DDP) <sup>7</sup> extends data parallelism across multiple nodes. Each node computes gradients locally, then synchronizes with others. Below one can find differences from the PyTorch site. This is used by default in 🐍Accelerate library.

DataParallel	DistributedDataParallel
More overhead; model is replicated and destroyed at each forward pass	Model is replicated only once
Only supports single-node parallelism	Supports scaling to multiple machines
Slower; uses multithreading on a single process and runs into Global Interpreter Lock (GIL) contention	Faster (no GIL contention) because it uses multiprocessing

---

<sup>7</sup>Getting Started with Distributed Data Parallel

## Naive model parallelism

Model parallelism divides the model across multiple GPUs. Each GPU handles a subset of the model layers, reducing memory load per GPU. Allows to work with the models, that won't fit in the single GPU Poor resource utilization.

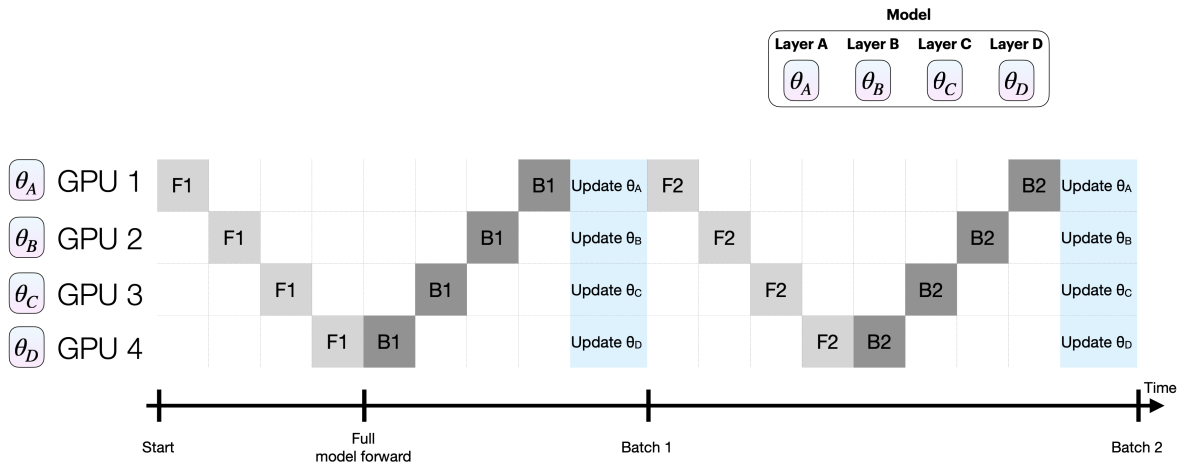
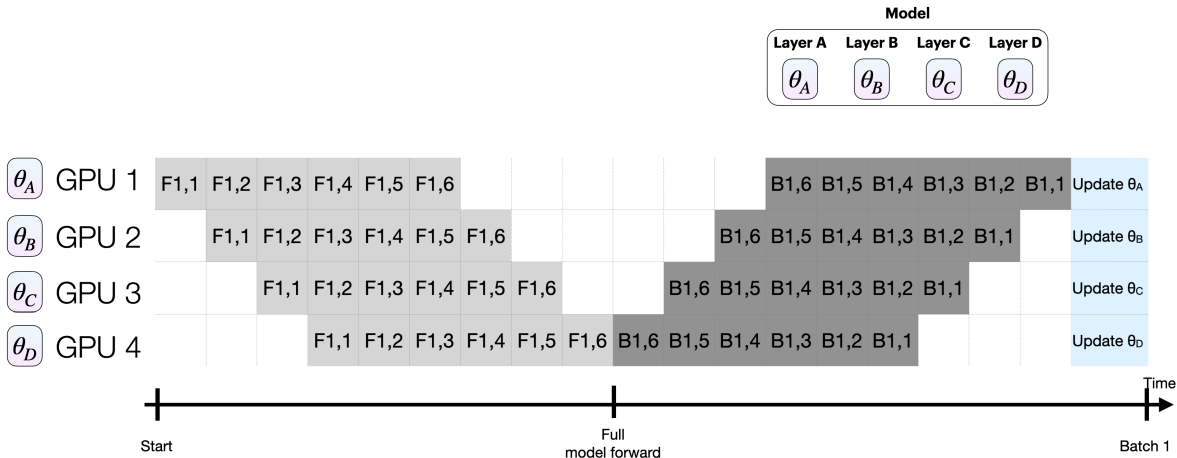


Figure 5: Model parallelism

## Pipeline model parallelism (GPipe) <sup>8</sup>

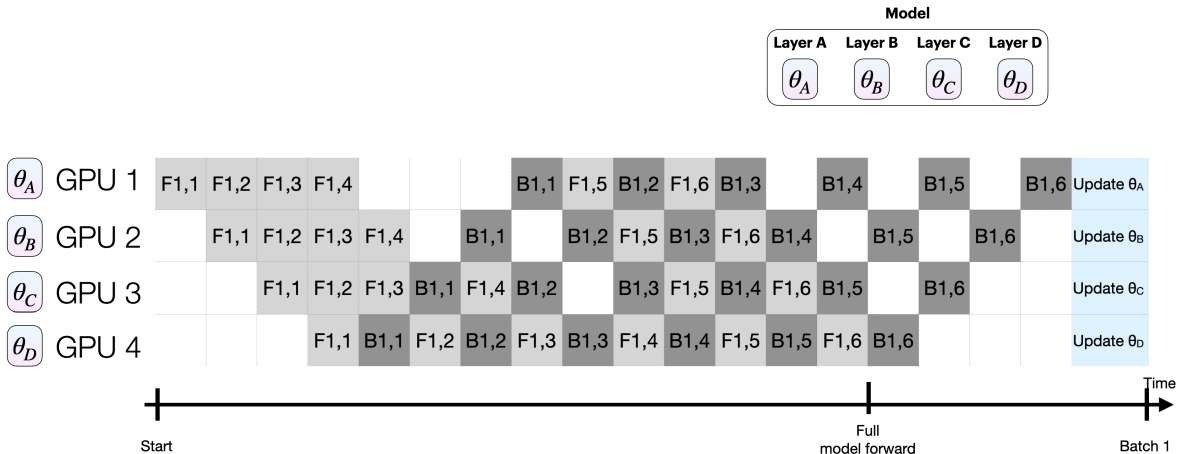
GPipe splits the model into stages, each processed sequentially. Micro-batches are passed through the pipeline, allowing for overlapping computation and communication:



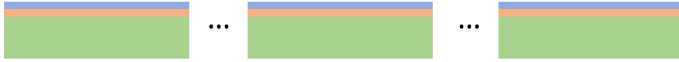



<sup>8</sup>GPipe: Efficient Training of Giant Neural Networks using Pipeline Parallelism

## Pipeline model parallelism (PipeDream) <sup>9</sup>

PipeDream uses asynchronous pipeline parallelism, balancing forward and backward passes across the pipeline stages to maximize utilization and reduce idle time:

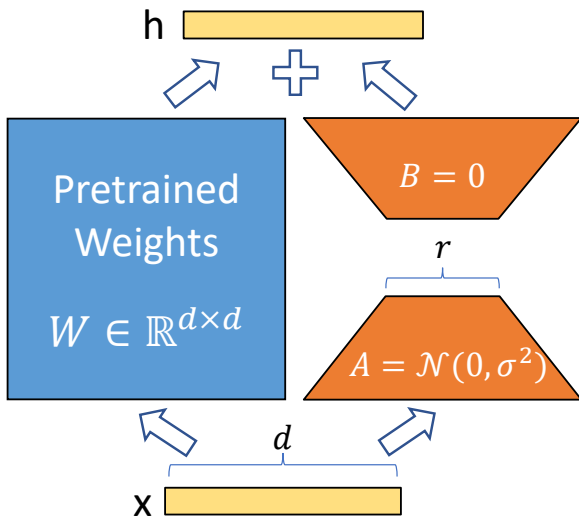


<sup>9</sup>PipeDream: Generalized Pipeline Parallelism for DNN Training

	gpu <sub>0</sub> ... gpu <sub>i</sub> ... gpu <sub>N-1</sub>	Memory Consumed	K=12 $\Psi=7.5\text{B}$ $N_d=64$
Baseline		$(2 + 2 + K) * \Psi$	120GB
P <sub>os</sub>		$2\Psi + 2\Psi + \frac{K * \Psi}{N_d}$	31.4GB
P <sub>os+g</sub>		$2\Psi + \frac{(2+K)*\Psi}{N_d}$	16.6GB
P <sub>os+g+p</sub>		$\frac{(2 + 2 + K) * \Psi}{N_d}$	1.9GB

■ Parameters   
 ■ Gradients   
 ■ Optimizer States

<sup>10</sup>ZeRO: Memory Optimizations Toward Training Trillion Parameter Models

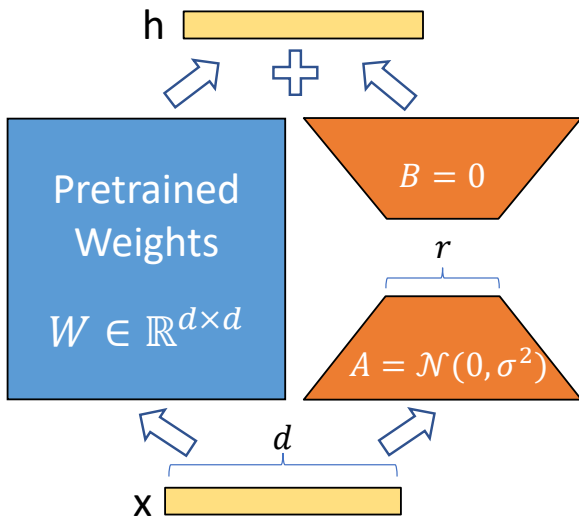


LoRA reduces the number of parameters by approximating weight matrices with low-rank factorization:

$$W_{\text{new}} = W + \Delta W$$

where  $\Delta W = AB^T$ , with  $A$  and  $B$  being low-rank matrices. This reduces computational and memory overhead while maintaining model performance.

- $A$  is initialized as usual, while  $B$  is initialized with zeroes in order to start from identity mapping

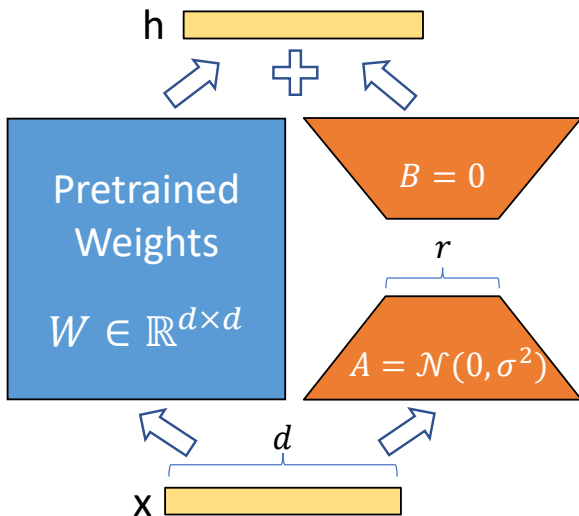


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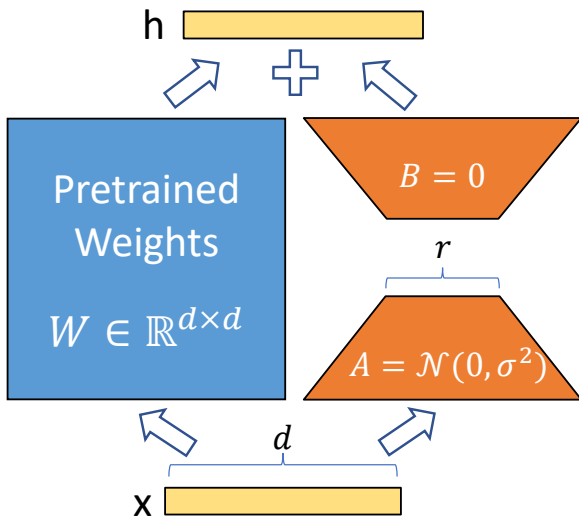
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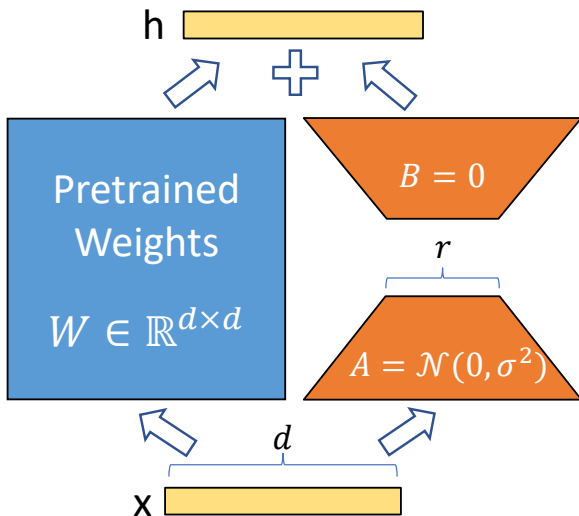
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<sup>11</sup>LoRA: Low-Rank Adaptation of Large Language Models



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# Feedforward Architecture

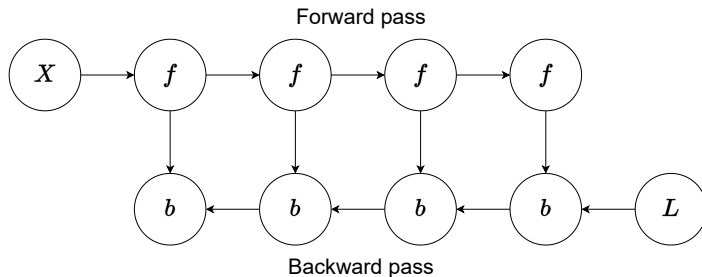


Figure 6: Computation graph for obtaining gradients for a simple feed-forward neural network with  $n$  layers. The activations marked with an  $f$ . The gradient of the loss with respect to the activations and parameters marked with  $b$ .

# Feedforward Architecture

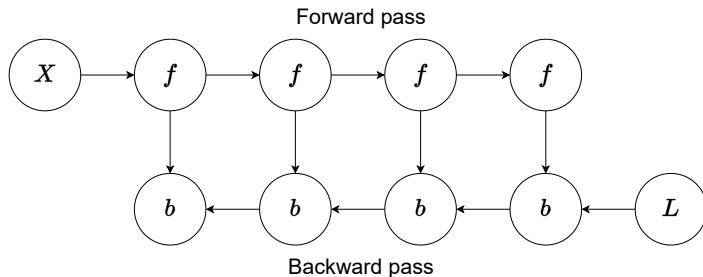


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## ! Important

The results obtained for the  $f$  nodes are needed to compute the  $b$  nodes.

## Vanilla backpropagation

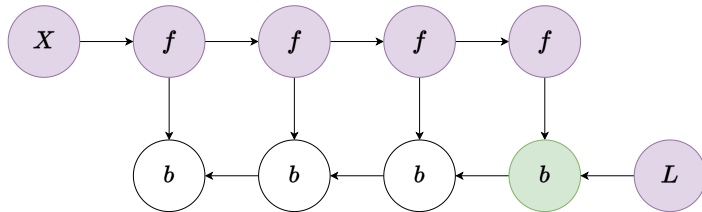


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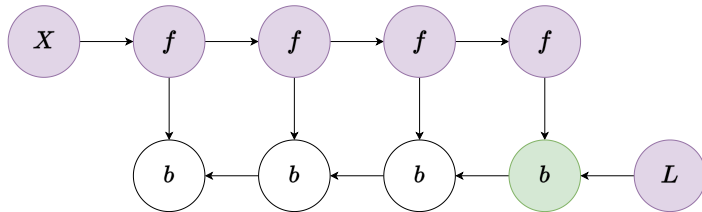


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- All activations  $f$  are kept in memory after the forward pass.
- Optimal in terms of computation: it only computes each node once.
- High memory usage. The memory usage grows linearly with the number of layers in the neural network.

## Memory poor backpropagation



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- Each activation  $f$  is recalculated as needed.
- Optimal in terms of memory: there is no need to store all activations in memory.

## Memory poor backpropagation

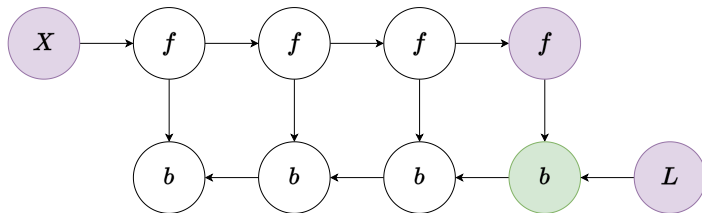


Figure 8: Computation graph for obtaining gradients for a simple feed-forward neural network with  $n$  layers. The purple color indicates nodes that are stored in memory.

- Each activation  $f$  is recalculated as needed.
- Optimal in terms of memory: there is no need to store all activations in memory.

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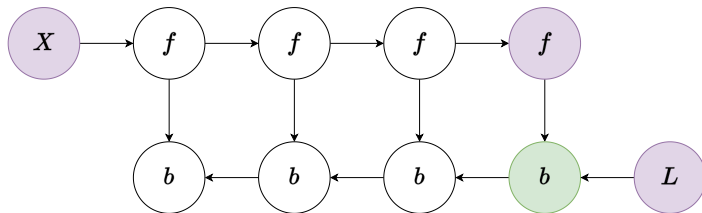


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- Each activation  $f$  is recalculated as needed.
- Optimal in terms of memory: there is no need to store all activations in memory.
- Computationally inefficient. The number of node evaluations scales with  $n^2$ , whereas it vanilla backprop scaled as  $n$ : each of the  $n$  nodes is recomputed on the order of  $n$  times.



## Checkpointed backpropagation

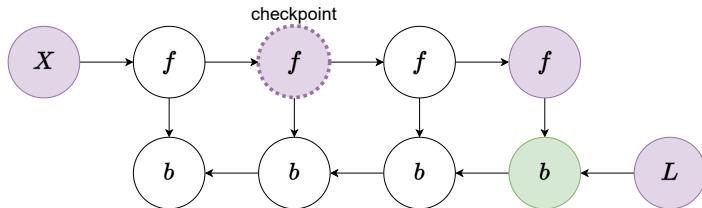


Figure 9: Computation graph for obtaining gradients for a simple feed-forward neural network with  $n$  layers. The purple color indicates nodes that are stored in memory.

## Checkpointed backpropagation



Figure 9: Computation graph for obtaining gradients for a simple feed-forward neural network with  $n$  layers. The purple color indicates nodes that are stored in memory.

- Trade-off between the **vanilla** and **memory poor** approaches. The strategy is to mark a subset of the neural net activations as checkpoint nodes, that will be stored in memory.

## Checkpointed backpropagation

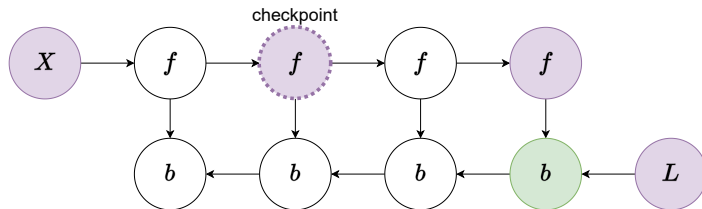


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## Checkpointed backpropagation

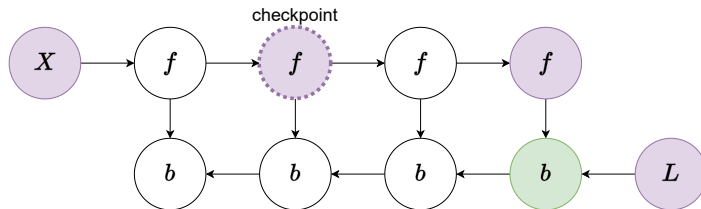


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- Trade-off between the **vanilla** and **memory poor** approaches. The strategy is to mark a subset of the neural net activations as checkpoint nodes, that will be stored in memory.
- Faster recalculation of activations  $f$ . We only need to recompute the nodes between a  $b$  node and the last checkpoint preceding it when computing that  $b$  node during backprop.

## Checkpointed backpropagation

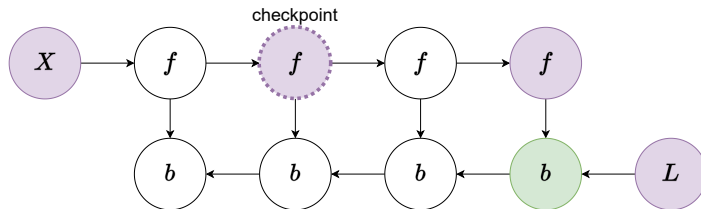


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# Checkpointed backpropagation

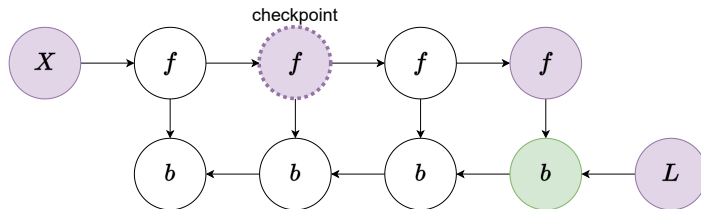




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- Trade-off between the **vanilla** and **memory poor** approaches. The strategy is to mark a subset of the neural net activations as checkpoint nodes, that will be stored in memory.
- Faster recalculation of activations  $f$ . We only need to recompute the nodes between a  $b$  node and the last checkpoint preceding it when computing that  $b$  node during backprop.
- Memory consumption depends on the number of checkpoints. More effective than **vanilla** approach.

# Gradient checkpointing visualization

The animated visualization of the above approaches 

An example of using a gradient checkpointing 

## Split the weight matrix into 2 well clustered factors <sup>12</sup>

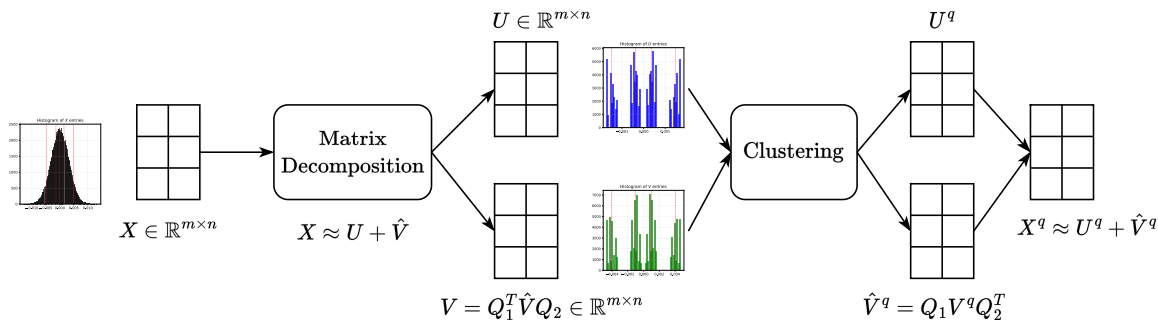


Figure 10: Scheme of post-training quantization approach.

<sup>12</sup>Quantization of Large Language Models with an Overdetermined Basis