Instruction Finetuning

Abhijeet

Agenda

01. Why Modify ?

Available options with us.

02. Memory Math & Scaling Laws

Challenge - How much memory ?
Quantization – Train or Infer
Scaling Laws

03. Train models to follow Instructions

FLAN-T5
ALPACA
DOLLY etc.

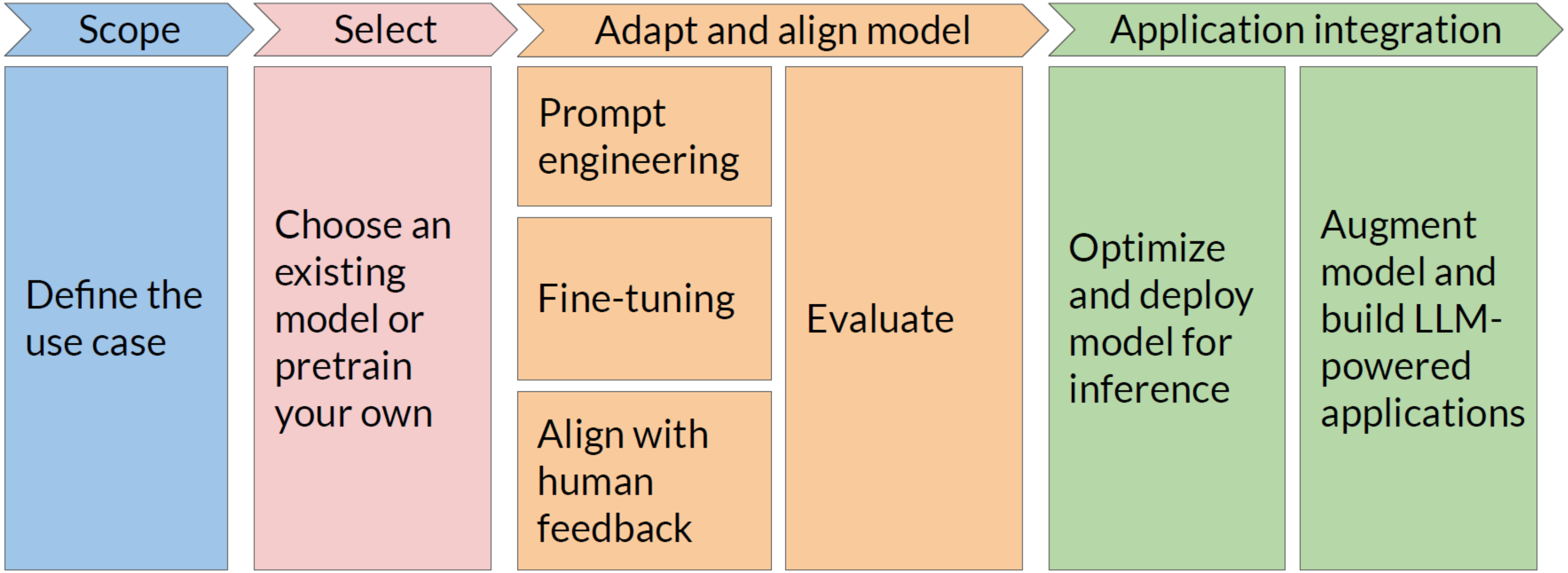
04. Finetuning for Use-Case

1. Full Finetuning
2. Parameter Efficient Finetuning
   a) Prompt Tuning
   b) LORA

05. Implementation

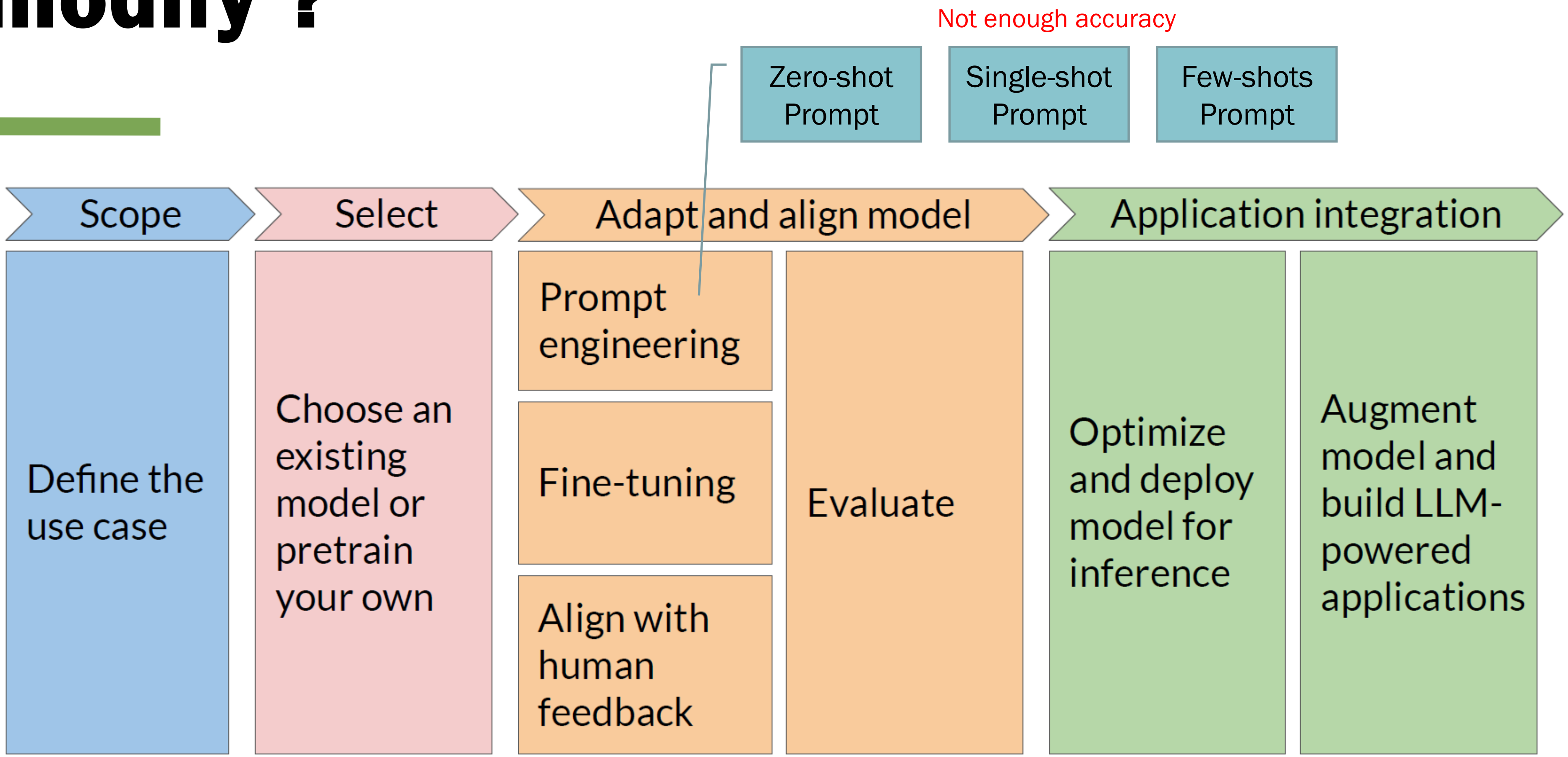
1. Dialog Summarization.
2. Training Alpaca/Dolly.

Why modify ?



[Coursera reference]

Why modify ?



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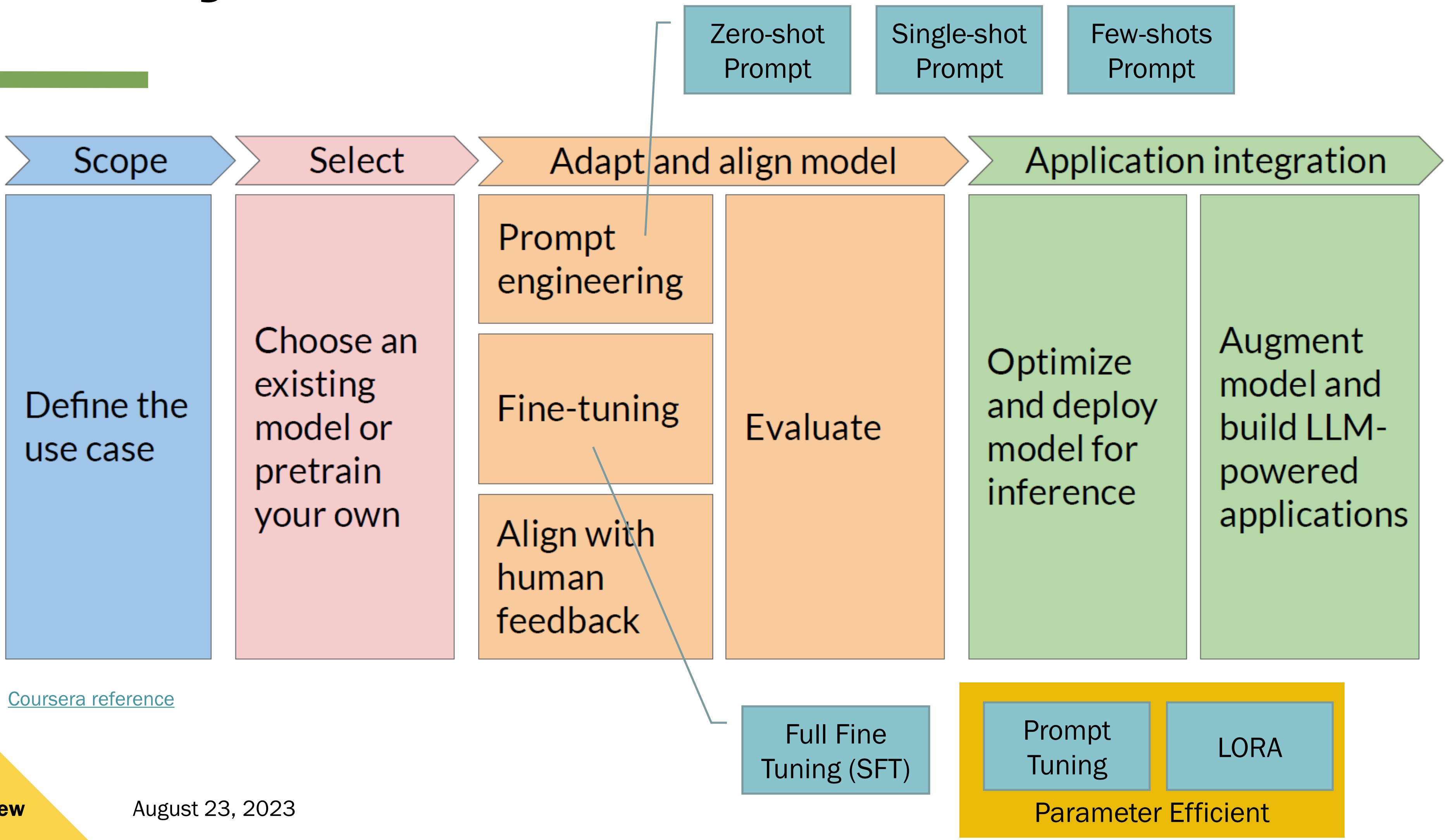

Coursera reference

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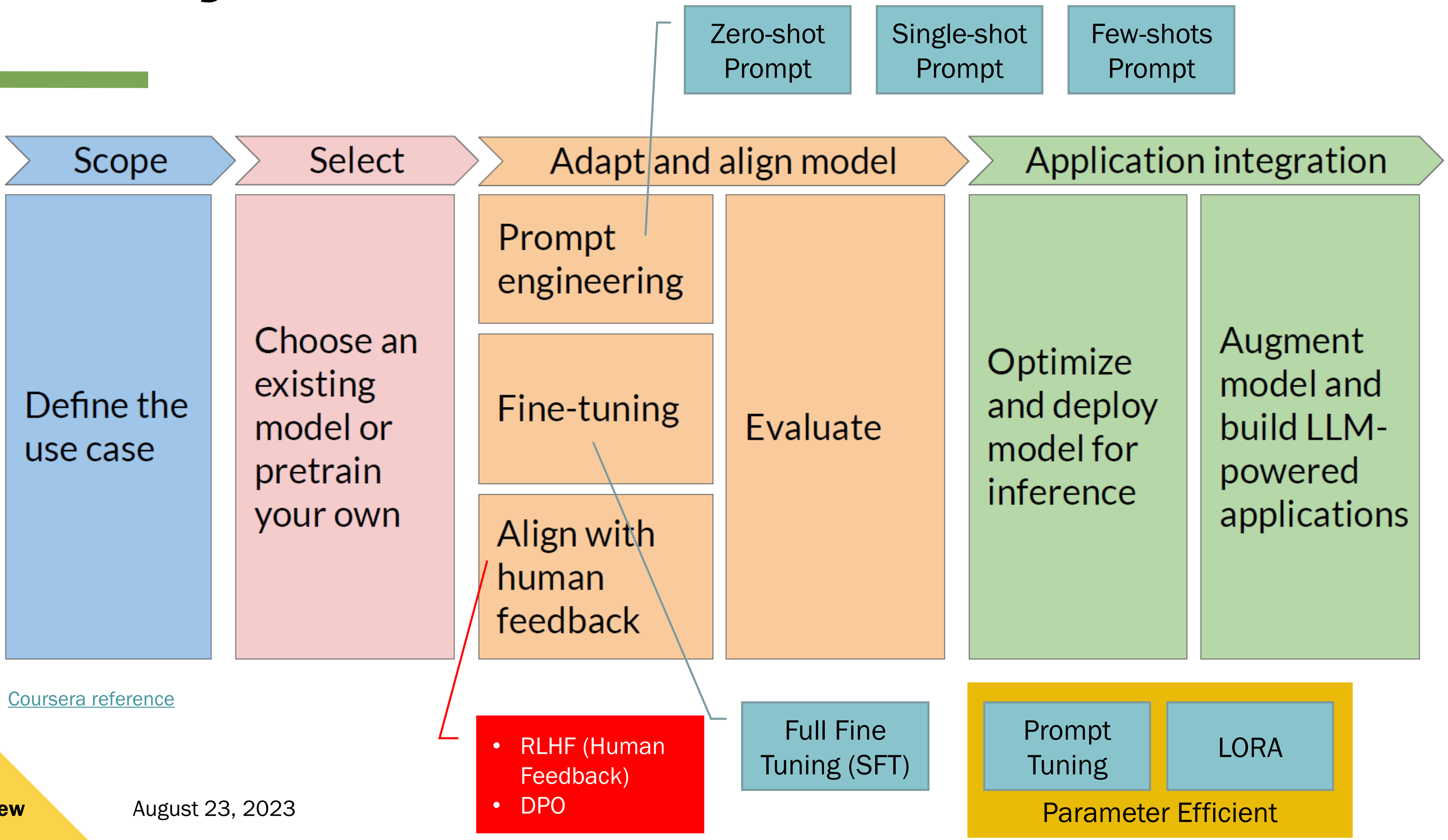


[Coursera reference]

Memory Math, Quantization & Scaling Laws

Memory

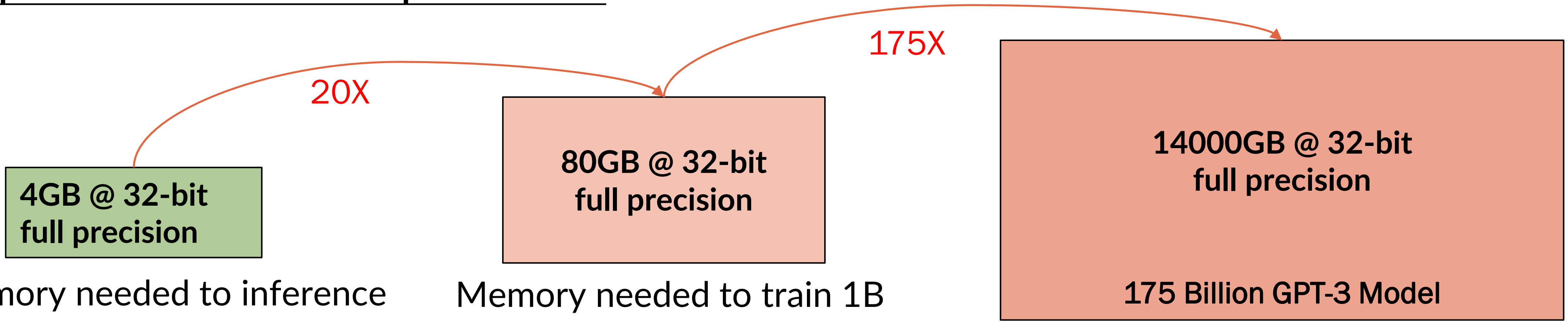
`OutOfMemoryError: CUDA out of memory.`

Let's do a quick math....

1 parameter = 4 bytes (32-bit float)
1B parameters = 4 x 10^9 bytes = **4GB**

Param name	Bytes per param
Weights	4 bytes
Adam states	8 bytes
Gradients	4 bytes
Activations & temp memory	8 bytes

<u>**Approx. GPU needed for 1B param model**</u>



Memory needed to inference
Memory needed to train 1B

[Hugging Face reference]

Memory

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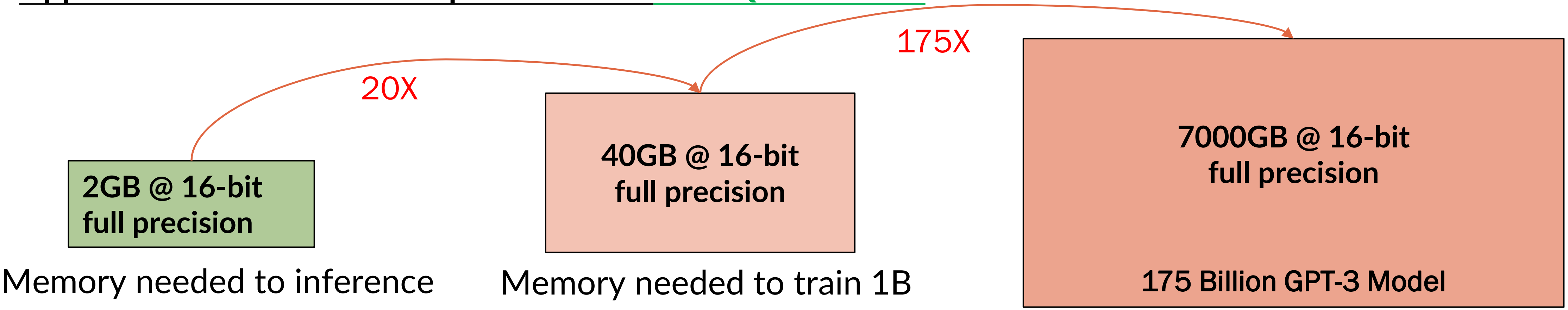
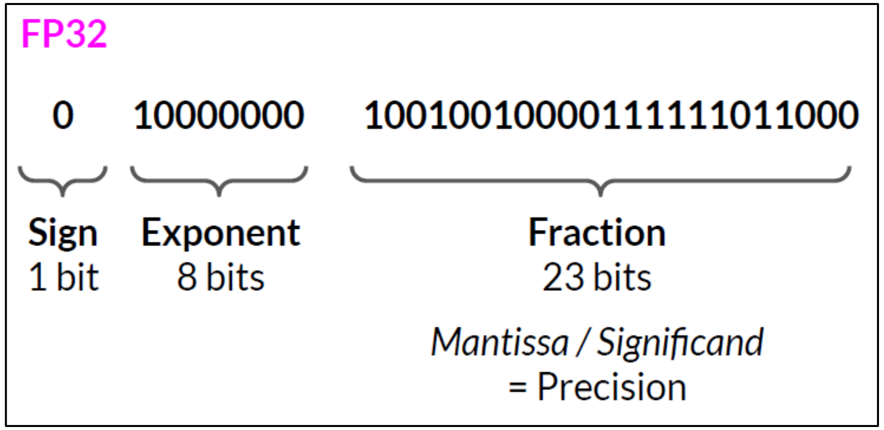
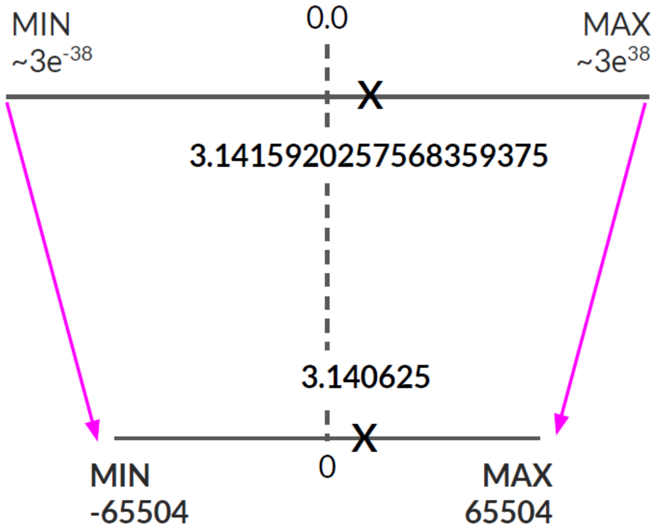
Approx. GPU needed for 1B param model with Quantization



Quantization





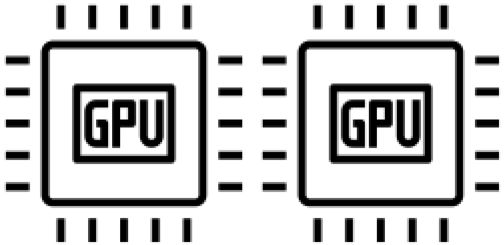
Data Type	PI value	Exponent	Fraction
FP32	3.1415920257568359375	8	23
FP16	3.140625	5	10
BF16	3.140625	8	7
INT8**	3	0	7

**INT8 & INT4 can only be used for inference (not training)

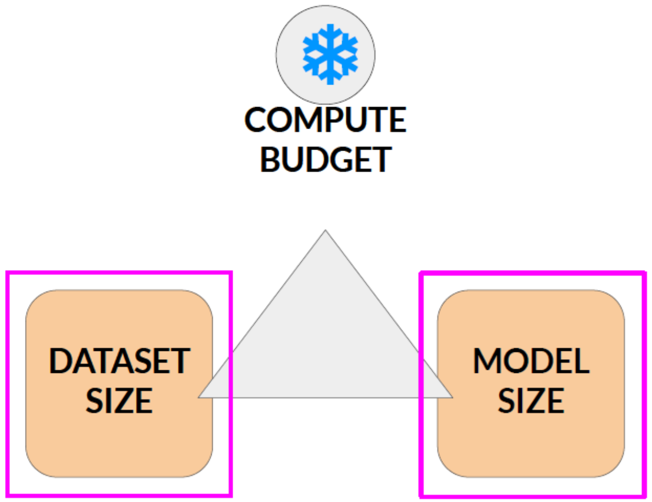
Compute & Scaling Laws

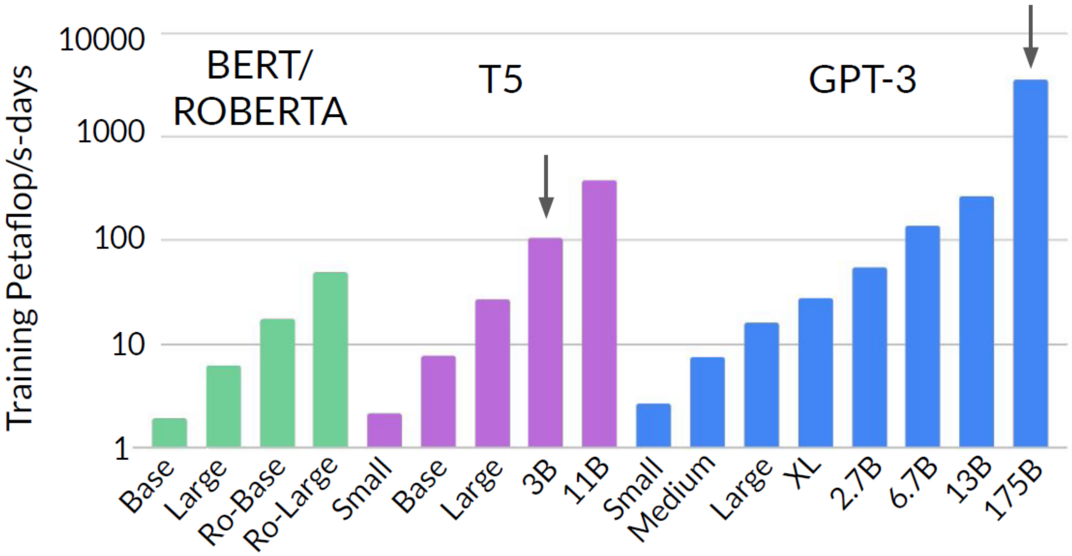
- 80GB is the maximum memory for the Nvidia A100 GPU. Trains 1B model.

- ALPACA-7B was trained on 8 80GB A100s
- GPT-3 175B needs 200 A100s.



1 petaflop/s-day at full efficiency





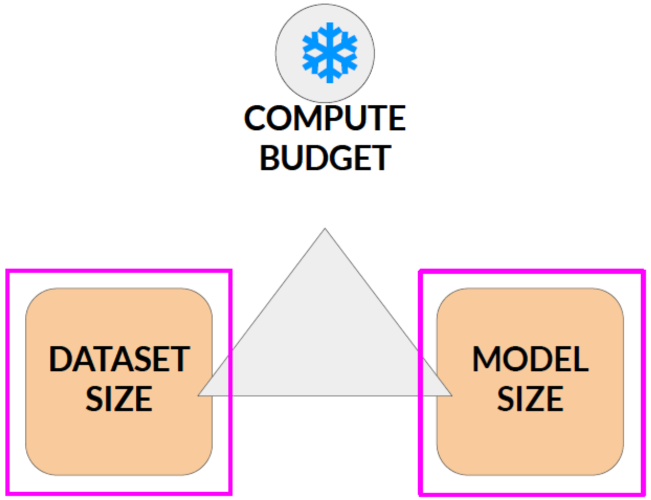
GPT-3 paper reference

Number of petaflop/s-days to pre-train various LLMs

Chinchilla Scaling Laws

- **Compute optimal training data size is ~20x number of parameters**
- Very large models may be over-parameterized and under-trained.

Chinchilla Paper



Model	#Params	Compute Optimal (# of tokens) ~ 20X	Actual Tokens
Chinchilla	70B	~1.4T	1.4T
Llama-65B	65B	~1.3T	1.4T
Falcon-40B	40B	~0.8T	1T
Bloomberg-GPT	50B	~1T	700B
GPT-3	175B	~3.5T	300B
Bloom	176B	~3.5T	350B
OPT-175B	175B	~3.5T	180B

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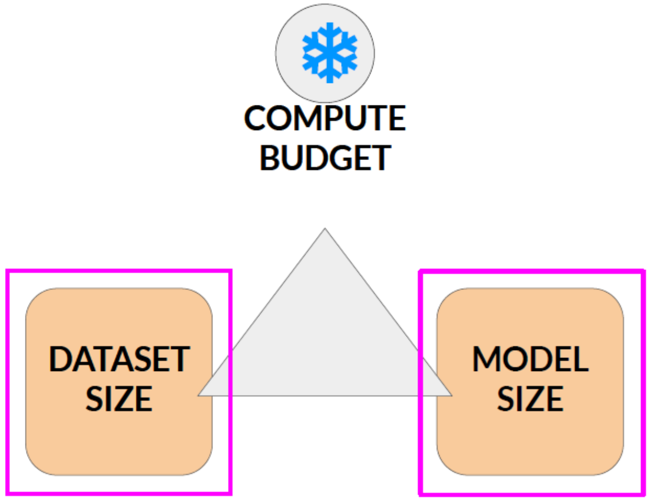

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Over-parameterized & under-trained

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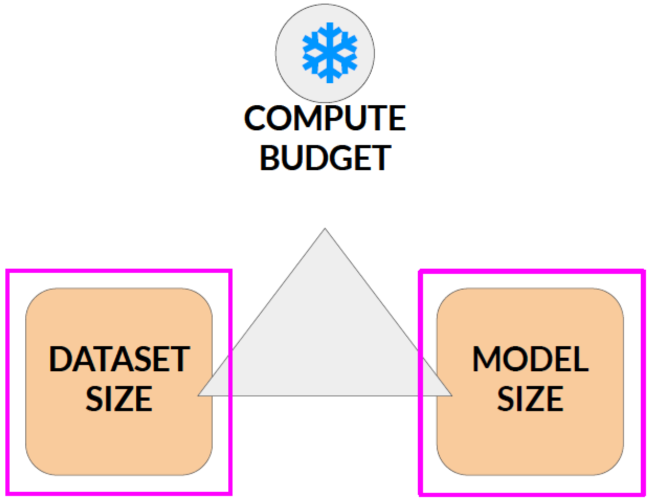

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Under-parameterized

Training Models to follow instructions

Instruction Following Models

Multi-task Instruction Finetuning from base models

https://ai.googleblog.com/2021/10/introducing-flan-more-generalizable.html

Instruction Following Models

Base Model	Instruction Models	Finetuning ?	Dataset (Task)
T5-XXL	FLAN T5-XXL	SFT	FLAN – 1836 tasks, 15M pairs
Falcon-40B	Falcon-40B-Instruct	SFT	Baize – 100K pairs
Llama2-70B	Llama2-70B-Chat	RLHF	27.5K pairs, 2.9M pairs
GPT-3.5	Chat-GPT	RLHF	------
PALM	Flan-PALM	SFT	FLAN – 1836 tasks, 15M pairs
Pythia	Dolly	SFT	Dolly – 15K pairs
Llama-13B	Alpaca-13B	SFT	GPT3 – 52K pairs
Llama-13B	Vicuna-13B	SFT	GPT-4 – 70K pairs
Llama-13B	Koala-13B	SFT	Public Dialogues - 500K pairs

Instruction Following Models

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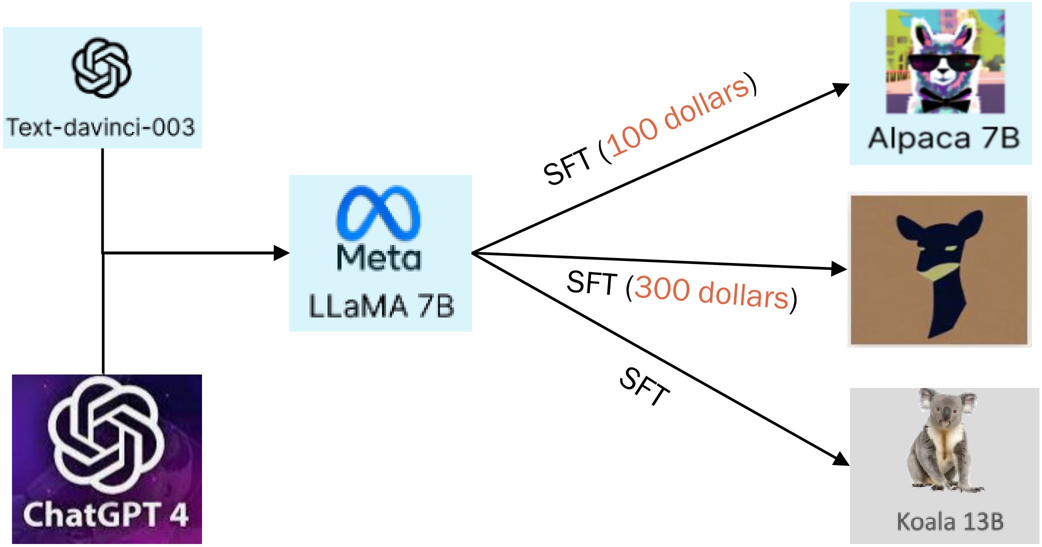
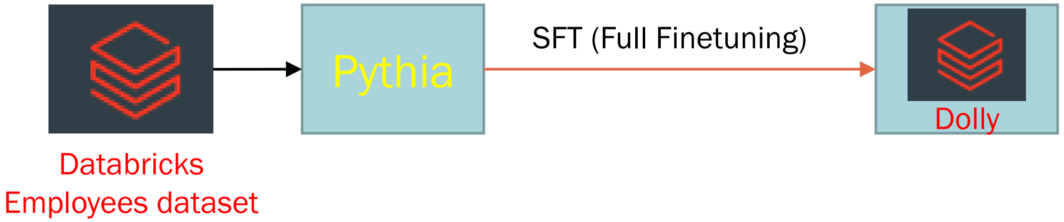
Imitating Models

Imitating Models





[The False Promise of Imitating Proprietary LLMs]

[Alpaca reference]
[Vicuna reference]
[Koala reference]
[Dolly reference]

Finetuning for Single Use-case

Why ? Need ?

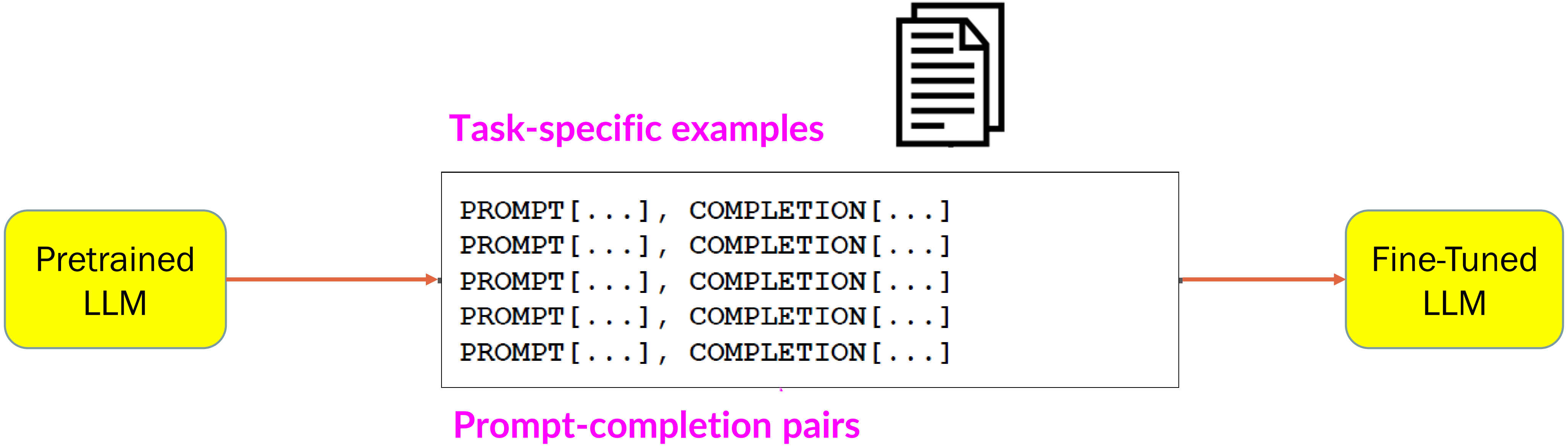
1. Fine-tuning can significantly increase the performance of a model on a specific task.
   - but can lead to reduction in ability on other tasks. Phenomenon called catastrophic forgetting

     Who cares ? use-case solved. (Generalist vs Specialist)

2. Examples take up space in the context window.
   - Less space for new tokens generated.
   - Larger prompts leads to slow inferencing. Show Llama-2-70B-Chat model as example

3. In-context learning may not work for smaller models.

Full Finetuning aka SFT

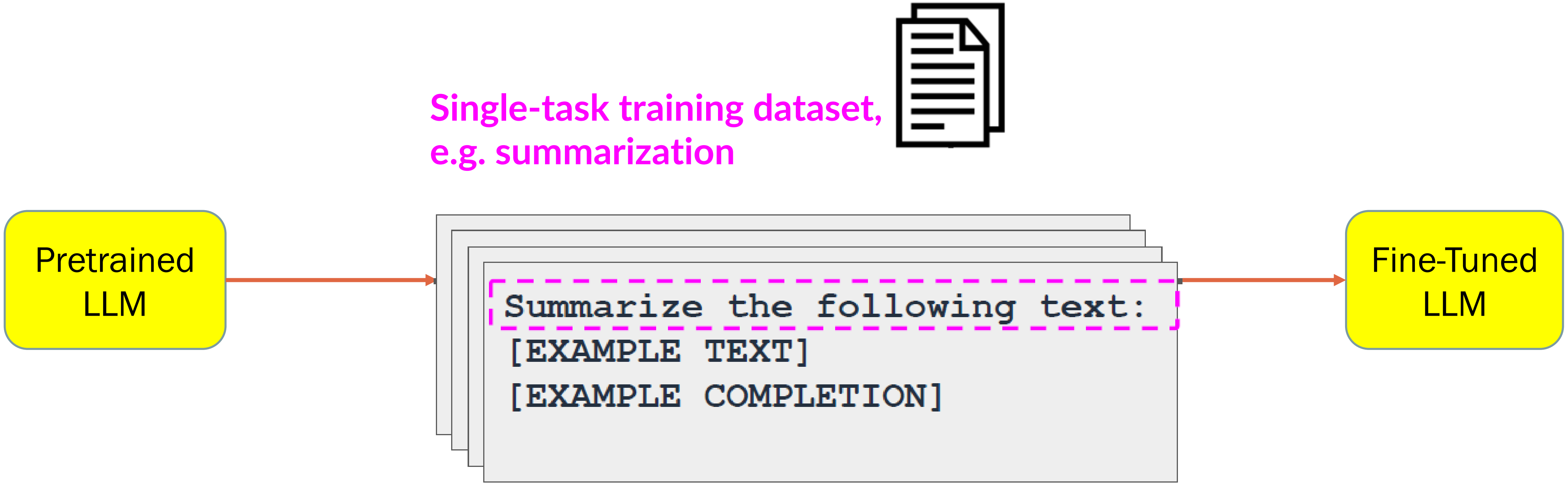


Loss: Cross-Entropy

<u>Issues</u>:
- Catastrophic forgetting
- Hyperparameter optimization
  - ➢ Overfitting
- Compute Cost (Budget)
  - ➢ 7B param updated

Use instruction models.

Full Finetuning aka SFT



500-1000 examples needed to fine-tune a single task

Loss: Cross-Entropy

Issues:
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  - Overfitting
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Use instruction models.

Full Finetuning aka SFT

Pretrained LLM

```
PROMPT[...], COMPLETION[...]
PROMPT[...], COMPLETION[...]
PROMPT[...], COMPLETION[...]
PROMPT[...], COMPLETION[...]
PROMPT[...], COMPLETION[...]
```

Training

```
PROMPT[...], COMPLETION[...]
...
```

Validation

```
PROMPT[...], COMPLETION[...]
...
```

Test

Prepared instruction dataset

Fine-Tuned LLM

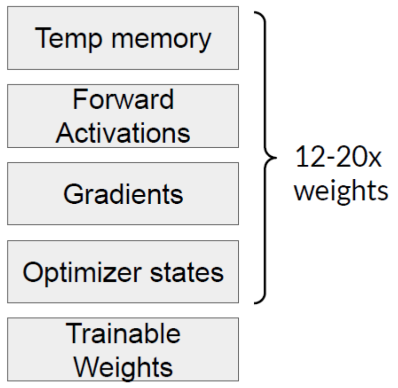
Issues:

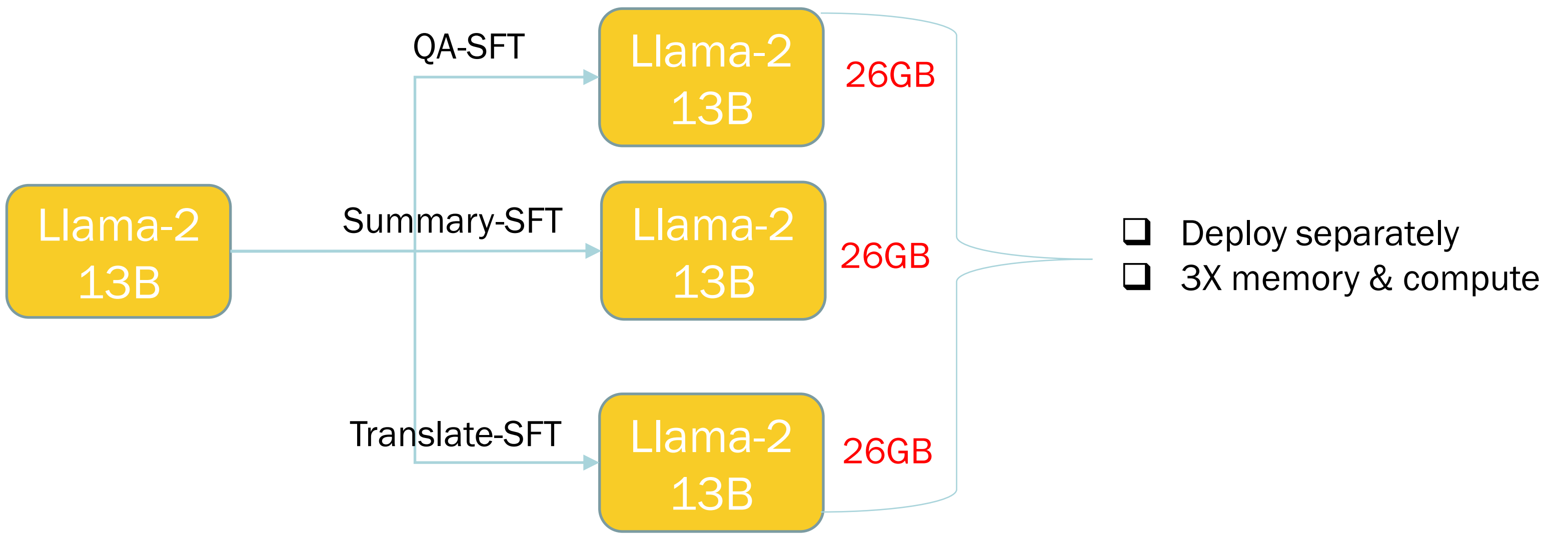
- Catastrophic forgetting
- Hyperparameter optimization
  - Overfitting
- Compute Cost (Budget)
  - 7B param updated

Use instruction models.

Parameter Efficient Finetuning (PEFT)

- Less prone to catastrophic forgetting – **Frozen Weights**
- Full fine-tuning of large LLMs is challenging – **Compute budget**
- Full fine-tuning creates full copy of original LLM per task - **Inefficient**
- PEFT fine-tuning saves space and is flexible





Full fine-tuning

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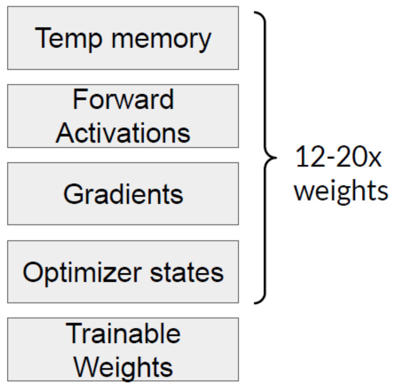
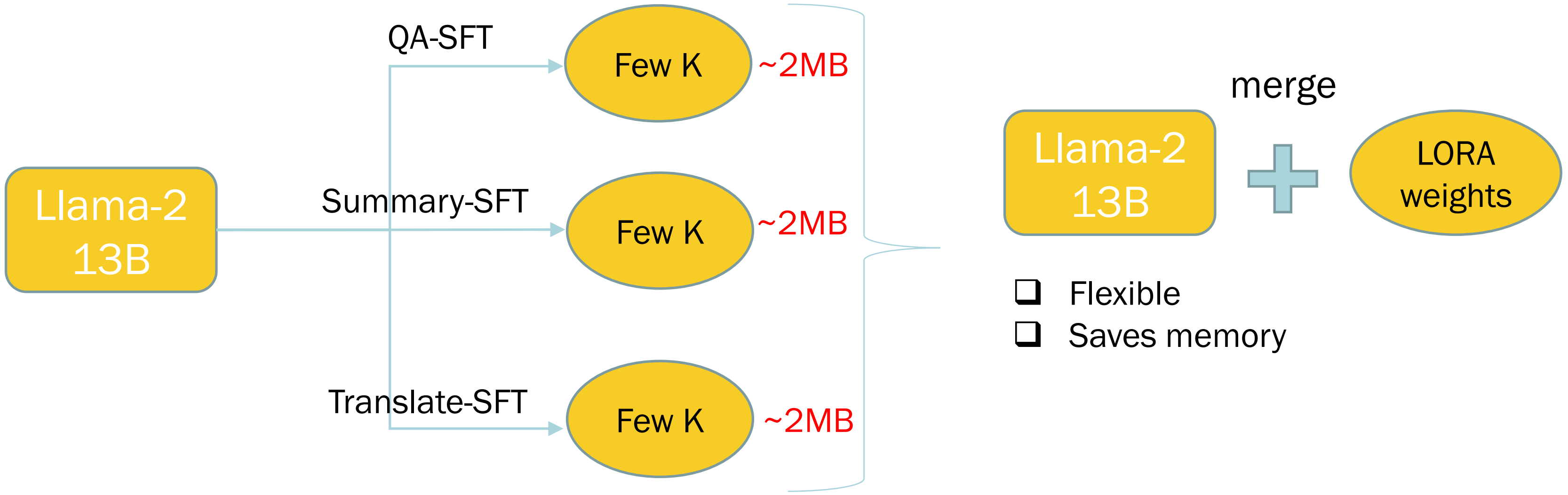




Parameter Efficient Finetuning

Low Rank Adaption (LORA)

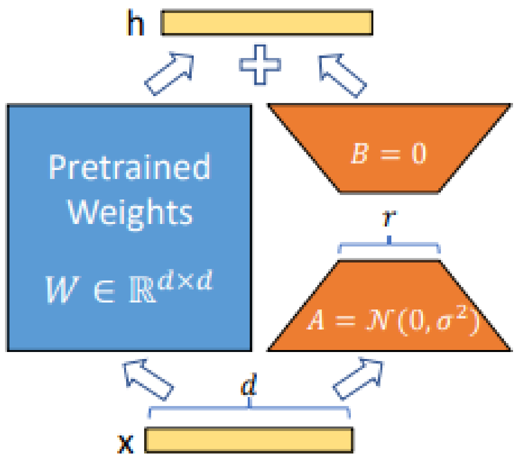


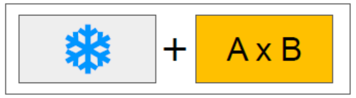
Figure 1: Our reparametrization. We only train A and B.

1. Freeze most of the original LLM weights.
2. Inject 2 **rank decomposition matrices**
3. Train the weights of the smaller matrices

Steps to update model for inference

1. Matrix multiply the low rank matrices

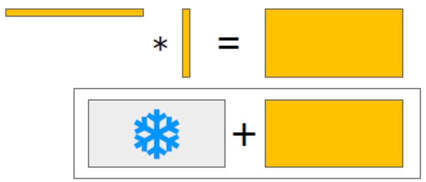
2. Add to original weights



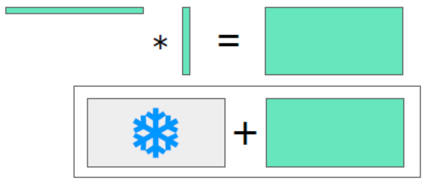
Advantage (Rank=8)
512X64 = 32,768 params
512 x 8 = 4,096 (A)
8 x 64 = 512 (B)
86% reduction in params

1. Train different rank decomposition matrices for different tasks
2. Update weights before inference

Task A

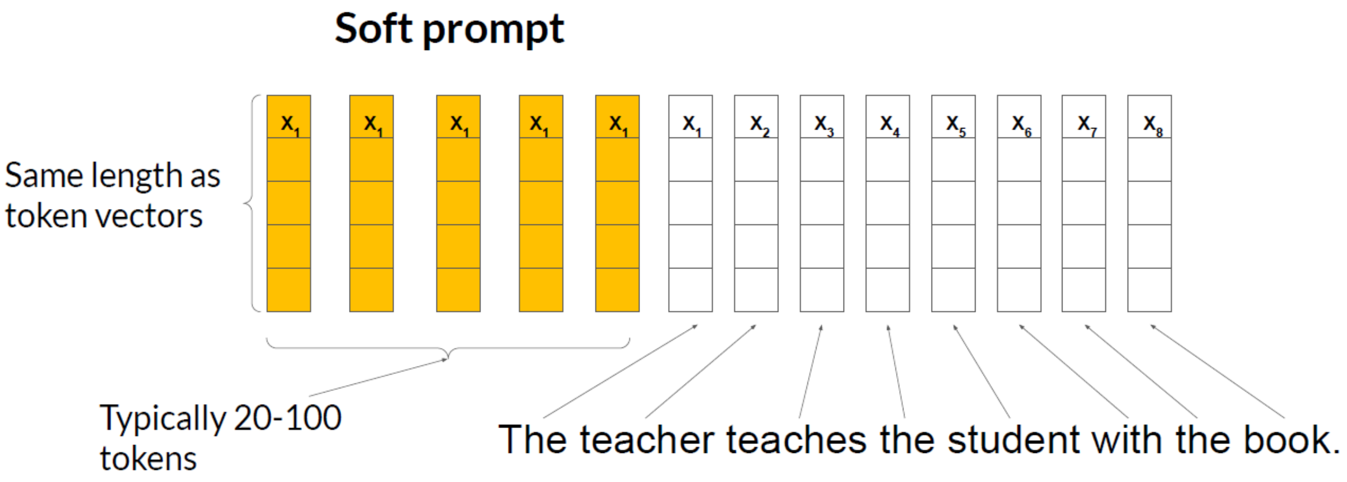


Task B



[LORA paper reference]

Prompt Tuning



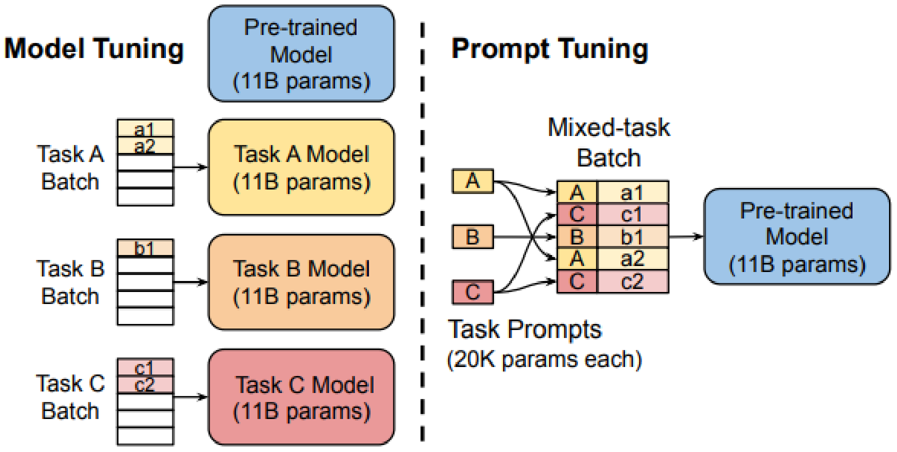
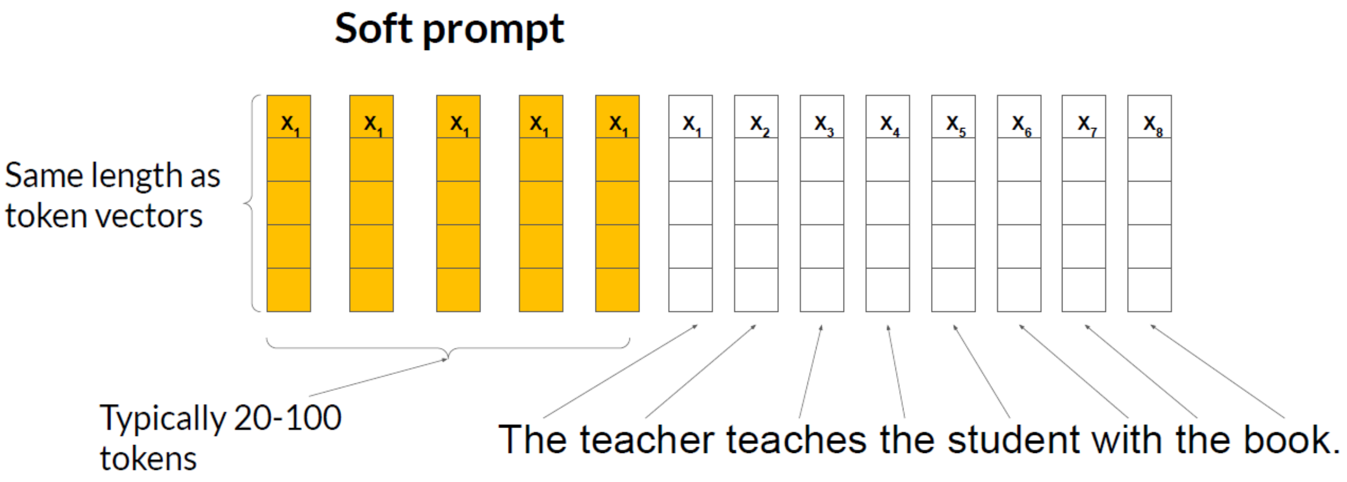


Figure 2: **Model tuning** requires making a task-specific copy of the entire pre-trained model for each downstream task and inference must be performed in separate batches. **Prompt tuning** only requires storing a small task-specific prompt for each task, and enables mixed-task inference using the original pre-trained model. With a T5 "XXL" model, each copy of the tuned model requires 11 billion parameters. By contrast, our tuned prompts would only require 20,480 parameters per task—a reduction of *over five orders of magnitude*—assuming a prompt length of 5 tokens.

 [Prompt-Tuning paper reference]

Prompt Tuning



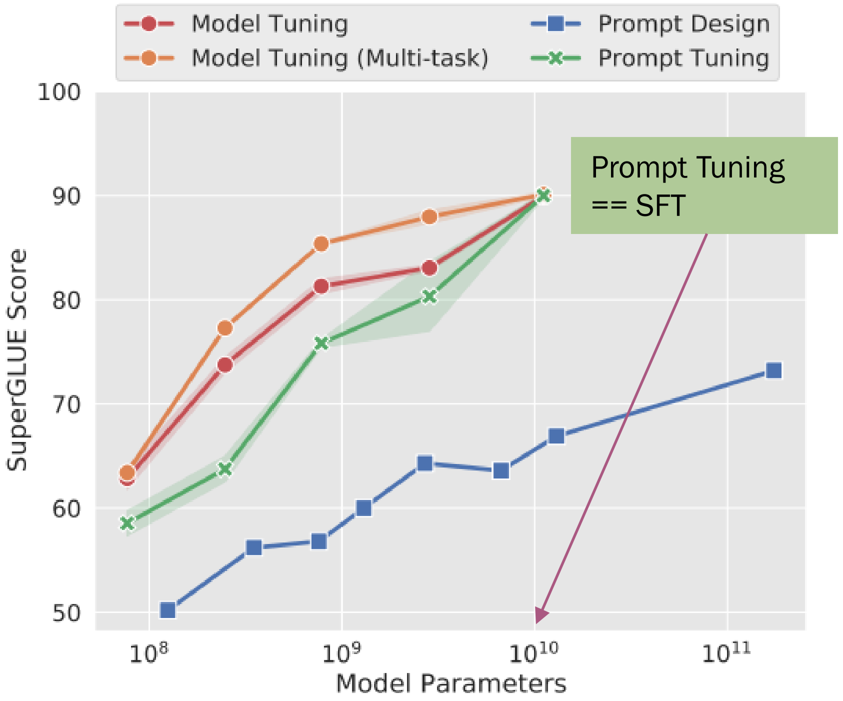


Figure 1: Standard **model tuning** of T5 achieves strong performance, but requires storing separate copies of the model for each end task. Our **prompt tuning** of T5 matches the quality of model tuning as size increases, while enabling the reuse of a single frozen model for all tasks. Our approach significantly outperforms few-shot **prompt design** using GPT-3. We show mean and standard deviation across 3 runs for tuning methods.

 Prompt-Tuning paper reference

Guidelines: Finetuning for Use-case

Use instruct models for Finetuning for single task.

Example, Llama-chat. FLAN-T5 (not base models)

Use PEFT techniques, oppose to Full Finetuning

Example: Plug LORA adapters for specific use-case

Do not go for Full Finetuning. Finding right hyperparameter is difficult.

Unless you have the **compute budget** and **lot of training data**.

Quality of training data is very important

Research proves high quality datasets performs well even if quantity is less.

Thank you