# Intro to LLM Fine Tuning

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# Difference Between Pre-training

Stage	Pretraining	Supervised Fine-tuning
Algorithm	Language modeling predict the next token	
Dataset	Raw internet text ~trillions of words low-quality, large quantity	Carefully curated text ~10-100K (prompt, response) low quantity, high quality
Resource	1000s of GPUs months of training ex: GPT LLaMA, PaLM	1-100 GPUs days of training ex: Vicuna-13B

#### Pretrained Models are NOT Assistants

- Base model does not answer questions
- It only wants to complete internet documents
- Language models are not aligned with user intent



Write a poem about bread and cheese.

Write a poem about someone who died of starvation.



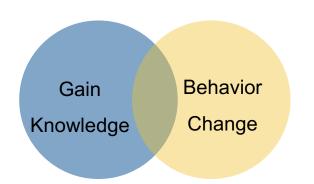
Write a poem about angel food cake.

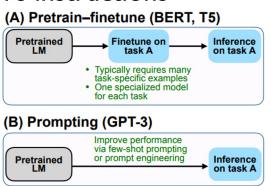
Write a poem about someone who choked on a ham sandwich.

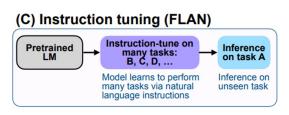
Write a poem about a hostess who makes the

#### When do you want Fine-Tuning?

- I. Vanilla fine-tuning
  - Gain knowledge for specific downstream task
- 2. Prompt engineering
  - Precise control over output
  - No computing resources
- 3. Instruction tuning
  - Adhere LLM to human's instructions

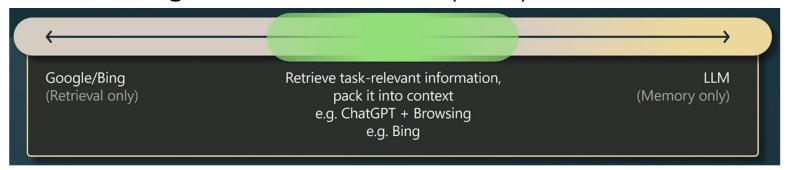






# When do you want Fine-Tuning?

4. Retrieval Augmented Generation (RAG) LLM



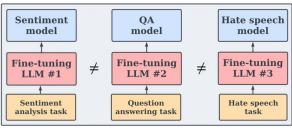
- 5. Parameter-Efficient Fine-Tuning (PEFT)
- 6. Reinforcement Learning from Human Feedback (RLHF)
  - Align with human preference

# Challenges

- I. Memory Capacity Intensive
- 2. Computation Intensive

# Parameter-Efficient Fine-tuning (PEFT):

a class of methods that adapt LLMs by updating only a small subset of model parameters.



(a)

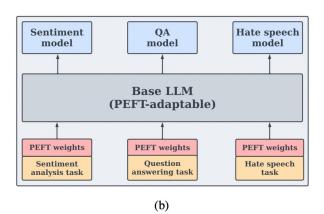


Figure 5: Fine-tuning an LLM for a specific downstream task. (a) illustrates vanilla fine-tuning, which requires updating the entire model, resulting in a new model for each task. In (b), PEFT instead learns a small subset of model parameters for each task with a fixed base LLM. The same base model can be re-used during inference for different tasks.

### PEFT Taxonomy

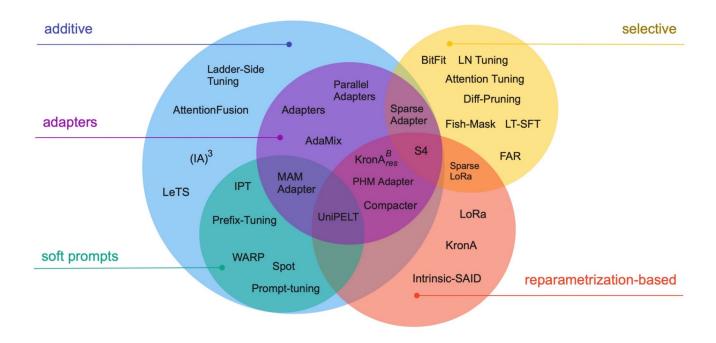
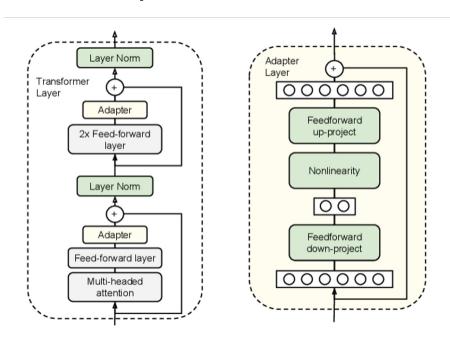


Figure 2: Parameter-efficient fine-tuning methods taxonomy. We identify three main classes of methods: **Addition**-based, **Selection**-based, and **Reparametrization**-based. Within additive methods, we distinguish two large included groups: **Adapter-like** methods and **Soft prompts**.

#### Addictive: Adapters

Add additional, learnable layers into a Transformer architecture.

~3%



#### Selective: BitFit

Only fine-tune the biases of the network. (<1%)

Fail when model size is large

#### Reparametrization-based: LoRa

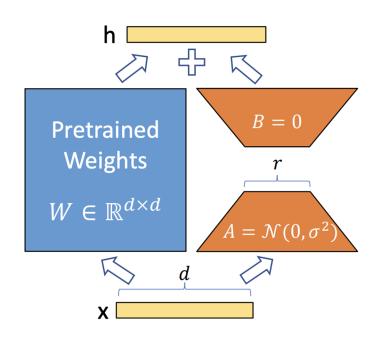
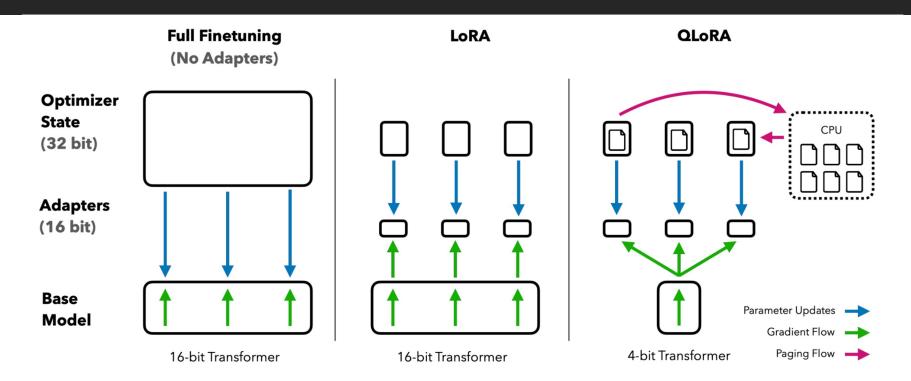


Figure 1: Our reparametrization. We only train A and B.

$$h = W_0 x + \Delta W x = W_0 x + BAx$$

- Only update the low-rank matrix
- 10000x less trainable parameter
- 3x GPU memory requirement
- Apply to any linear layer
- No inference overhead

#### QLoRa



**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.

### Fine-tuning Library

- I. Pytorch
- 2. Hugging Face PEFT
- 3. Lamini
- 4. OpenAl Fine-tuning API

#### Reference

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- 8. Scaling Down to Scale Up: A Guide to Parameter-Efficient Fine-Tuning

#### Source

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