

# LLM Sys

## 11868 LLM Systems

# Parameter Efficient Fine-Tuning for LLM

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# Recap

- Direct quantization for low-bit numbers
  - absmax: linearly scale according to max abs value
  - zero-point: finding zero-point and scale
- Layer-wise quantization approaches
  - AdaQuant / KD: ZeroQuant / LLM.int8()
- GPTQ
  - approximate second-order of weights
  - accurately compress some of the largest publicly-available models down to 3 and 4 bits, and bring end-to-end speedups

# Outline

- Overview of Parameter Efficient Fine-Tuning
- LoRA: Low-rank Adaptation (Counter-interference adapter, CIAT)
- QLoRA: Quantization + Low-rank training
- Code Walkthrough

# LLM Fine-tuning is Expensive

- Full-parameter Fine-Tuning
  - Update all model parameters → Require large GPU memory
- e.g. Half-precision Fine-tuning cost per parameter (Adam)
  - Weight: 16 bits (2 bytes) \* N
  - Weight Gradient: 16 bits (2 bytes) \* N
  - Optimizer States: 2 \* 16 bits (4 bytes) \* N
  - Activations: ~ 1-2x of parameters
  - LLaMA-8B → ~ 80GB working memory

# Parameter Efficient Fine-tuning (PEFT)

- Only update a small subset (or low-rank) of parameters
- e.g. Fine-tuning cost per parameter with LoRA
  - Weight: 16 bits
  - Weight Gradient:  $\sim 0.4$  bits
  - Optimizer State:  $\sim 0.8$  bits
  - Adapter Weights:  $\sim 0.4$  bits
  - Activations:  $\sim 1\text{-}2\times$  of parameters
  - LLaMA-8B  $\rightarrow \sim 33\text{GB}$  working memory, fits a single A100.

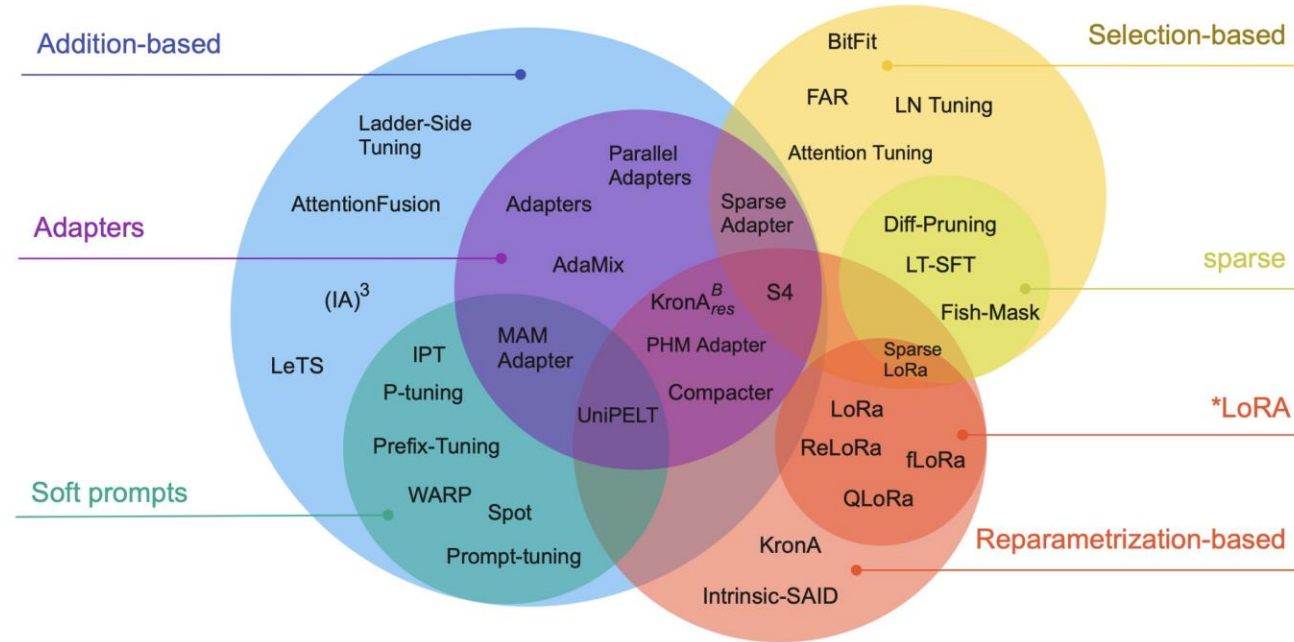
# PEFT with Quantization

- Parameter efficient fine-tuning together with quantization
- e.g. Fine-tuning cost per parameter with QLoRA
  - Weight: 4 bits
  - Weight Gradient: ~0.4 bit
  - Optimizer State: ~0.8 bit
  - Adapter Weights: ~0.4 bit
  - Activations: ~ 1-2x of parameters
  - LLaMA-8B → ~ ~~33GB~~ **9.2GB** working memory



# PEFT Approaches

- Selective Methods:
  - fine-tune selected subsets
- Reparameterization Method:
  - low-rank representation weights
- Additive Methods:
  - add trainable layers or parameters
  - e.g. Adapters, Soft prompts (Prompt Tuning)



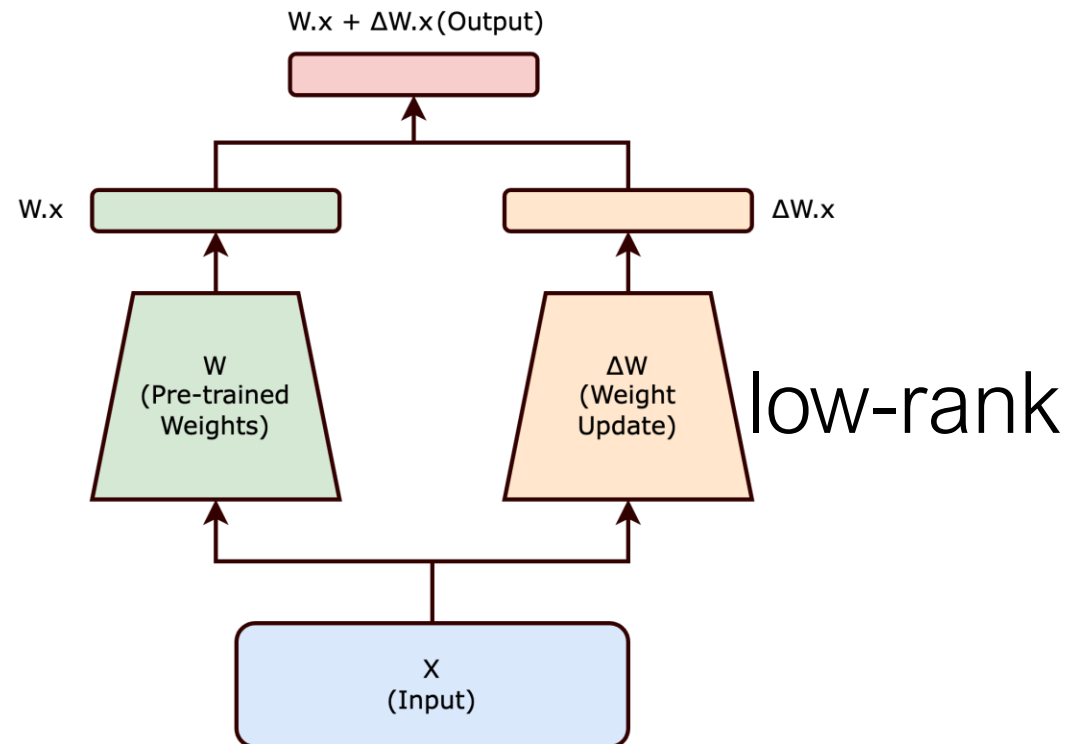
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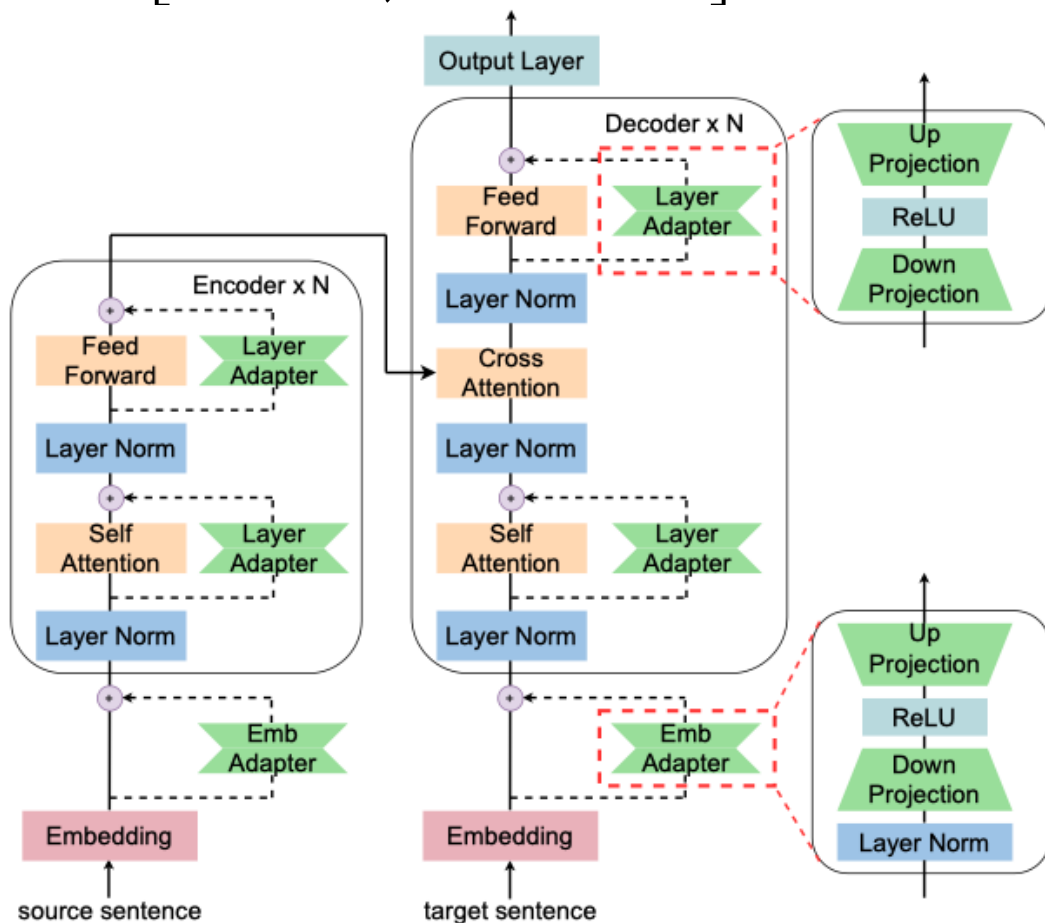
# Additive Fine-tuning

- Freeze the pre-trained parameters  $W_0$
- Train a low-rank update to the parameters  $\delta_W$ 
  - $W' = W_0 + \delta_W$



# Low-rank Adaption (LoRA) for Fine-tuning

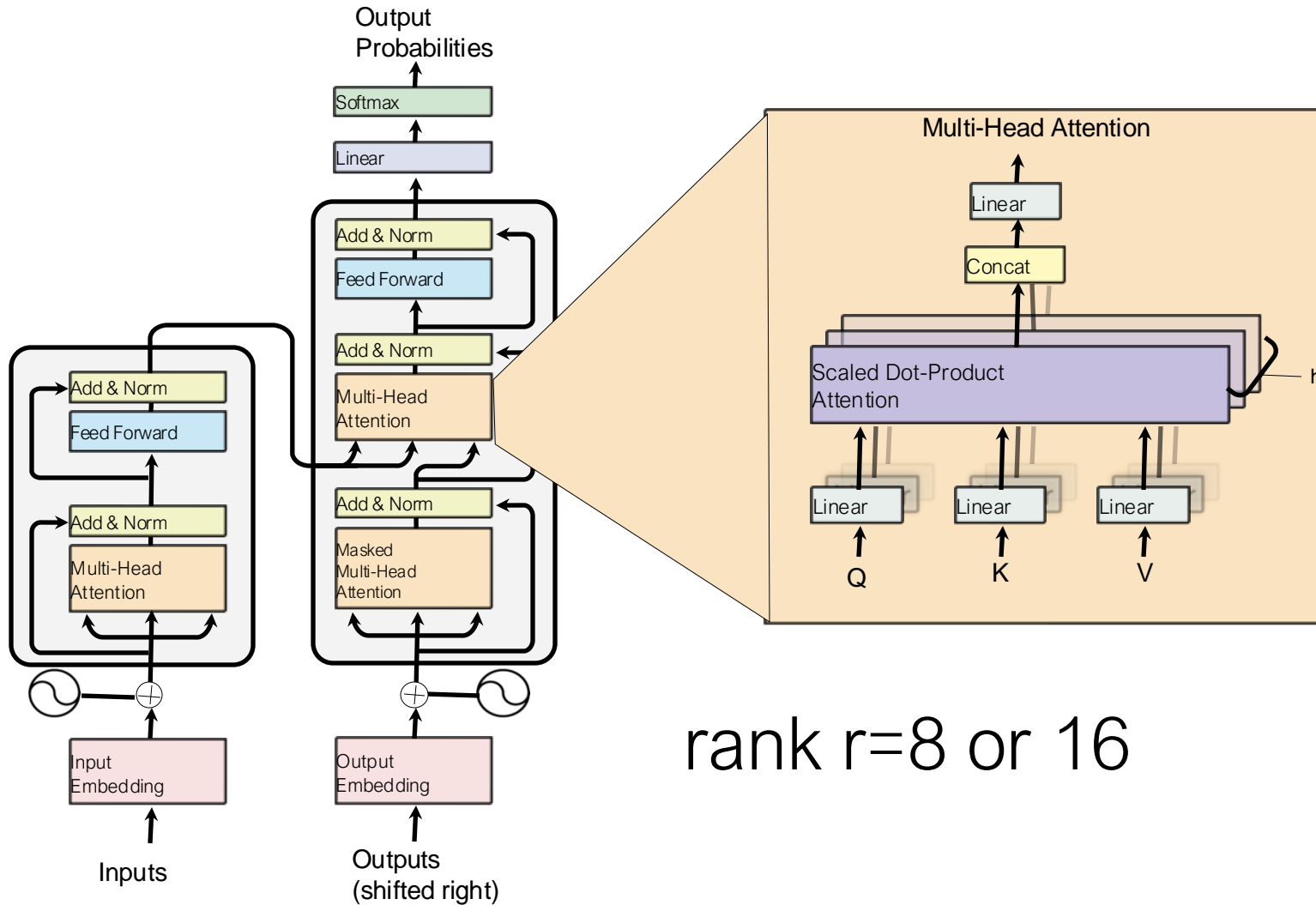
first invented in **Counter-Interference Adapter (CIAT) for Multilingual Machine Translation** [Zhu et al, EMNLP 2021], later re-invented by **Low-Rank Adaptation of Large Language Models** [Hu et al, ICLR 2022]



$$W' = W + A_{d \times r} \cdot B_{r \times d}$$

low rank  $r \ll d$

# Applying LoRA to LLM



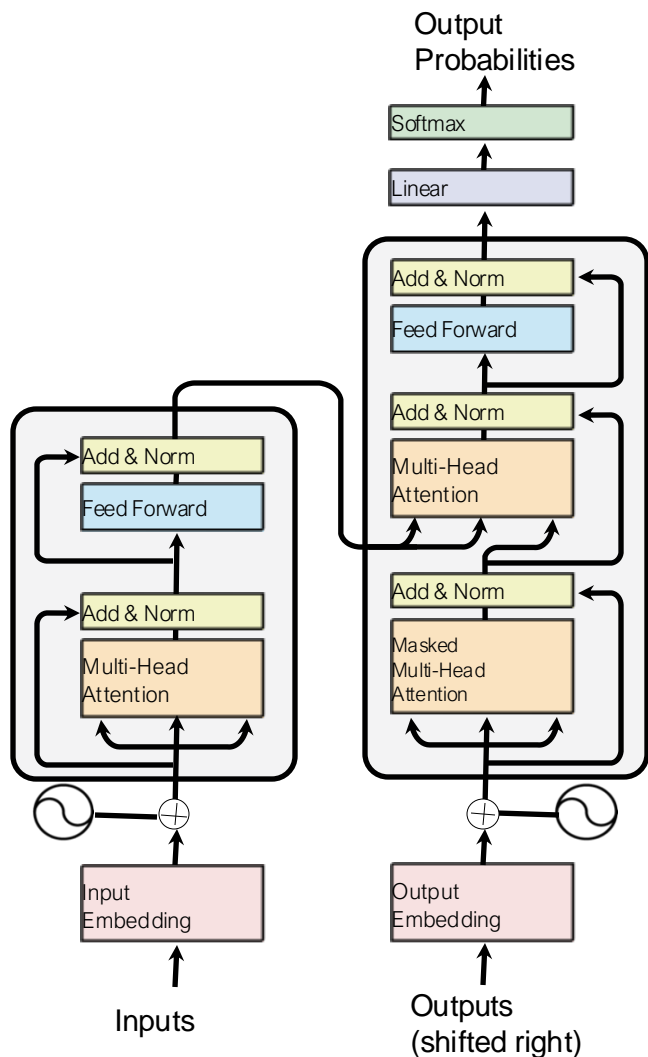
Apply LoRA to weights in attention layer

$$W_Q, W_K, W_V, W$$

but not to FFN's linear weights (storing knowledge)

In CIAT method, it is also applied to embeddings and FFN layers, and improves.

# Inference for LoRA-trained models



- Inference: use  $W' = W + A \cdot B$  for each weight matrix and store A,B as well (small additional cost,  $r=8$  or  $16$ )
- We can switch between LoRA weight for each task/domain

$$\circ W'' = W' - A \cdot B + A'' \cdot B''$$

LoRA weights for  
current domain

LoRA weights for  
new domain

# Backward Computation of LoRA

$$W' = W_0 + A \cdot B$$

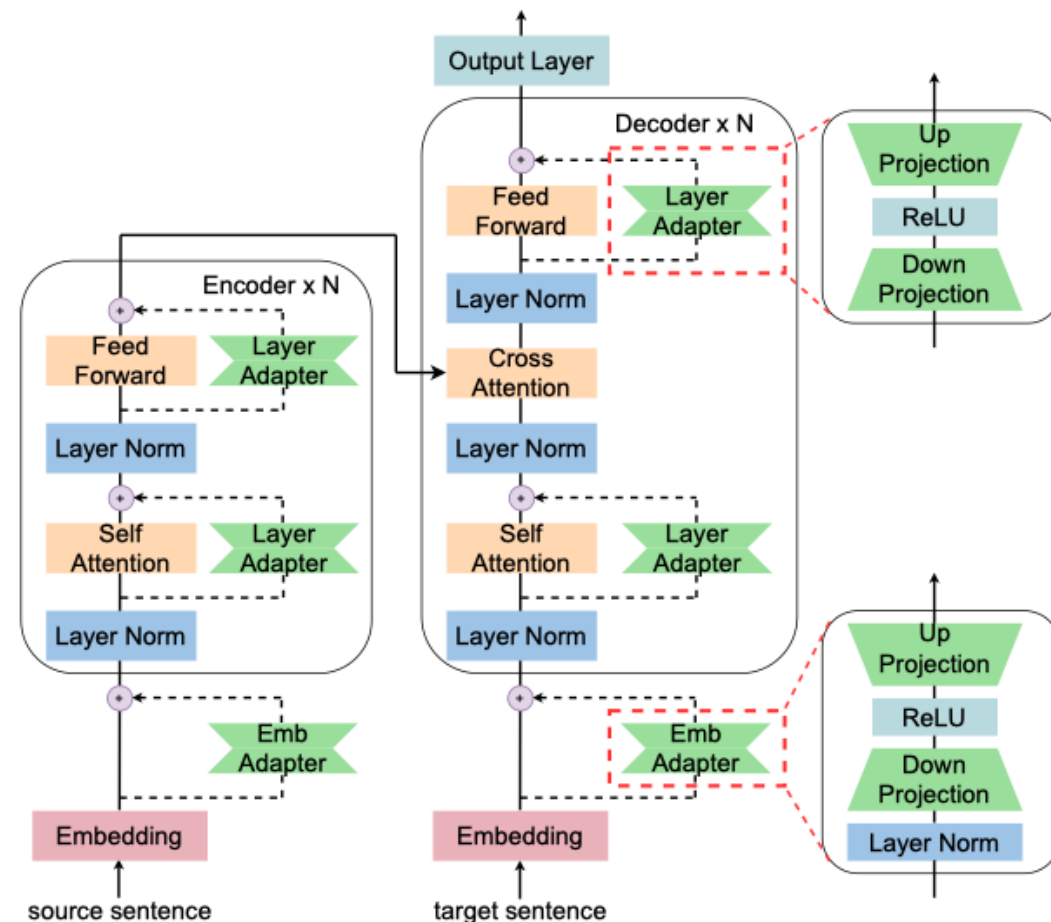
- The original pre-trained weight matrix is fixed. We only need to compute the gradients with respect to A and B.

$$\frac{\partial L}{\partial A} = g_{out} \cdot \frac{\partial (W_0 x + A \cdot Bx)}{\partial A} = g_{out} \cdot (Bx)^T$$

$$\frac{\partial L}{\partial B} = g_{out} \cdot \frac{\partial (W_0 x + A \cdot Bx)}{\partial B} = (g_{out}^T \cdot A) x^T$$

# Training LoRA

- No need to store original parameter states
- Only need to store:
  - original parameters
  - adapter weights:  $2 \times d \times r$
  - adapter gradients:  $2 \times d \times r$
  - adapter states: first and second moments,  $2 \times d \times r$
  - activations



# Memory Consumption of LoRA Training

- LoRA reduce the number of trainable parameters thus reducing the GPU memory requirement
- LLaMA 8B:  
8B parameters -> 16GB (BF16)  
optimizer states -> 48GB (Adam)
- With Lora:  
4M parameters -> 8MB  
optimizer states -> 24MB (Adam)

# Benefits of LoRA for Large Models

- Reduced Memory Footprint
  - no need to store state for frozen params
  - LLaMA 8B: 8B → 4M
- Faster Training (fine-tuning)
  - training time
- ➔ Enable fine-tuning of large models, and on smaller devices.
- Inference is as normal LLM.



# Experiments of LoRA

- Tasks
  - Natural Language Understanding (NLU): RoBERTa, DeBERTa
    - Subtasks: MNLI, SST-2, MRPC, CoLA, QNLI, QQP, RTE, STS-B
  - Natural Language Generation (NLG): GPT-2, GPT-3
    - Metrics: BLEU, NIST, MET, ROUGE-L, CIDEr
- Six Baselines
  - Fine-Tuning, Bias-only or BitFit, Prefix-embedding tuning (PreEmbed), Prefix-layer tuning (PreLayer), Adapter tuning, LoRA

# LoRA is more effective than other fine-tuning methods

LoRA enhances model adaptation with fewer parameters, ensuring both efficiency and improved performance

## NLU Tasks

Model & Method	# Trainable Parameters	GLUE Benchmark								Avg.
		MNLI	SST-2	MRPC	CoLA	QNLI	QQP	RTE	STS-B	
RoB <sub>base</sub> (FT)*	125.0M	<b>87.6</b>	94.8	90.2	<b>63.6</b>	92.8	<b>91.9</b>	78.7	91.2	86.4
RoB <sub>base</sub> (BitFit)*	0.1M	84.7	93.7	<b>92.7</b>	62.0	91.8	84.0	81.5	90.8	85.2
RoB <sub>base</sub> (Adpt <sup>D</sup> )*	0.3M	87.1 $\pm$ 0	94.2 $\pm$ 1	88.5 $\pm$ 1.1	60.8 $\pm$ 4	93.1 $\pm$ 1	90.2 $\pm$ 0	71.5 $\pm$ 2.7	89.7 $\pm$ 3	84.4
RoB <sub>base</sub> (Adpt <sup>D</sup> )*	0.9M	87.3 $\pm$ 1	94.7 $\pm$ 3	88.4 $\pm$ 1	62.6 $\pm$ 9	93.0 $\pm$ 2	90.6 $\pm$ 0	75.9 $\pm$ 2.2	90.3 $\pm$ 1	85.4
RoB <sub>base</sub> (LoRA)	<b>0.3M</b>	87.5 $\pm$ 3	<b>95.1<math>\pm</math>2</b>	89.7 $\pm$ 7	63.4 $\pm$ 1.2	<b>93.3<math>\pm</math>3</b>	90.8 $\pm$ 1	<b>86.6<math>\pm</math>7</b>	<b>91.5<math>\pm</math>2</b>	<b>87.2</b>
RoB <sub>large</sub> (FT)*	355.0M	90.2	<b>96.4</b>	<b>90.9</b>	68.0	94.7	<b>92.2</b>	86.6	92.4	88.9
RoB <sub>large</sub> (LoRA)	0.8M	<b>90.6<math>\pm</math>2</b>	96.2 $\pm$ 5	<b>90.9<math>\pm</math>1.2</b>	<b>68.2<math>\pm</math>1.9</b>	<b>94.9<math>\pm</math>3</b>	91.6 $\pm$ 1	<b>87.4<math>\pm</math>2.5</b>	<b>92.6<math>\pm</math>2</b>	<b>89.0</b>
RoB <sub>large</sub> (Adpt <sup>P</sup> )†	3.0M	90.2 $\pm$ 3	96.1 $\pm$ 3	90.2 $\pm$ 7	<b>68.3<math>\pm</math>1.0</b>	<b>94.8<math>\pm</math>2</b>	<b>91.9<math>\pm</math>1</b>	83.8 $\pm$ 2.9	92.1 $\pm$ 7	88.4
RoB <sub>large</sub> (Adpt <sup>P</sup> )†	0.8M	<b>90.5<math>\pm</math>3</b>	<b>96.6<math>\pm</math>2</b>	89.7 $\pm$ 1.2	67.8 $\pm$ 2.5	<b>94.8<math>\pm</math>3</b>	91.7 $\pm$ 2	80.1 $\pm$ 2.9	91.9 $\pm$ 4	87.9
RoB <sub>large</sub> (Adpt <sup>H</sup> )†	6.0M	89.9 $\pm$ 5	96.2 $\pm$ 3	88.7 $\pm$ 2.9	66.5 $\pm$ 4.4	94.7 $\pm$ 2	92.1 $\pm$ 1	83.4 $\pm$ 1.1	91.0 $\pm$ 1.7	87.8
RoB <sub>large</sub> (Adpt <sup>H</sup> )†	0.8M	90.3 $\pm$ 3	96.3 $\pm$ 5	87.7 $\pm$ 1.7	66.3 $\pm$ 2.0	94.7 $\pm$ 2	91.5 $\pm$ 1	72.9 $\pm$ 2.9	91.5 $\pm$ 5	86.4
RoB <sub>large</sub> (LoRA)†	<b>0.8M</b>	<b>90.6<math>\pm</math>2</b>	96.2 $\pm$ 5	<b>90.2<math>\pm</math>1.0</b>	68.2 $\pm$ 1.9	<b>94.8<math>\pm</math>3</b>	91.6 $\pm$ 2	<b>85.2<math>\pm</math>1.1</b>	<b>92.3<math>\pm</math>5</b>	<b>88.6</b>
DeB <sub>XXL</sub> (FT)*	1500.0M	91.8	<b>97.2</b>	92.0	72.0	<b>96.0</b>	92.7	93.9	92.9	91.1
DeB <sub>XXL</sub> (LoRA)	<b>4.7M</b>	<b>91.9<math>\pm</math>2</b>	96.9 $\pm$ 2	<b>92.6<math>\pm</math>6</b>	<b>72.4<math>\pm</math>1.1</b>	<b>96.0<math>\pm</math>1</b>	<b>92.9<math>\pm</math>1</b>	<b>94.9<math>\pm</math>4</b>	<b>93.0<math>\pm</math>2</b>	<b>91.3</b>

Table 2: RoBERTa<sub>base</sub>, RoBERTa<sub>large</sub>, and DeBERTa<sub>XXL</sub> with different adaptation methods on the GLUE benchmark. We report the overall (matched and mismatched) accuracy for MNLI, Matthew’s correlation for CoLA, Pearson correlation for STS-B, and accuracy for other tasks. Higher is better for all metrics. \* indicates numbers published in prior works. † indicates runs configured in a setup similar to [Houlsby et al. \(2019\)](#) for a fair comparison.

## NLG Tasks

Model & Method	# Trainable Parameters	E2E NLG Challenge				
		BLEU	NIST	MET	ROUGE-L	CIDEr
GPT-2 M (FT)*	354.92M	68.2	8.62	46.2	71.0	2.47
GPT-2 M (Adapter <sup>L</sup> )*	0.37M	66.3	8.41	45.0	69.8	2.40
GPT-2 M (Adapter <sup>L</sup> )*	11.09M	68.9	8.71	46.1	71.3	2.47
GPT-2 M (Adapter <sup>H</sup> )	11.09M	67.3 $\pm$ 6	8.50 $\pm$ 0.7	46.0 $\pm$ 2	70.7 $\pm$ 2	2.44 $\pm$ 0.1
GPT-2 M (FT <sup>1+2</sup> )*	25.19M	68.1	8.59	46.0	70.8	2.41
GPT-2 M (PreLayer)*	0.35M	69.7	8.81	46.1	71.4	2.49
GPT-2 M (LoRA)	0.35M	<b>70.4<math>\pm</math>1</b>	<b>8.85<math>\pm</math>0.2</b>	<b>46.8<math>\pm</math>2</b>	<b>71.8<math>\pm</math>1</b>	<b>2.53<math>\pm</math>0.2</b>
GPT-2 L (FT)*	774.03M	68.5	8.78	46.0	69.9	2.45
GPT-2 L (Adapter <sup>L</sup> )	0.88M	69.1 $\pm$ 1	8.68 $\pm$ 0.3	46.3 $\pm$ 0	71.4 $\pm$ 2	<b>2.49<math>\pm</math>0</b>
GPT-2 L (Adapter <sup>L</sup> )	23.00M	68.9 $\pm$ 3	8.70 $\pm$ 0.4	46.1 $\pm$ 1	71.3 $\pm$ 2	2.45 $\pm$ 0.2
GPT-2 L (PreLayer)*	0.77M	70.3	8.85	46.2	71.7	2.47
GPT-2 L (LoRA)	0.77M	<b>70.4<math>\pm</math>1</b>	<b>8.89<math>\pm</math>0.2</b>	<b>46.8<math>\pm</math>2</b>	<b>72.0<math>\pm</math>2</b>	2.47 $\pm$ 0.2

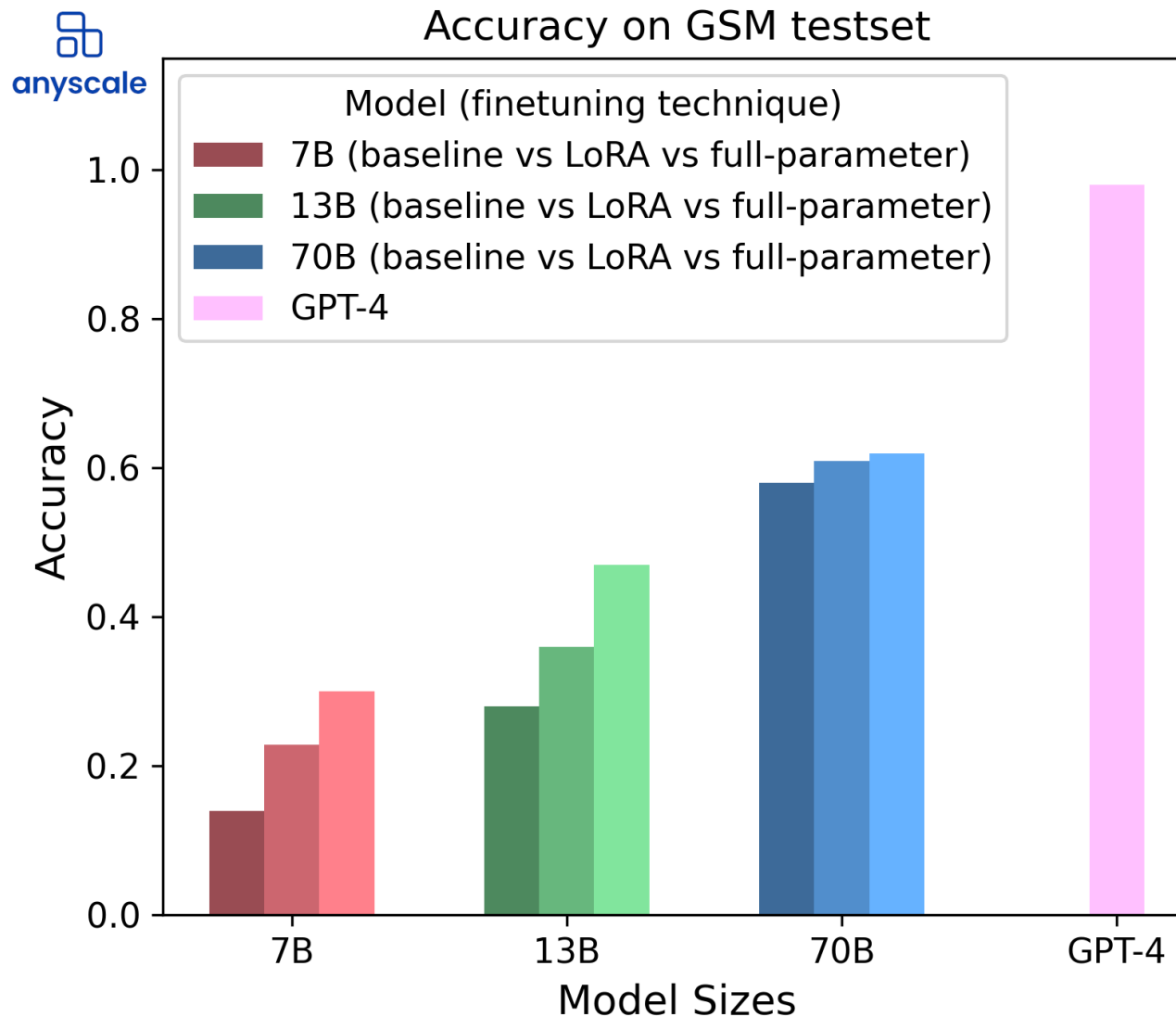
Table 3: GPT-2 medium (M) and large (L) with different adaptation methods on the E2E NLG Challenge. For all metrics, higher is better. LoRA outperforms several baselines with comparable or fewer trainable parameters. Confidence intervals are shown for experiments we ran. \* indicates numbers published in prior works.

# How to choose a proper rank in LoRA?

- Increasing rank does not cover more meaningful subspaces  
→ a low-rank adaptation matrix ( $r=8$ )

	Weight Type	$r = 1$	$r = 2$	$r = 4$	$r = 8$	$r = 64$
WikiSQL( $\pm 0.3\%$ )	$W_q, W_v$	73.4	73.3	<b>73.7</b>	<b>73.8</b>	73.5
	$W_q$	68.8	69.6	<b>70.5</b>	<b>70.4</b>	70.0
MultiNLI ( $\pm 0.1\%$ )	$W_q, W_v$	91.3	91.4	91.3	<b>91.7</b>	91.4

# LoRA Performance on Math (GSM8K)



# Experiments of LoRA

NLG Stress Test: Scale up to GPT-3 with 175B parameter

Not all methods benefit monotonically from an increase in trainable parameters.

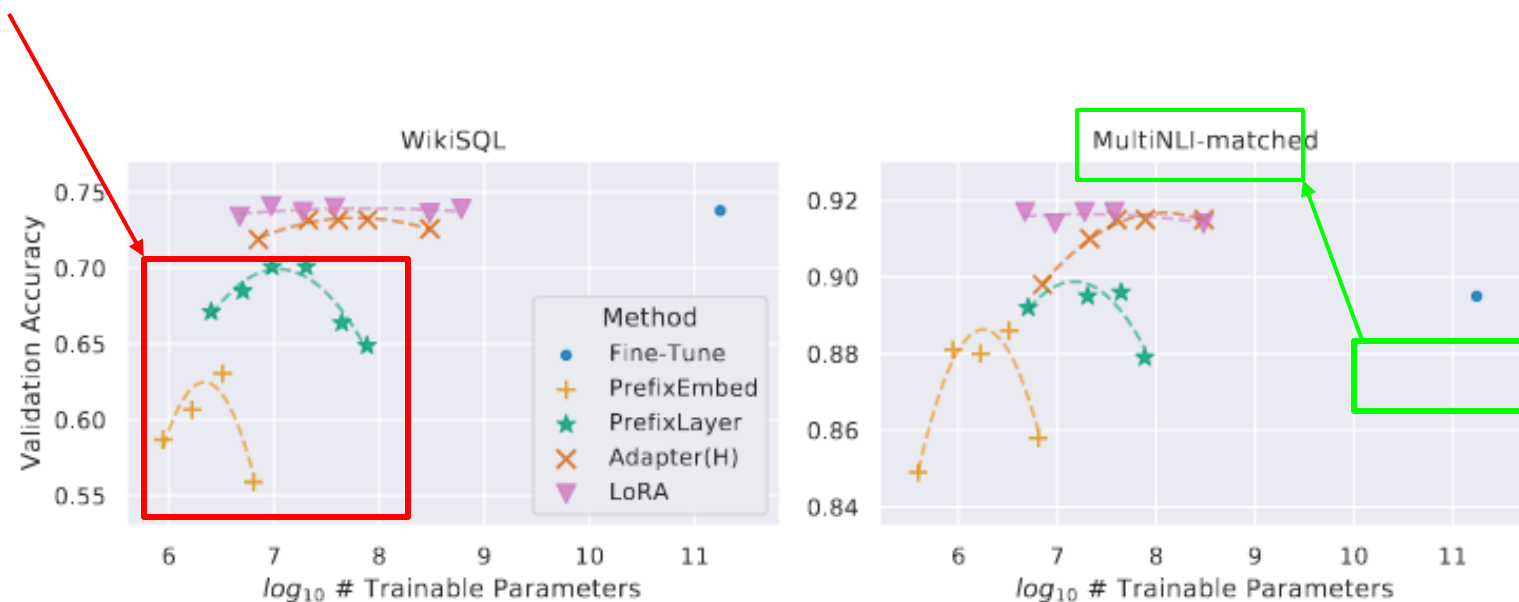



Figure 2: GPT-3 175B validation accuracy vs. number of trainable parameters of several adaptation methods on WikiSQL and MNLI-matched. LoRA exhibits better scalability and task performance. See [Section F.2](#) for more details on the plotted data points.

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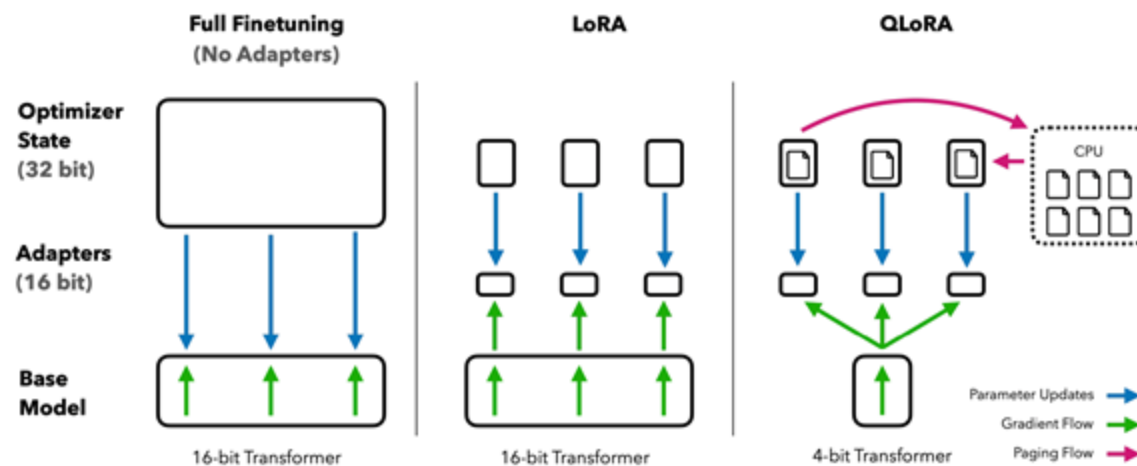
# Quantization-Aware Training

- GPTQ is Post-Training Quantization (PTQ): converting the weights of an already trained model to a lower precision without any retraining.
- Quantization-Aware Training (QAT): integrates the weight conversion process during the training stage. often superior model performance. (QLoRA)

# Overview of QLoRA

QLoRA = Low-rank + Quantized training

- Major innovations:
  - 4-bit Normal Float for storage
  - Double Quantization
  - Page Optimizer
- BF16 for computation



**Figure 1:** Different finetuning methods and their memory requirements. QLoRA improves over LoRA by quantizing the transformer model to 4-bit precision and using paged optimizers to handle memory spikes.

- Reduces the average memory requirements of fine-tuning a 65B parameter model from 780GB of GPU memory to 48GB on a single GPU.
- Preserving performance compared to a 16-bit finetuning



# QLoRA algorithm

QLORA has one storage data type (usually 4-bit NormalFloat) and a computation data type (BF16)

1. Double Quantize the model weights to NF4 format
2. Double De-quantize the weights to BF16
3. Perform forward and backward pass in BF16
4. Compute weight gradients (BF 16) only for the LoRA parameters

# 4-bit Number

- A 4-bit number can represent 16 values
- Standard quantization (absmax) divides data into equal-sized bins
  - high quantization error for non-uniform distributed data
  - lots of data with small difference, all get quantized to the same value

# Normal Float 4 bit quantization (NF-4)

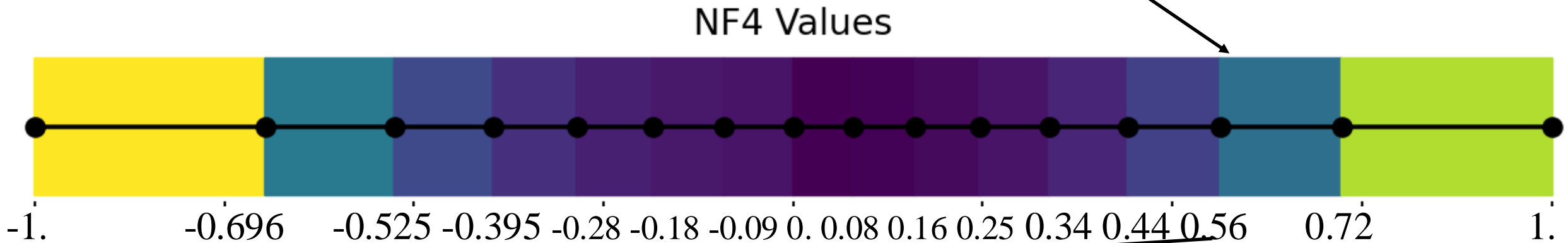
- split weights into blocks of 64 numbers
- Find max abs value → scale
- Normalize the 64 numbers w/ scale ( $\hat{x} = \frac{x}{scale}$ )
- Find the nearest value from a lookup table  
[-1. -0.6962 -0.5251 -0.3949 -0.2844 -0.1848 -0.0911 0. 0.0796 0.1609 0.2461  
0.3379 0.4407 0.5626 0.723 1.]
- Output the quantized values (index from lookup table) [-7, 8]

# Illustration: NF-4

value = 0.0045

scale =  $\max(\text{abs}(x)) = 0.0071$

normalized value =  $0.0045 / 0.0071 = 0.63$

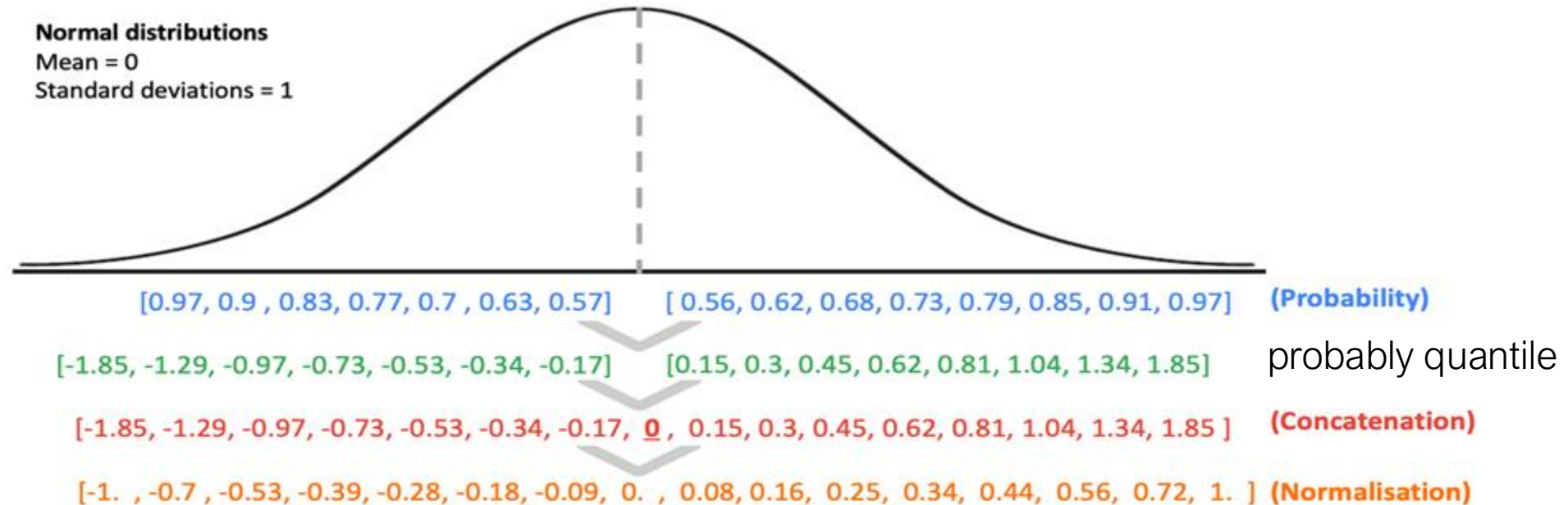


mapped value = 0.56

quantized value = 6

# Constructing NF-4 Lookup Table

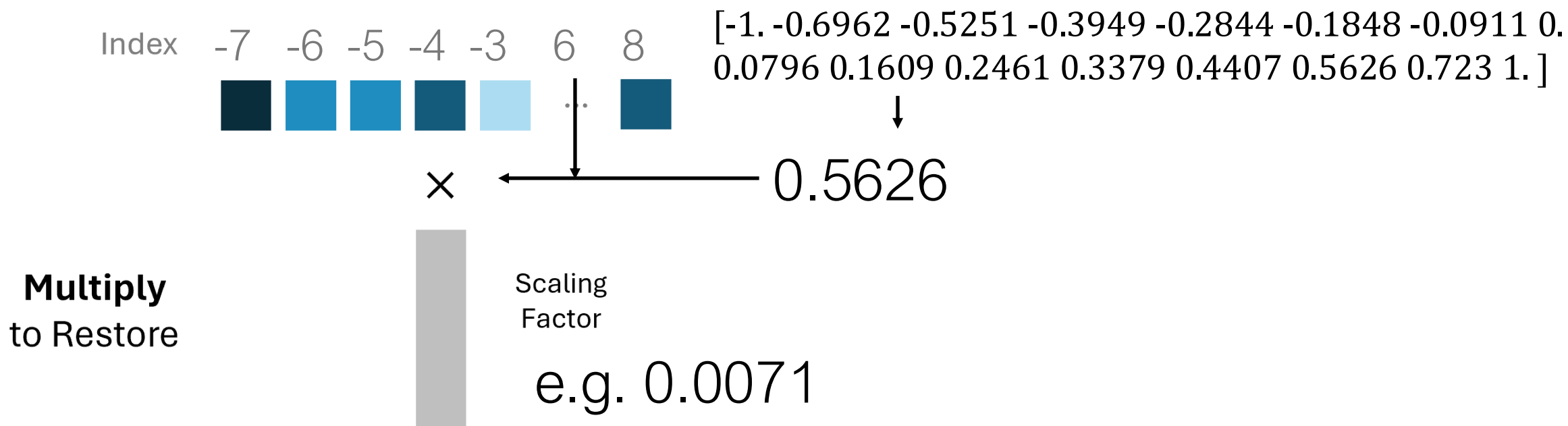
Exact values of the NF4 data type:



**Steps for generating the NF4 data type values:**

1. Generate 8 evenly spaced values from 0.56 to 0.97 (Set I).
2. Generate 7 evenly spaced values from 0.57 to 0.97 (Set II).
3. Calculate the z-score values for the probabilities generated in Step 1 and Step 2. For Set II, calculate the negative inverse of the z-scores.
4. Concatenate Set I, a zero value, and Set II together.
5. Normalize the values by dividing them by the absolute maximum value.

# De-quantization of NF-4



(with slight rounding error)

de-quantized value = 0.00399  
rounding error =  $0.0045 - 0.00399$   
= 0.0005

# Double Quantization for Scale Factors

**Motivation:** While a small blocksize is required for precise 4-bit quantization, it also has a considerable overhead.

- E.g. using 32-bit constants and a blocksize of 64, quantization constants add  $32/64 = 0.5$  bits per parameter on average.

Double Quantization (DQ) quantized the quantization constants for additional memory savings.

# QLoRA Double Quantization

- For every block of 64 values, apply NF-4 quantization
- For every block of 256 scales (from NF-4), apply FP8 quantization, store 2<sup>nd</sup> scale in FP32

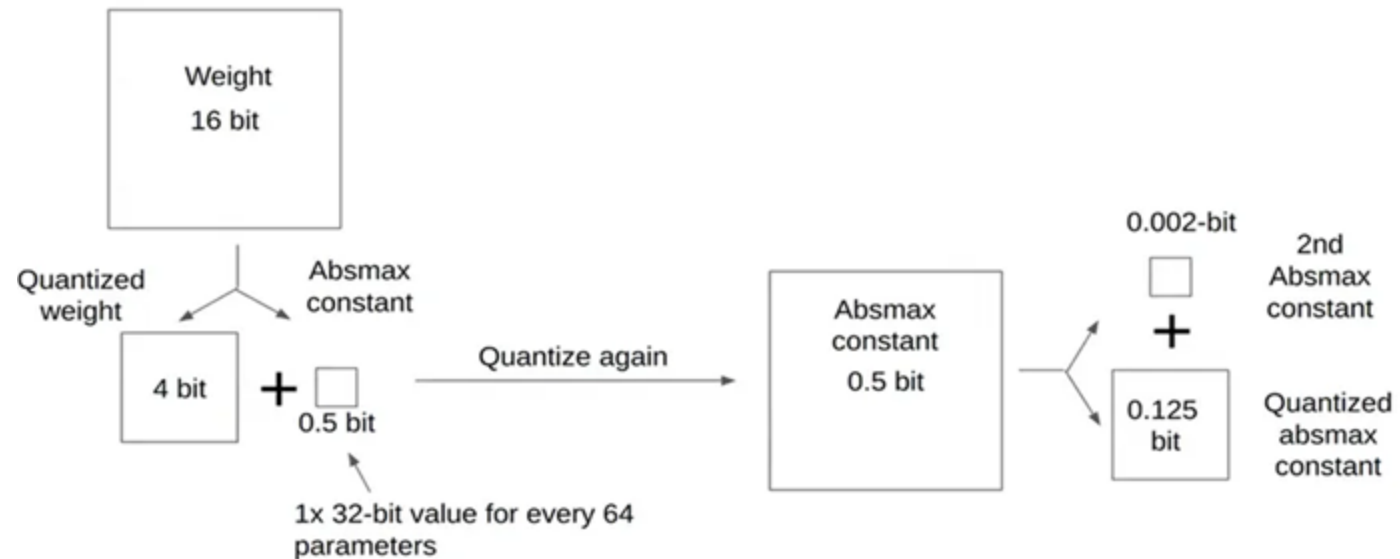


Image source: Democratizing Foundation Models via k-bit Quantization by Tim Dettmers

memory needed:  $0.5 + 1/64 + 1/(64 \cdot 256) \cdot 4 = 0.52$  bytes per param



# QLoRA

- Store pre-trained weights in NF4 with double quantization
  - C1 in FP32 (block size 256), C2 in FP8 (block size 64)
- Apply LoRA, store LoRA weights in BF16
- Store input in BF16, computing (forward/backward/opt) in BF16

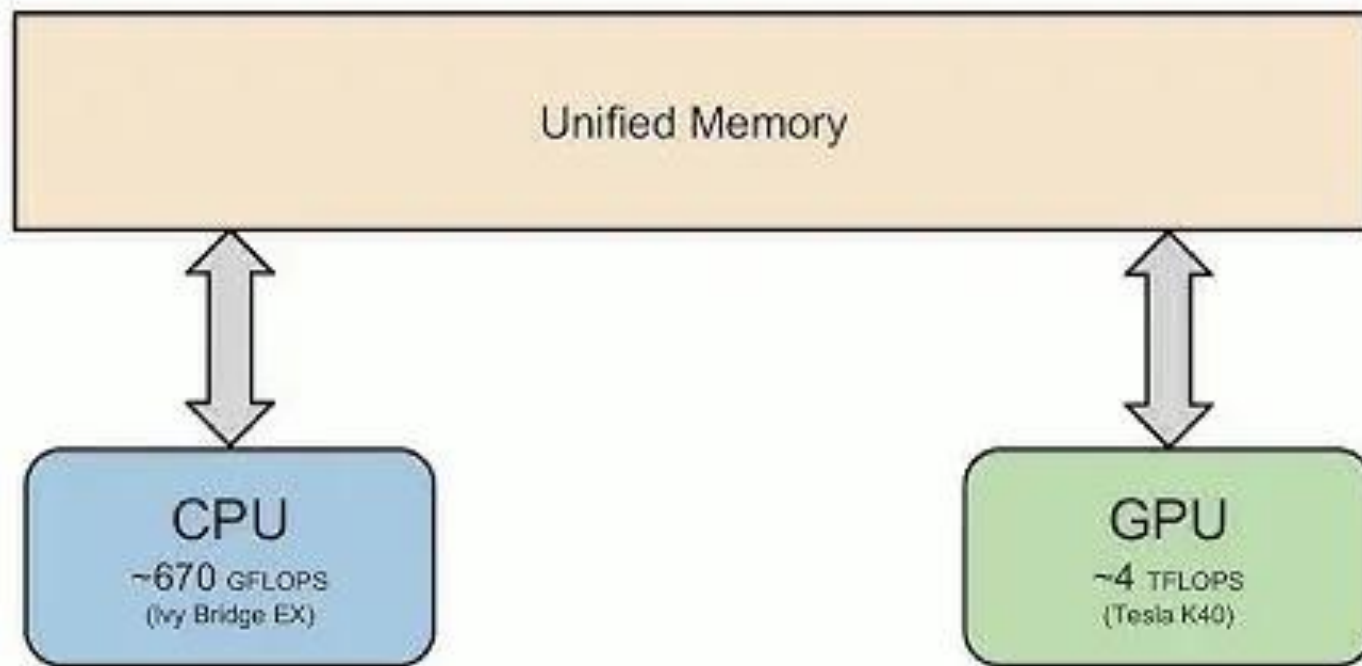
$$\mathbf{Y}^{\text{BF16}} = \mathbf{X}^{\text{BF16}} \text{doubleDequant}(c_1^{\text{FP32}}, c_2^{\text{k-bit}}, \mathbf{W}^{\text{NF4}}) + \mathbf{X}^{\text{BF16}} \mathbf{L}_1^{\text{BF16}} \mathbf{L}_2^{\text{BF16}},$$

where  $\text{doubleDequant}(\cdot)$  is defined as:

$$\text{doubleDequant}(c_1^{\text{FP32}}, c_2^{\text{k-bit}}, \mathbf{W}^{\text{k-bit}}) = \text{dequant}(\text{dequant}(c_1^{\text{FP32}}, c_2^{\text{k-bit}}), \mathbf{W}^{\text{4bit}}) = \mathbf{W}^{\text{BF16}}$$

# Paged Optimizers

**Motivation:** When training LLMs, GPU's OOM error is a common problem.

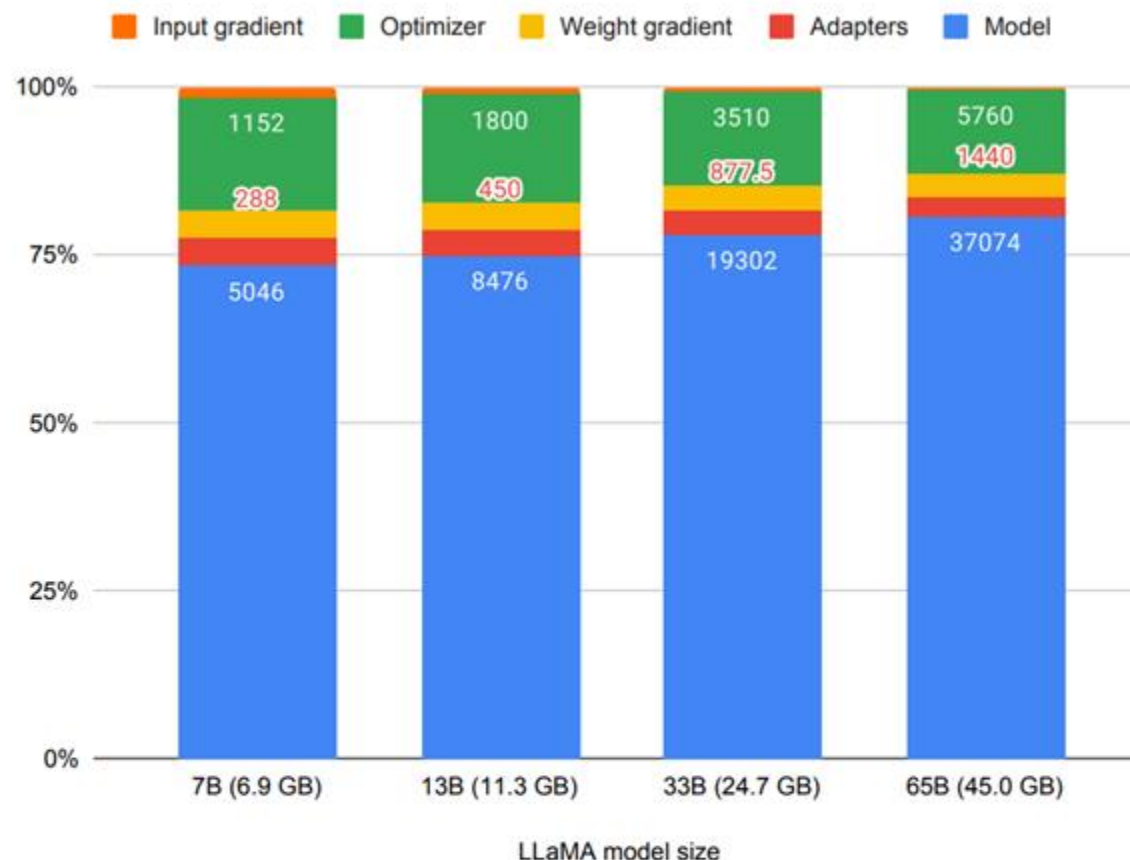


Paged optimizers are used to manage memory usage during training.

# Paged Optimizers

- Using the NVIDIA unified memory which does page-to-page transfers between the CPU and GPU for error-free GPU processing when the GPU occasionally runs out-of-memory.
  - like regular memory paging between CPU RAM and the disk.
  - Feature allocates paged memory for the optimizer states which are then automatically evicted to CPU during GPU OOM and back into GPU memory when memory is needed in the optimizer update step

# Paged Optimizers

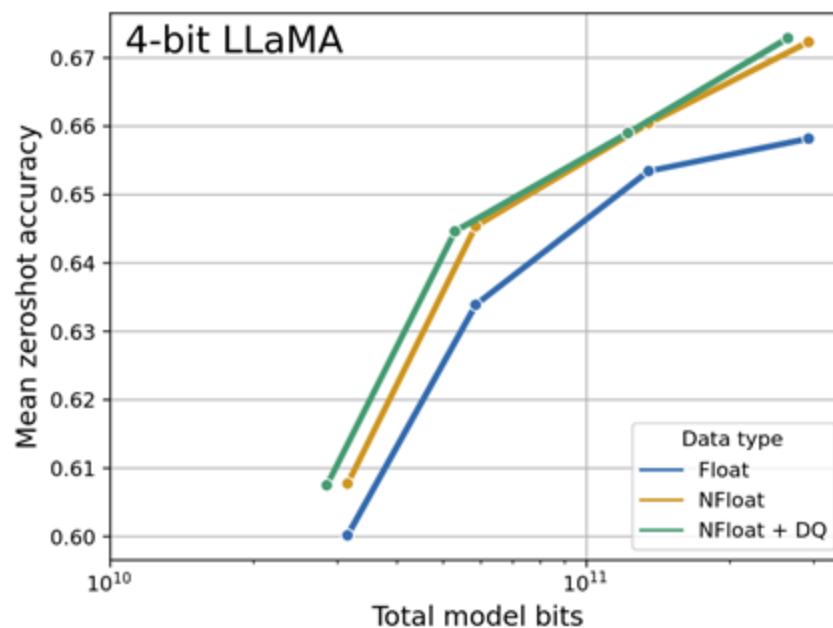
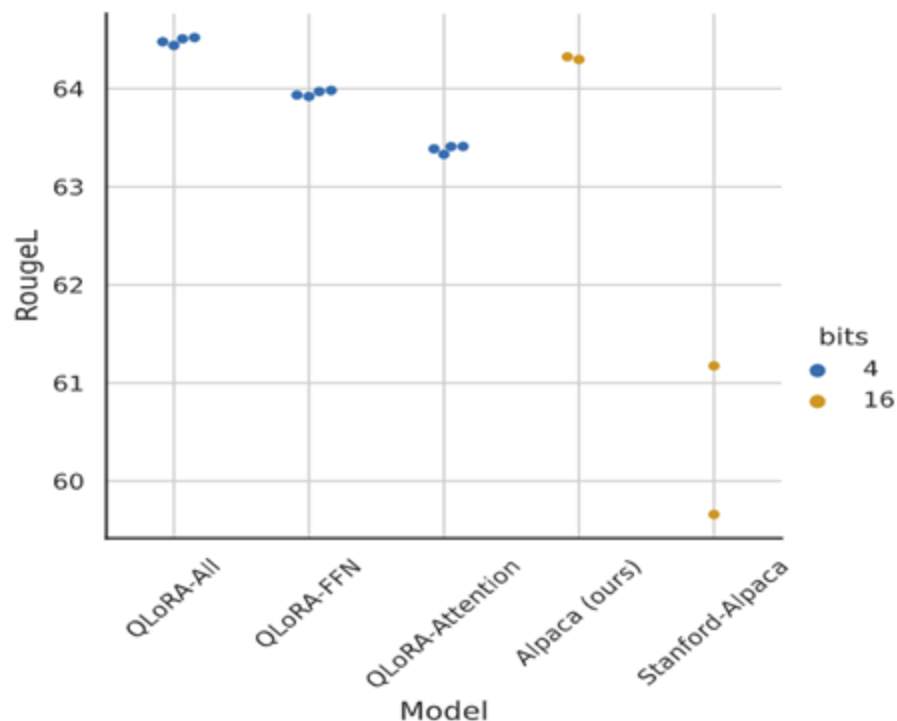


**Figure 6:** Breakdown of the memory footprint of different LLaMA models. The input gradient size is for batch size 1 and sequence length 512 and is estimated only for adapters and the base model weights (no attention). Numbers on the bars are memory footprint in MB of individual elements of the total footprint. While some models do not quite fit on certain GPUs, paged optimizer provide enough memory to make these models fit.

Dettmers et al. QLORA: Efficient Finetuning of Quantized LLMs. NeurIPS 2023.

# Performance of QLoRA

- Default LoRA Hyperparameters do not match 16-bit performance
- NF4 yield better performance than 4-bit Float (FP4)



**Table 2:** Pile Common Crawl mean perplexity for different data types for 125M to 13B OPT, BLOOM, LLaMA, and Pythia models.

Data type	Mean PPL
Int4	34.34
Float4 (E2M1)	31.07
Float4 (E3M0)	29.48
NFloat4 + DQ	<b>27.41</b>

# Experiments of QLoRA

- 4-bit QLoRA matches 16-bit full fine-tuning and 16-bit LoRA performance

**Table 4:** Mean 5-shot MMLU test accuracy for LLaMA 7-65B models finetuned with adapters on Alpaca and FLAN v2 for different data types. Overall, NF4 with double quantization (DQ) matches BFloat16 performance, while FP4 is consistently one percentage point behind both.

LLaMA Size Dataset	Mean 5-shot MMLU Accuracy								Mean
	7B		13B		33B		65B		
	Alpaca	FLAN v2	Alpaca	FLAN v2	Alpaca	FLAN v2	Alpaca	FLAN v2	
BFloat16	38.4	45.6	47.2	50.6	57.7	60.5	61.8	62.5	53.0
Float4	37.2	44.0	47.3	50.0	55.9	58.5	61.3	63.3	52.2
NFloat4 + DQ	39.0	44.5	47.5	50.7	57.3	59.2	61.8	63.9	53.1

# Outline

- Overview of Parameter Efficient Fine-Tuning
- LoRA: Low-rank Adaptation (Counter-interference adapter, CIAT)
- QLoRA: Quantization + Low-rank training
- ➡ • Code Walkthrough

# LoRA Code Walkthrough

```
class LoRALayer():
    def __init__(
        self,
        r: int,
        lora_alpha: int,
        lora_dropout: float,
        merge_weights: bool,
    ):
        self.r = r
        self.lora_alpha = lora_alpha
        # Optional dropout
        if lora_dropout > 0.:
            self.lora_dropout = nn.Dropout(p=lora_dropout)
        else:
            self.lora_dropout = lambda x: x
        # Mark the weight as unmerged
        self.merged = False
        self.merge_weights = merge_weights
```

- Define the LoRA Layer



# LoRA Code Walkthrough

```
class Linear(nn.Linear, LoRALayer):
    # LoRA implemented in a dense layer
    def __init__(
        self,
        in_features: int,
        out_features: int,
        r: int = 0,
        lora_alpha: int = 1,
        lora_dropout: float = 0.,
        fan_in_fan_out: bool = False, # Set this to True if the layer to replace stores weight like (fan_in, fan_out)
        merge_weights: bool = True,
        **kwargs
    ):
        nn.Linear.__init__(self, in_features, out_features, **kwargs)
        LoRALayer.__init__(self, r=r, lora_alpha=lora_alpha, lora_dropout=lora_dropout,
                           merge_weights=merge_weights)

        self.fan_in_fan_out = fan_in_fan_out
        # Actual trainable parameters
        if r > 0:
            self.lora_A = nn.Parameter(self.weight.new_zeros((r, in_features)))
            self.lora_B = nn.Parameter(self.weight.new_zeros((out_features, r)))
            self.scaling = self.lora_alpha / self.r
            # Freezing the pre-trained weight matrix
            self.weight.requires_grad = False
        self.reset_parameters()
        if fan_in_fan_out:
            self.weight.data = self.weight.data.transpose(0, 1)
```

- LoRA implement in the linear layer
- Initialize the LoRA A and B layer
- Freeze the pre-trained weight matrix

# LoRA Code Walkthrough

```
def train(self, mode: bool = True):
    def T(w):
        return w.transpose(0, 1) if self.fan_in_fan_out else w
    nn.Linear.train(self, mode)
    if mode:
        if self.merge_weights and self.merged:
            # Make sure that the weights are not merged
            if self.r > 0:
                self.weight.data -= T(self.lora_B @ self.lora_A) * self.scaling
            self.merged = False
    else:
        if self.merge_weights and not self.merged:
            # Merge the weights and mark it
            if self.r > 0:
                self.weight.data += T(self.lora_B @ self.lora_A) * self.scaling
            self.merged = True
```

```
def forward(self, x: torch.Tensor):
    def T(w):
        return w.transpose(0, 1) if self.fan_in_fan_out else w
    if self.r > 0 and not self.merged:
        result = F.linear(x, T(self.weight), bias=self.bias)
        result += (self.lora_dropout(x) @ self.lora_A.transpose(0, 1) @ self.lora_B.transpose(0, 1)) * self.scaling
        return result
    else:
        return F.linear(x, T(self.weight), bias=self.bias)
```

- Train module merge the weights of LoRA layer into the pre-train weights
- Given an input  $x$ , the forward process compute the sum of the result from two branches:

$$h = W_0x + \Delta Wx = W_0x + BAx$$

# QLoRA code

To train with QLoRA, load the model with the quantization config, then run with LoRA. BitsAndBytes contains custom wrapper for CUDA quantization operations.

```
AutoModelForCausalLM.from_pretrained( "meta-llama/Llama-2-70b",  
quantization_config=BitsAndBytesConfig(  
    load_in_4bit=args.bits == 4,  
    load_in_8bit=args.bits == 8,  
    llm_int8_threshold=6.0,  
    llm_int8_has_fp16_weight=False,  
    bnb_4bit_compute_dtype=compute_dtype,  
    bnb_4bit_use_double_quant=args.double_quant,  
    bnb_4bit_quant_type=args.quant_type,))
```

Inference Demo:

[https://github.com/artidoro/qlora/blob/main/examples/guanaco\\_7B\\_demo\\_colab.ipynb](https://github.com/artidoro/qlora/blob/main/examples/guanaco_7B_demo_colab.ipynb)

# Summary

- LoRA/CIAT enables cost-effective adaptation of large models by modifying fewer parameters (low-rank).
- Scalability: Effective for giant models like GPT-3, making adaptation more accessible.
- Low-Data Efficacy: Superior in low-data settings, reducing the need for large datasets.

# Summary

- QLoRA: double quantizing weights using NF4, computing in BF16
- QLoRA matches original Low-rank Adapter performance.
- 1<sup>st</sup> method that enables fine-tuning of 33B LLM on a single consumer GPU