Efficient Finetuning of LLMs

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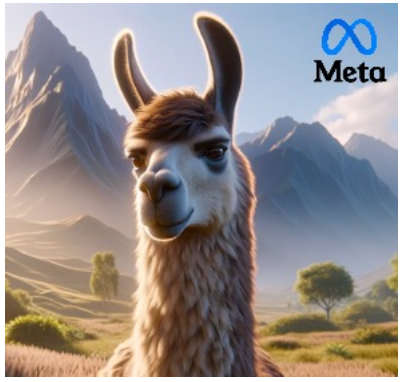
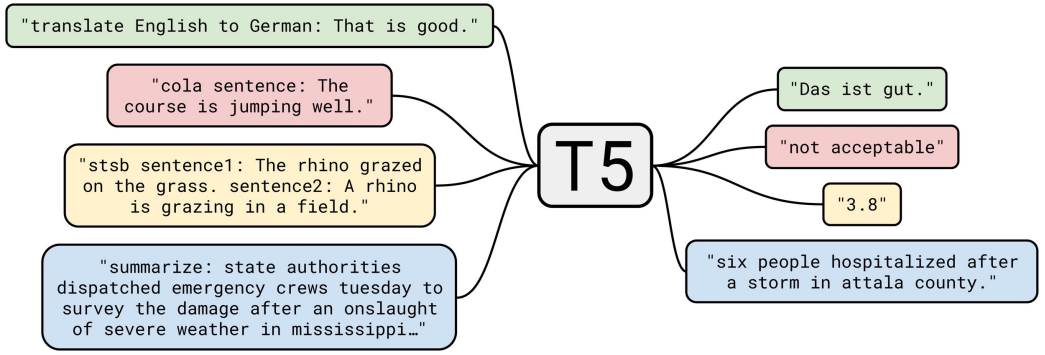
Outline

- A Primer on Large Language Models (LLMs)
- Fine-tuning LLMs
  - The What And The Why?
  - Metrics
  - Throughput/ Memory Optimizations
    - Mixed Precision
    - Parameter-Efficient Fine-tuning
    - Quantization
    - Gradient Checkpointing
    - Gradient Accumulation
- The Decision Tree

A Primer on Large Language Models

- “Large” : Billions of parameters
- “Language Model”: Predicts the probability of word(s) occurring in a sentence.
- Different variants: Causal language models (LLaMA, GPTs, etc) and Seq2Seq (T5, BART, etc)
- Underlying architecture (Usually): The Transformer (Vaswani *et a*l)





T5

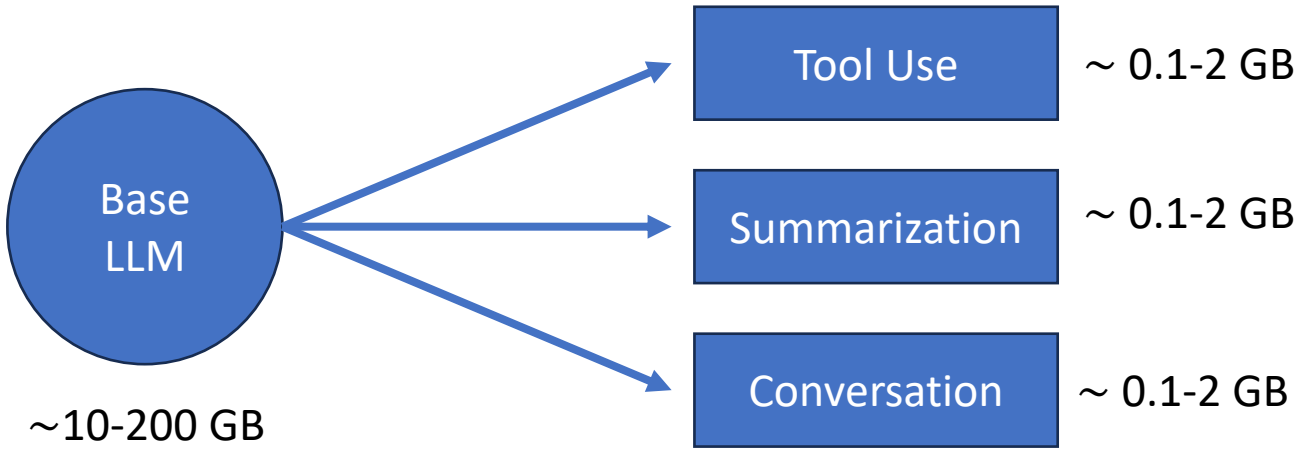
What's so special about LLMs?

- World Knowledge: Trained on 1T+ tokens of internet-scale data
- Unsupervised Learning: Many skills learnt without explicit labels
- "Emergence": Scaling from N to 10N params – with dataset scaling – leads to "significant" performance gains on many tasks.
- Emergence is about (1) new skills (2) new ability to *compose* different skills.[1]

1: A Theory for Emergence of Complex Skills in Language Models by Prof. Sanjeev Arora

A New Era in DL Systems

- Llama 2 – 7B, 13B, 70B. GPT-3: 175B parameters
- 1T+ tokens for pre-training, 100M+ tokens for finetuning.
- 10s of GBs for inference, 100s of GBs for training even for <10B models
- *One model to do them all:* Multiple use cases, single model
  - New parameter-efficient techniques: multi-task + use-case-specific weights.



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Fine-tuning LLMs

- Pre-training: Training an LLM from scratch (months)
- Prompting/In-Context Learning: Prompt an LLM with task details *in context* with a few examples. (seconds)
- Fine-tuning: Middle-ground, update a pre-trained model with 1000s-1M+ examples (hours/days).
  - Better use-case-specific performance than prompting.

Efficient Fine-tuning: Metrics

- Typically, we want training to:
  - Be as fast as possible (Speed)
  - Use as little as possible (Memory)
  - Make the model as performant as possible (Performance)
- "How much time will it take?" $T = T_{mem} + T_{math} + Latency$
- *GPU Utilization*: % of GPU processing power used
- *Throughput*: Rate at which we process/operate on training samples
  - Data view: Samples/ second or Tokens/second
  - Compute view: FLOPS
- *Model FLOPs Utilization (MFU) :* $\frac{Observed\ Throughput}{Peak\ Achievable\ Throughput}$

$\max(T_{mem}, T_{math})$ is what matters!

Efficient Fine-tuning: Optimizations

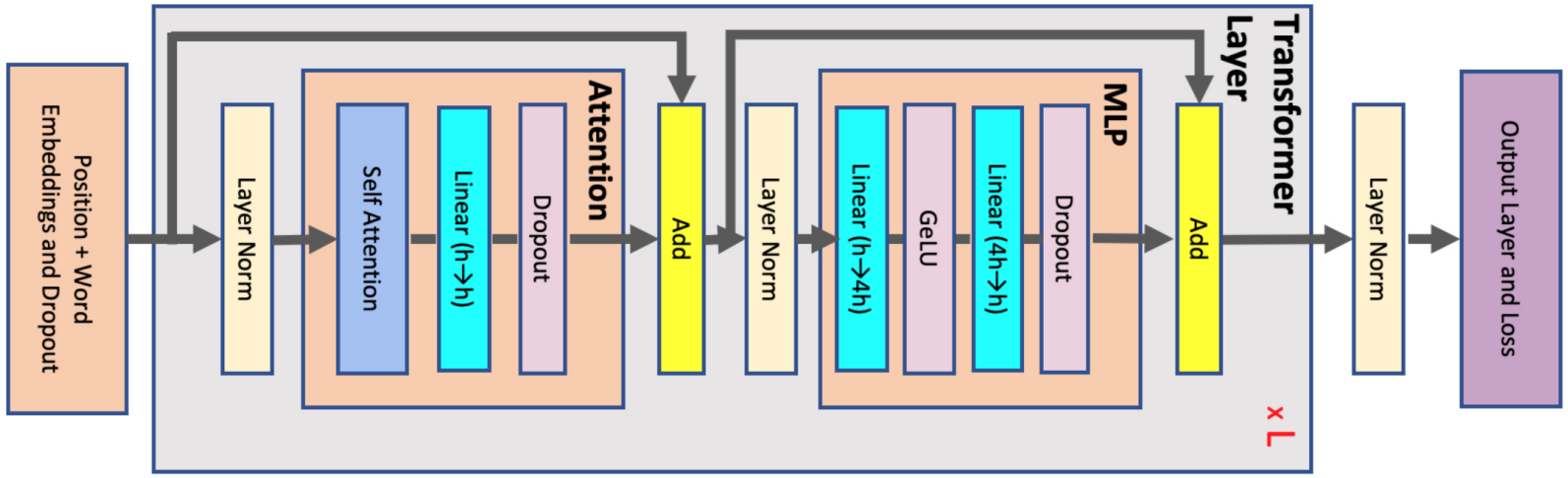
- The Memory Requirements Breakdown
- Mixed Precision
- Parameter-Efficient Fine-tuning (PEFT)
- Quantization
- Gradient Checkpointing
- Gradient Accumulation

The Memory Requirements Breakdown

Total memory = Model weights + Gradients + Optimizer State + Activations

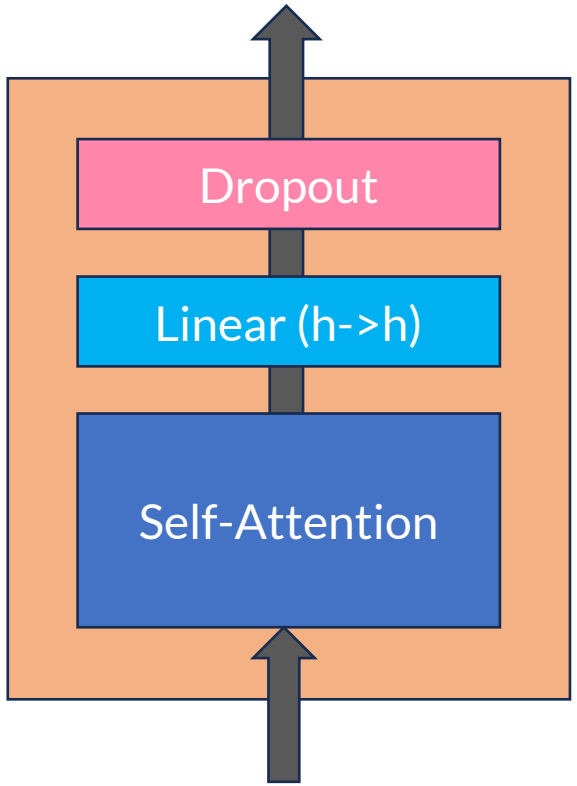
- Model weights = 4 bytes / param
- Gradients = 4 bytes / param
- Optimizer State – Depends!
- Adam/ AdamW:
  - Momentum: 4 bytes / param
  - Variance 4 bytes / param
  - Total = 8 bytes / param
- Activations?
  - Architecture and Input dependent (Not a simple “x bytes/param/token”)

Activation memory for a Transformer



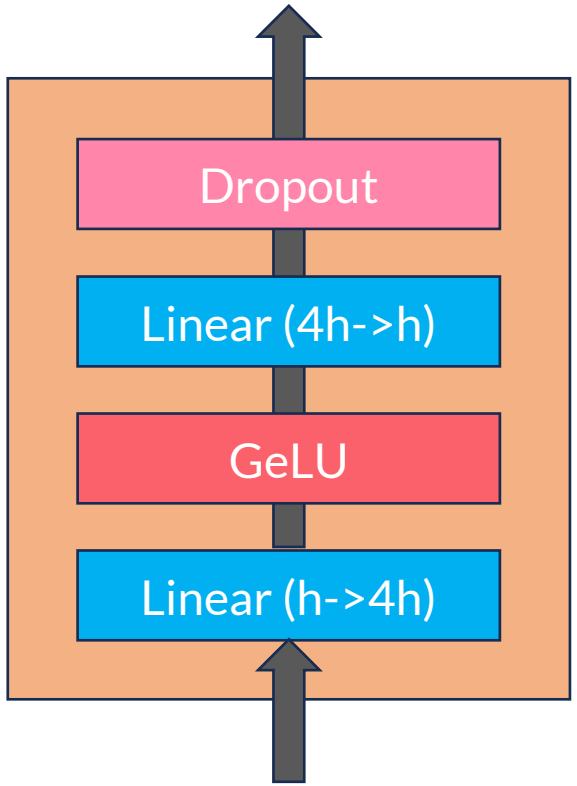
- Number of bytes per element N_b (4 – FP32, 2 – FP16/BF16)
- Sequence length *s*, Batch size *b*, Hidden dimension *h*
- Assume *a* attention heads and *L* transformer layers
- Input/ Output size: N_b *sbh*

Activation memory for a Transformer



Attention block

$(4N_b)sbh + (2N_b + 1)as^2b$
$+ N_b\, sbh$
$+ sbh$



MLP block

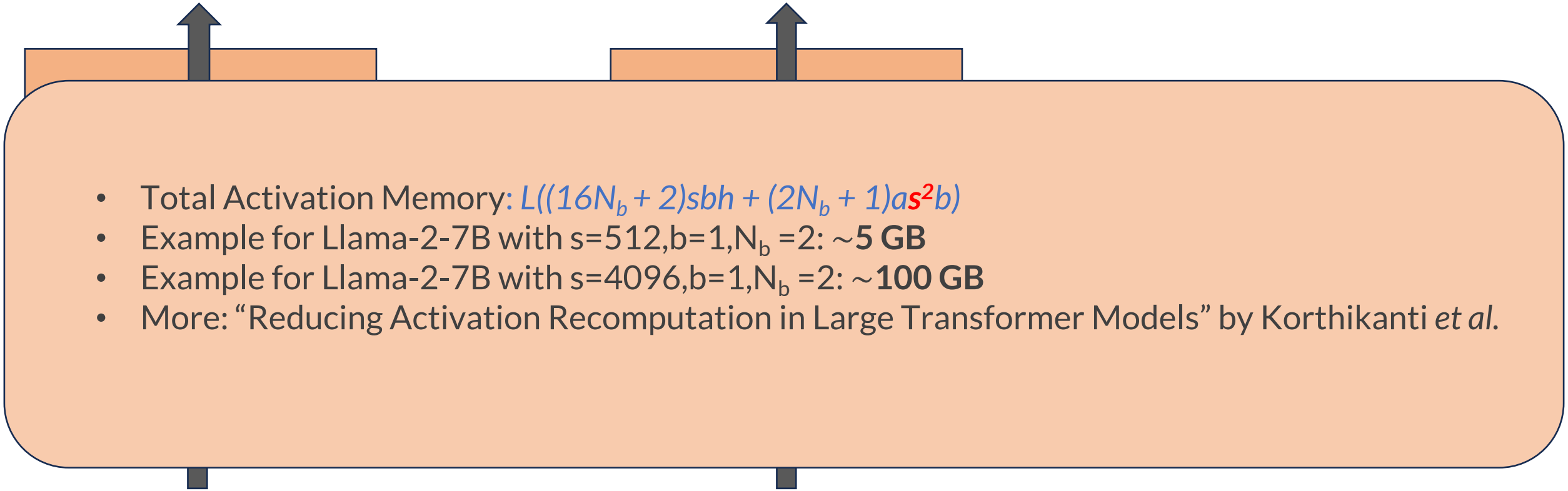
$N_b\, sbh$
$+ N_b\, sb(4h)$
$+ N_b\, sb(4h)$
$+ sbh$

Layer Norm

Layer Norm

$N_b\, sbh$
$+ N_b\, sbh$

Activation memory for a Transformer



- Total Activation Memory: $L((16N_b + 2)sbh + (2N_b + 1)as^2b)$
- Example for Llama-2-7B with s=512,b=1,N_b =2: ~**5 GB**
- Example for Llama-2-7B with s=4096,b=1,N_b =2: ~**100 GB**
- More: "Reducing Activation Recomputation in Large Transformer Models" by Korthikanti *et al.*

Attention block

$(4N_b)sbh + (2N_b + 1)as^2b$
$+ N_b\, sbh$
$+ sbh$

MLP block

$N_b\, sbh$
$+ N_b\, sb(4h)$
$+ N_b\, sb(4h)$
$+ sbh$

Efficient Fine-tuning

- Focus is on the single-GPU setting
- These are (mostly) memory optimizations
- Only two questions matter:
  - Can I train with `batchsize=1`? (0->1)
  - Can I go to `batchsize=n`? (1->n)
- The tradeoffs:
  - How much time will this take (throughput)?
  - How good will my model be (performance)?
- Keep in mind:
  - LLM finetuning can (typically) tolerate lower batch sizes (say, n=4)
  - Larger batch size != More throughput

Efficient Fine-tuning

Optimization	Memory	Throughput	Model Performance
Mixed Precision	●	↑	■
Parameter Efficient Fine tuning	↓	↑	●
Quantization	↓	↓	●
Gradient Accumulation	↓	●	■
Gradient Checkpointing	↓	↓	■

■ No Change

● It Depends

Mixed Precision

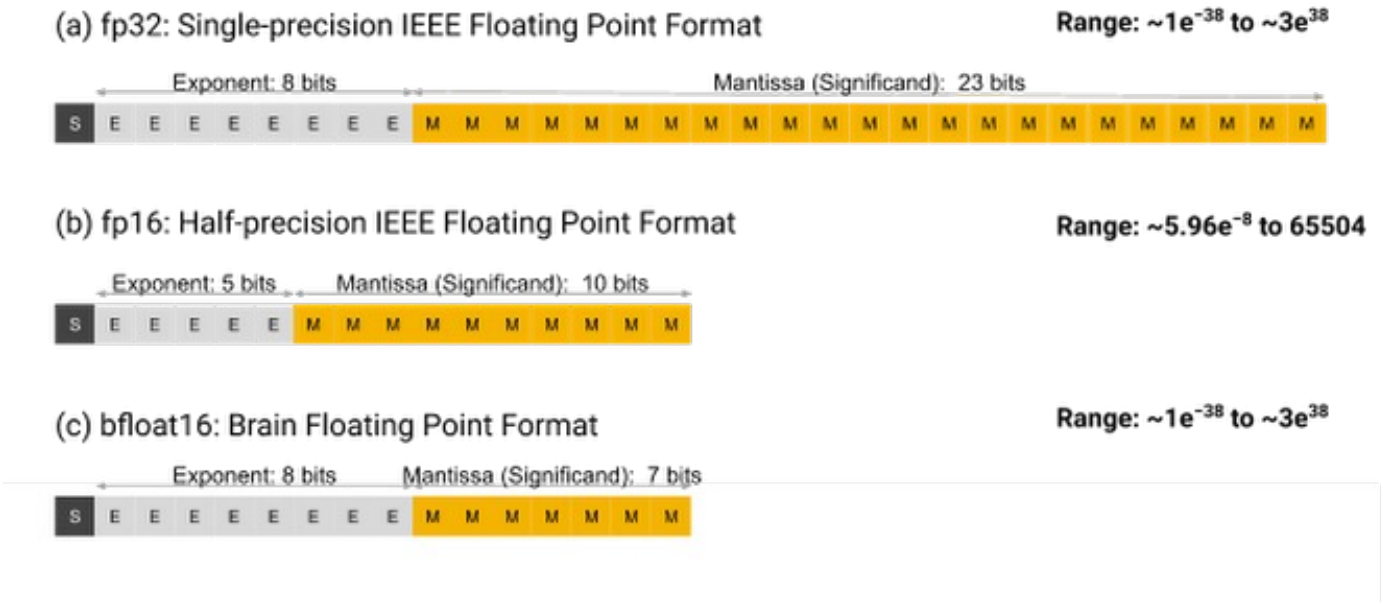
- -> Weights, activations, gradients - lower precision
  -> Optimizer states - full precision (Hence, “mixed”)
- Memory:
  - Model weights and Gradients*: 2 bytes / param
  - Activations: N_b= 2 (~0.5x reduction)
  - Optimizer (Adam): 12 bytes / param
    - “Master copy” of weights, Momentum and Variance all need 4 bytes / param
- Throughput:
  - NVIDIA: Tensor Core – 2-4x speedup

Gradients take 4 bytes in reality! Non-activation memory has **increased**!

*In reality, with `torch.autocast`, assume 4 bytes

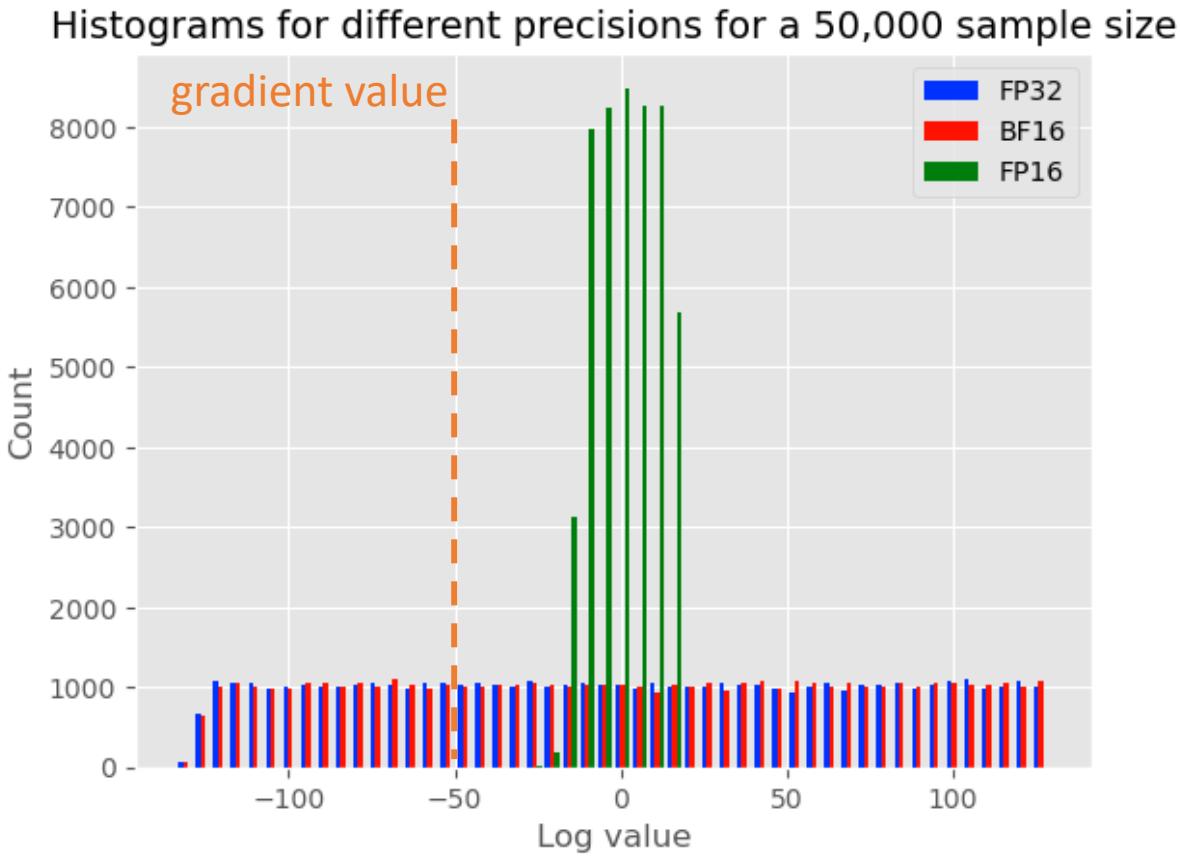
Mixed Precision: Formats

- Popular formats: FP16 and BF16 (Brain Float 16)
- FP16 has much smaller range => Affects training stability!
- FP16 needs loss scaling.
- BF16 doesn't have this issue!
- New format: FP8 (just 1 byte!)



Source: Google Cloud's BF16 guide

Mixed Precision: Formats



- Loss scaling is like moving FP16's fixed bucket/range across the FP32 range.
- Dynamic loss scaling implemented for you in Pytorch AMP.

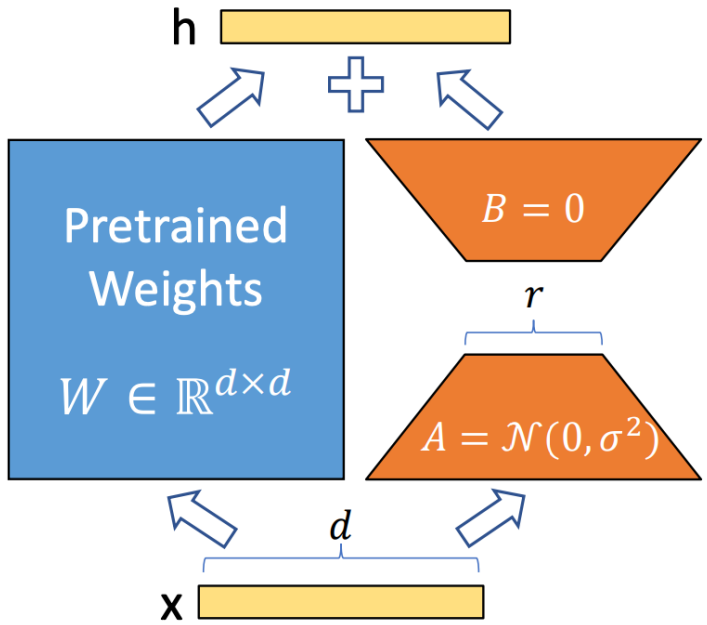
Lower Precision Formats: Summary

- How should I think about FP16, BF16, FP8, etc?
- Pros:
  - Lesser memory : 4 bytes -> 2 bytes/ 1 byte
  - Lower T_{mem} and T_{math}
- Cons:
  - Accumulation is lossy
    - Direct weight updates will be noisy
  - Smaller range implies small gradients are lost

Parameter-Efficient Fine-Tuning (PEFT)

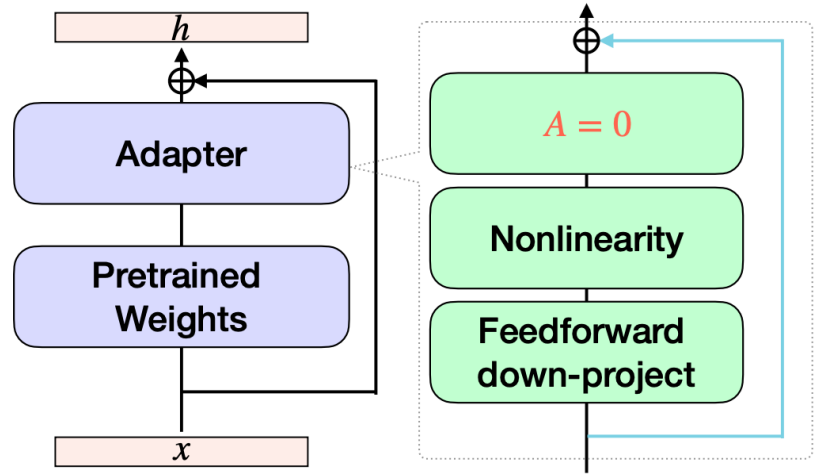
- Motivation: Do we really need to update all model weights?
- Motivation: A separate fine-tuned model for each downstream task gets expensive. (7B -> 14GB)
- Idea: Train a small number of (extra) model parameters and freeze pre-trained weights.
- Benefits: Lesser memory requirements, better throughput
- Where's the tradeoff?
  - Performance! (but not much)
  - (sometimes) Inference latency

Parameter-Efficient Fine-Tuning (PEFT)

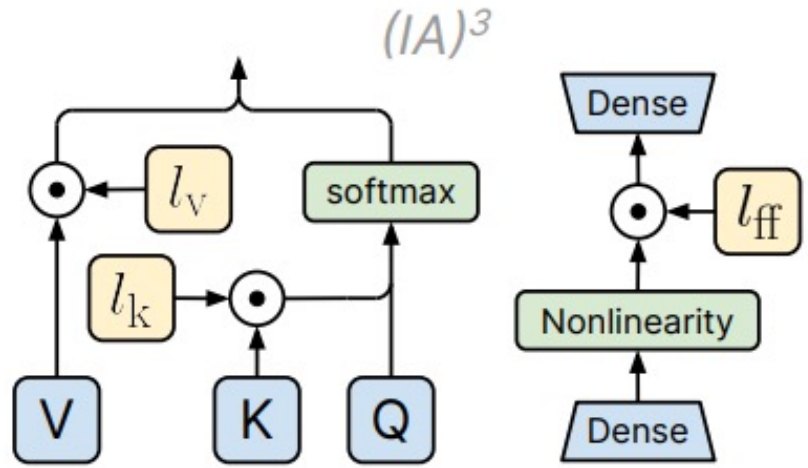


LoRA (Hu *et al*, 2021)

Adapter (Houlsby *et al*, 2019)

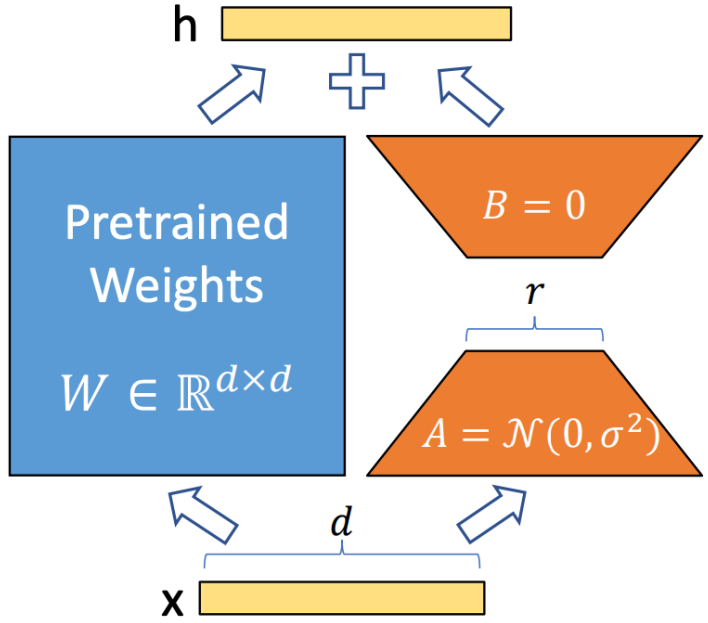


IA^3 (Liu *et al*, 2022)



PEFT: Low Rank Adaptation (LoRA)

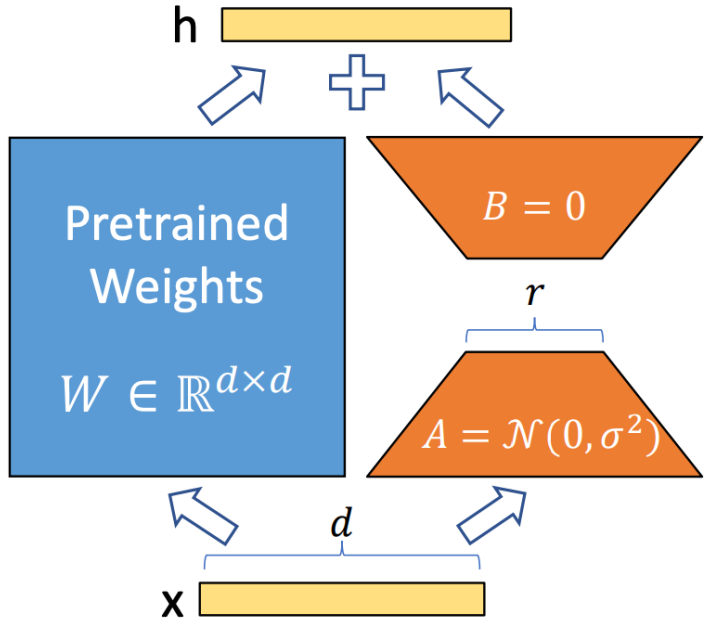
- Linear layers: h = Wx
- With LoRA: h = Wx + ΔW x = W_0x + sBA x
- Hyperparameters:
  - rank *r*
  - List of layers to apply to
  - Scaling factor s
- At inference time, *merge* LoRA weights: W = W_0 + BA. Same inference cost!



LoRA (Hu *et al*, 2021)

PEFT: LoRA

- Full-parameter fine-tuning for Llama-2-13B:
  - Weights: 2 bytes *13B= 26GB (BF16)
  - Gradients = 52 GB
  - Optimizer State: 12 bytes *13B = 156 GB
  - Total = 234 GB + Activation memory
- PEFT with LoRA (assume 0.4% more params):
  - Base weights: 2 bytes * 13B = 26GB
  - LoRA weights: 26GB * 0.4% = 0.10GB
  - Gradients: 52GB * 0.4% = 0.20 GB
  - Optimizer State = 12 bytes/ param * 13B * 0.4% = 0.62GB
  - Total = 26.92 GB + Activation memory
- Checkpoints become tiny in size! (~100 MB)



LoRA (Hu *et al*, 2021)

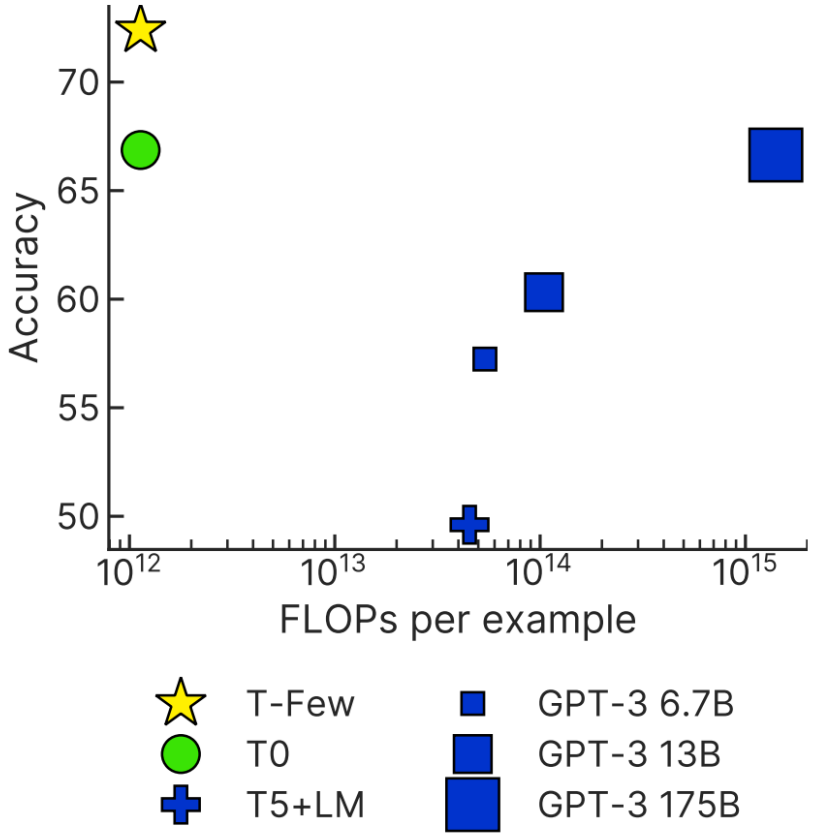
PEFT: TradeOffs

- LoRA and IA^3 enable efficient training *without* increase in inference latency
- Throughput?
  - Depends! Hu *et al.* report 25% speedup for GPT-3
- Performance??
  - Sometimes worse than full-parameter at default (e.g. a hard math dataset[1])
  - On many tasks, can match full fine-tuning performance (Dettmers *et al.*)!
    - `r=64` for all linear layers

1. https://www.anyscale.com/blog/fine-tuning-llms-lora-or-full-parameter-an-in-depth-analysis-with-llama-2

PEFT: An Ecosystem of Specialized Models

- Specialist models (vs large generalist models):
  - Usually *cheaper*
  - Can be *better* if finetuned
- PEFT methods: build a basket of finetunes on *different* tasks that *share* the same *base* model.
- Can even “route” different ex. to appropriate task at inference (like an MoE)

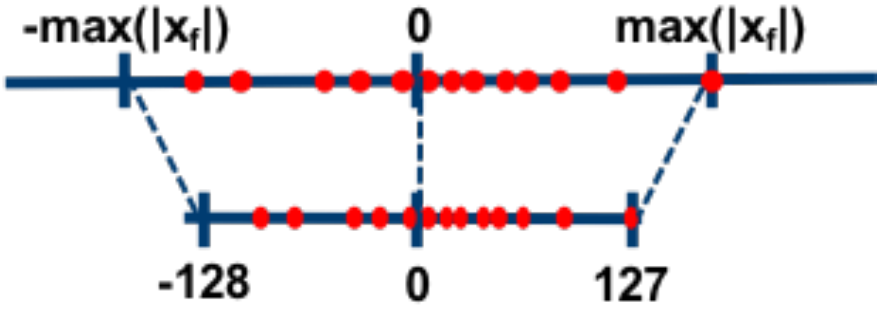


T-Few = T0 + IA^3 (finetuned)
T0 (zero-shot)
GPT3 – (few-shot ICL)

More: Build an Ecosystem, Not a Monolith by Prof. Colin Raffel

Quantization

- Quantization : essentially “rounding”
- But how can int8 handle the large range of fp16 ?



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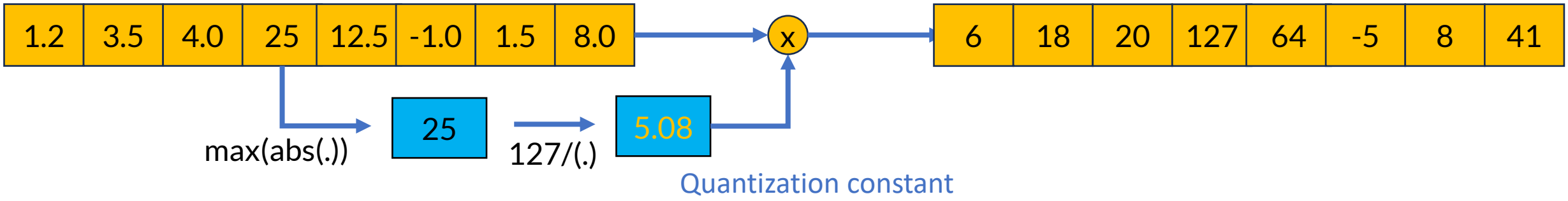
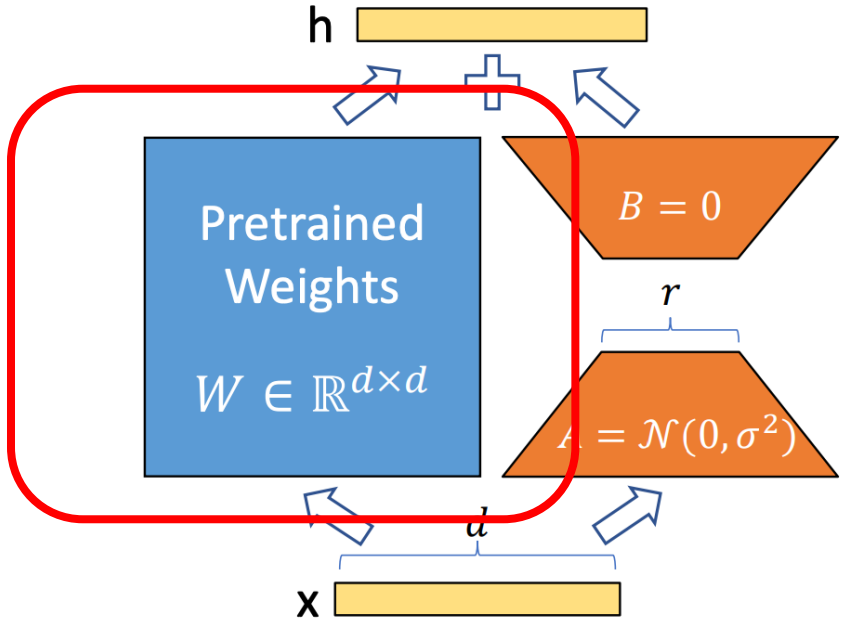


QLoRA

Quantize base weights



During Forward Pass:
Dequantize base weights and compute activations as usual

Simple? No!

- New 4-bit representation: NormalFloat (NF4)
- Custom 4-bit CUDA kernels for efficient matmuls
- Double Quantization: Quantize the quantization constants

QLoRA

- PEFT with LoRA (assume 0.4% more params):
  - Base weights: 2 bytes * 13B = 26GB
  - LoRA weights: 26GB * 0.4% = 0.10GB
  - Gradients: 52GB * 0.4% = 0.20 GB
  - Optimizer State = 12 bytes/ param * 13B * 0.4% = 0.62GB
  - Total = 26.92 GB + Activation memory
- QLoRA (4bit):
  - Base weights: 0.5 bytes * 13B = 6.5GB
  - LoRA weights: 26GB * 0.4% = 0.10GB
  - Gradients: 52GB * 0.4% = 0.20 GB
  - Optimizer State = 12 bytes/ param * 13B * 0.4% = 0.62GB
  - Total = 7.42 GB + Activation memory
- You can even finetune 20B models on a free Colab instance (1 T4 GPU)!

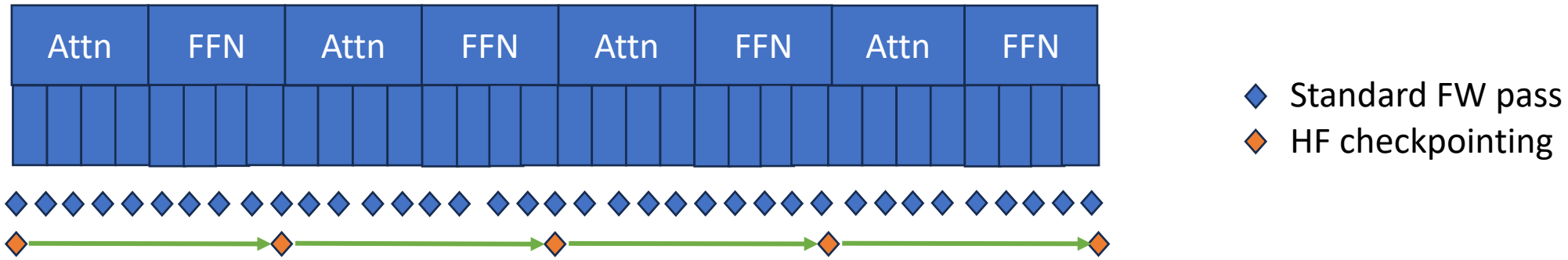
QLoRA: TradeOffs

- Throughput?
  - Quantization has worse throughput. (~30% for single-GPU)
  - Why? Extra dequantization step in forward pass! (T_{math})
- Performance?
  - Dettmers *et al*. show that QLoRA can match full-parameter finetuning
- QLoRA – to be used in a consumer hardware setup with 1-2 GPUs
  - Ex. 2 RTX 3090s (Total: 48GB HBM) to finetune a 33B model
- Quantization almost never needed with a multi-GPU (4+ GPUs) setting.

Optimization	Memory	Throughput	Model Performance
Quantization	↓	↓	●

Gradient/Activation Checkpointing

- Typically, all intermediate activations are saved during the forward pass
  - Needed during the backward pass.
- Llama-2-13B with N_b=2, s=512, b=4: 21 GB
- Activation checkpointing: instead of saving all activations, save a few!
- Reduces Activation Memory at the cost of some slowdown
  - Single-GPU: ~30% slowdown.
- New Memory: Depends on the strategy! For Llama-13B ex. + HF : 800 MB



Gradient Accumulation

- Goal: maximize batch size as much as possible
  - Why? Better gradient updates, Better throughput (usually…)
- Let's say you're able to train with batch size 4.
- Gradient accumulation: Do the optimization step only every few training steps
  - `gradient_accumulation_steps=4` Forward+Backward pass happen as usual
    Gradients get accumulated, optimization step every 4 steps
  - Effective batch size: 16
- Tradeoffs?

Gradient Accumulation

- Slower than regular training at the same effective batch size
- Compare with training w/o accumulation.
  - Typically faster (why?)
    - Lesser all-reduce ops / communication overhead per iteration
    - Gets better with multi-GPU/ multi-node setups
- Where are the memory savings again?
  - Activations – batch size gets scaled down

Optimization	Memory	Throughput	Model Performance
Gradient Accumulation	↓	●	■

Efficient Fine-tuning: Another Look

Optimization	Memory	Memory Terms affected	Throughput	Model Performance
Mixed Precision	●	All (Activation)	↑	■
PEFT	↓	Optimizer + Gradient	↑	●
Quantization	↓	Model	↓	●
Gradient Accumulation	↓	Activation	●	■
Gradient Checkpointing	↓	Activation	↓	■

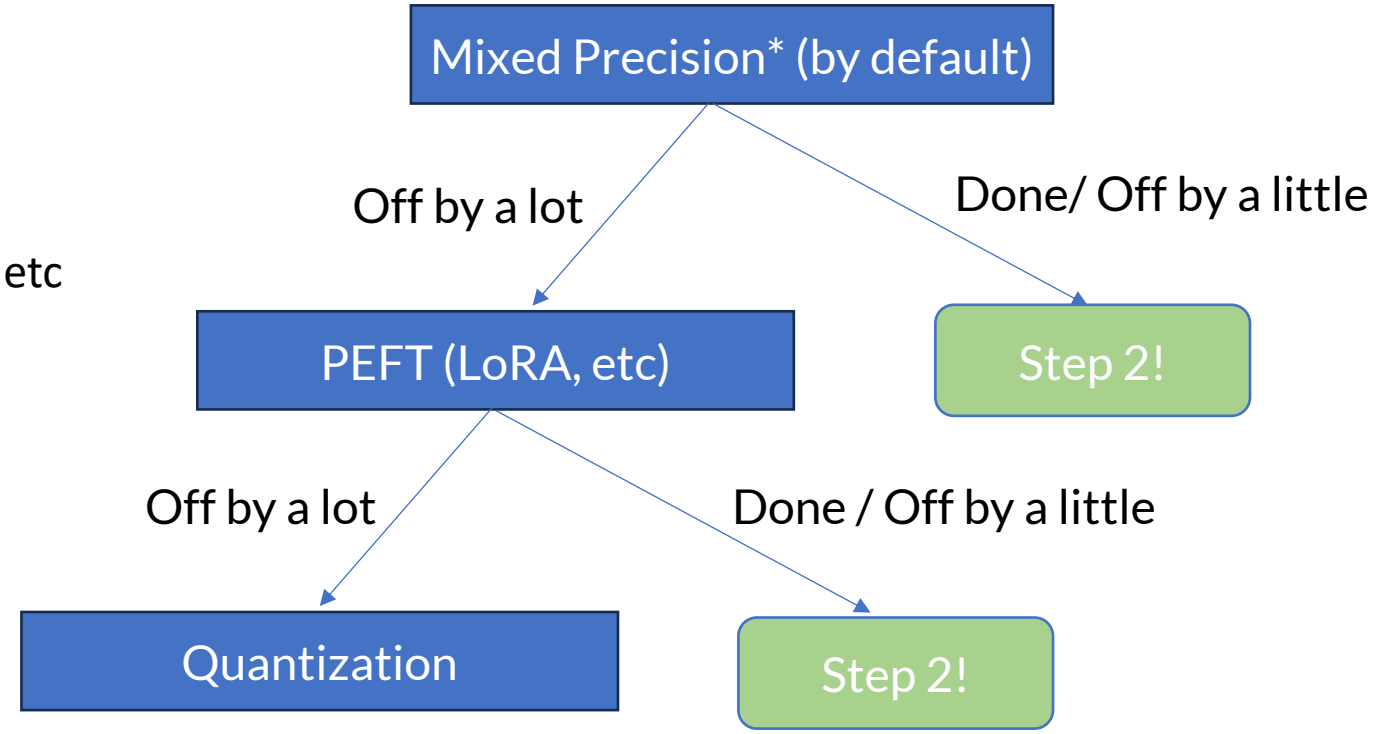
■ No Change

● It Depends

Efficient Fine-tuning: The Decision Tree

Step 1: Target Weights, Optimizer and Gradients (0->1)

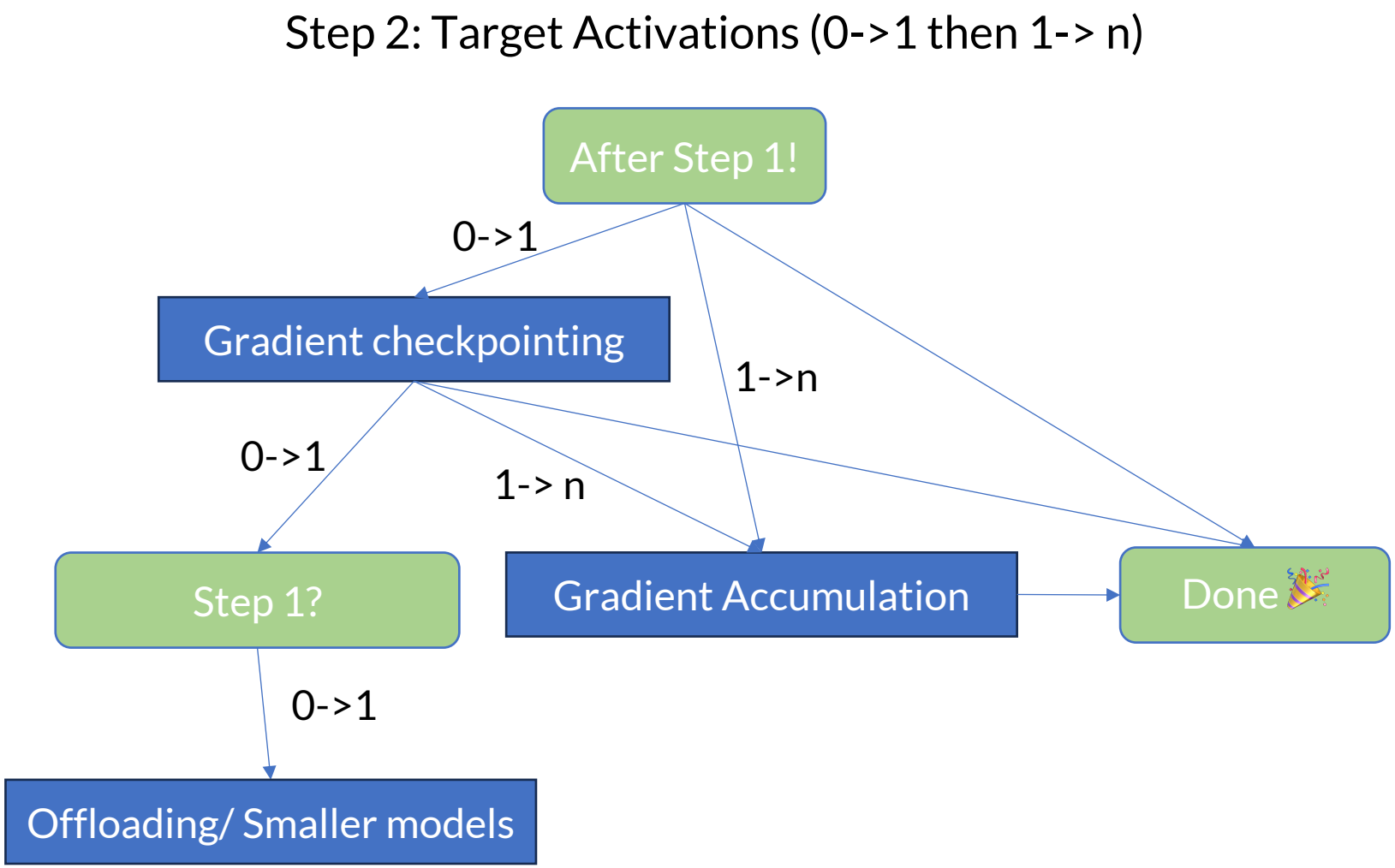
Can add more:
Optimizer Alternatives, etc



At each step, calculate: Total Memory (bs=1) - Available Memory

P.S: Flash Attention should be the default!

Efficient Fine-tuning: The Decision Tree



There’s More to Memory Usage…

- CUDA Kernels: Kernels loaded onto the GPU by your framework.
  - Pytorch: assume a max of 1GB
- Temporary Buffers: Intermediate activations, Backward pass, etc
  - Checkpointing: All activations between two checkpoints stored at once
- Memory Fragmentation: Not enough contiguous memory
- And more…..

Takeaways

- Intuition for Efficient but Fast finetuning
  - LoRA, Quantization, etc
- Memory: Every byte per parameter matters!
- Batch size, Utilization, Throughput
- “I wanted to increase batch size, so I added quantiza…”
  - Straight to Jail! 🚩
- Lot more you can do for throughput: fused optimizers, compilation, etc
- Multi-GPU setups: Also consider communication overhead

More on LLMs

- Stas Bekman's Engineering Blog: https://github.com/stas00/ml-engineering
- HuggingFace's Performance Guide: https://huggingface.co/docs/transformers/v4.20.1/en/performance
- More from me!
  - Everything about Distributed Training and Finetuning: https://sumanthrh.com/post/distributed-and-efficient-finetuning/
  - Everything about Tokenization: https://github.com/SumanthRH/tokenization/

Thank you!

Questions?