Large Language Models

(Part 2)

April 14, 2026

Plan for today

- **Review of last class:** introduction to large language models (LLMs)
- **Our goals today:**
  - What is fine-tuning in LLMs, and what can it be used for?
  - What are popular approaches to fine-tune a pre-trained LLM model?
  - How do we fine-tune an LLM model in python?

Review: Introduction to LLMs and ChatGPT

Core elements of LLMs/ChatGPT Development

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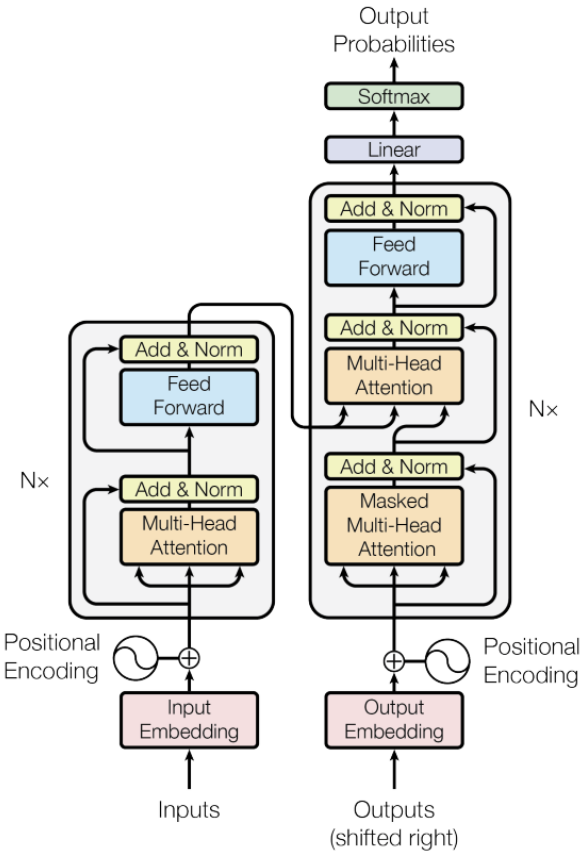
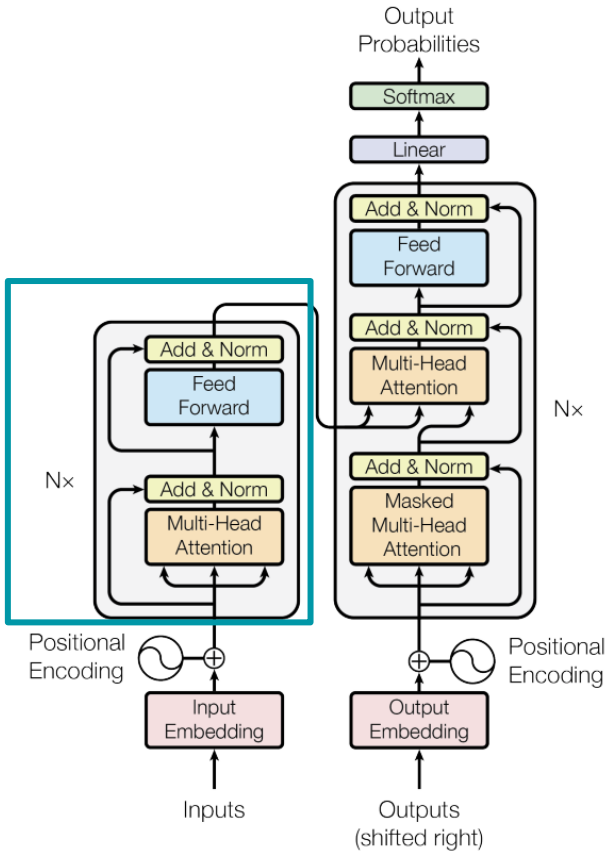
Transformer Architecture



Transformer Architecture

Encoder
[Learnt Representation or Embedding]



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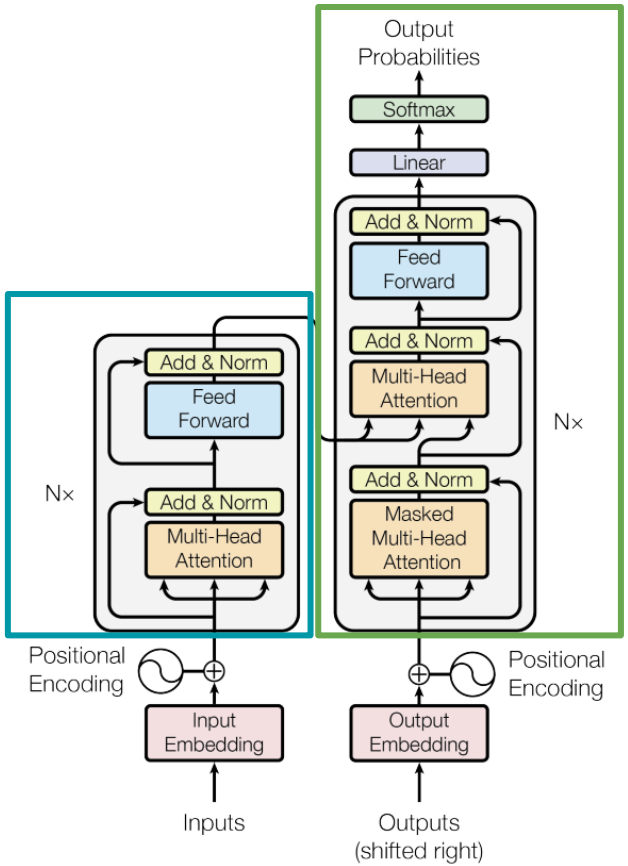

Decoder
[Generation]

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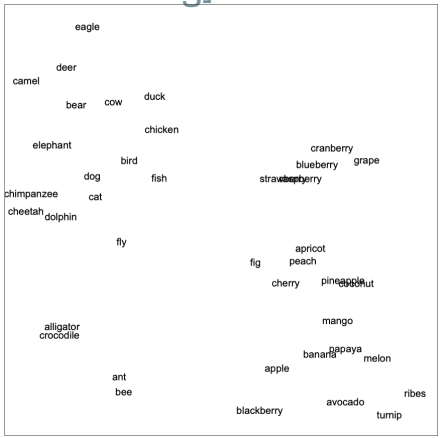
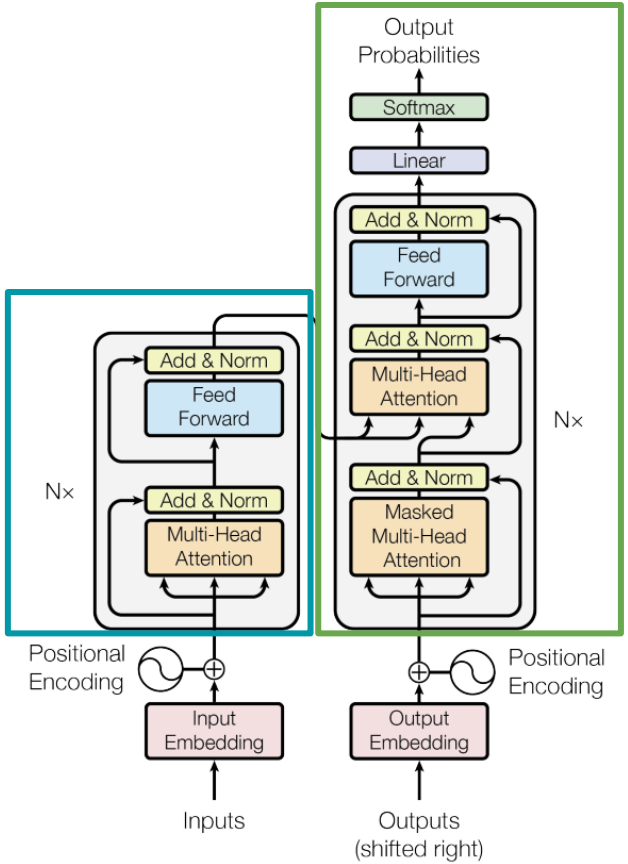


Example of learnt embeddings from encoder



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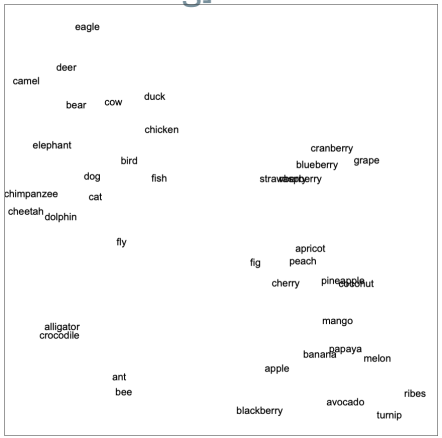

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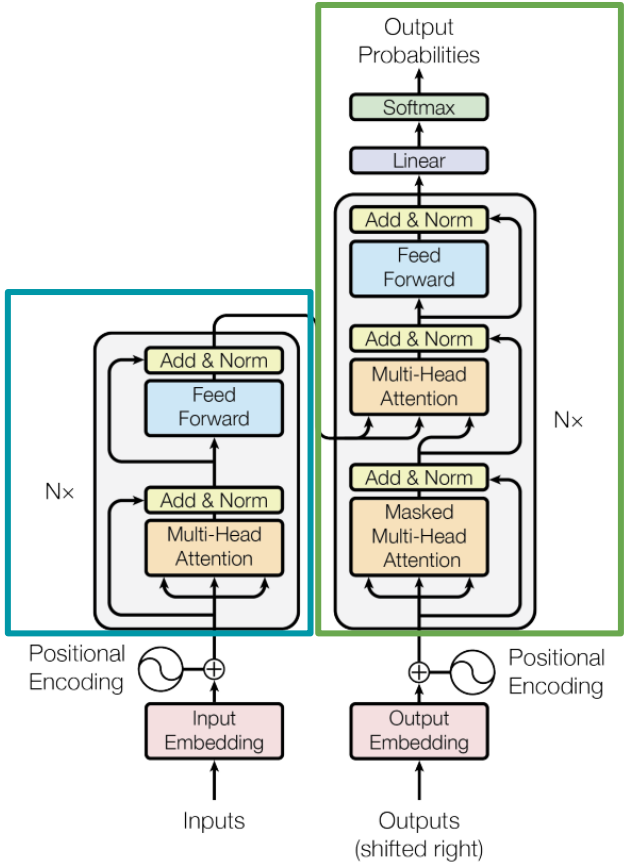

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[Generation]

The best thing about AI is its ability to

learn	4.5%
predict	3.5%
make	3.2%
understand	3.1%
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Example output of decoder

Transformer Architecture

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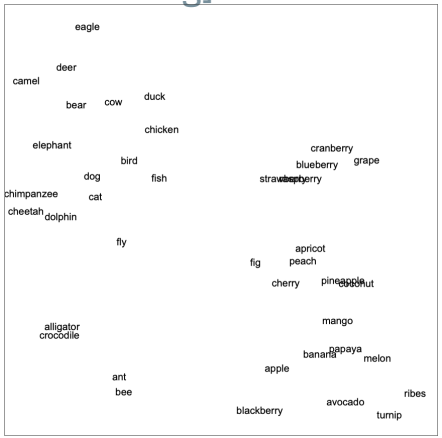

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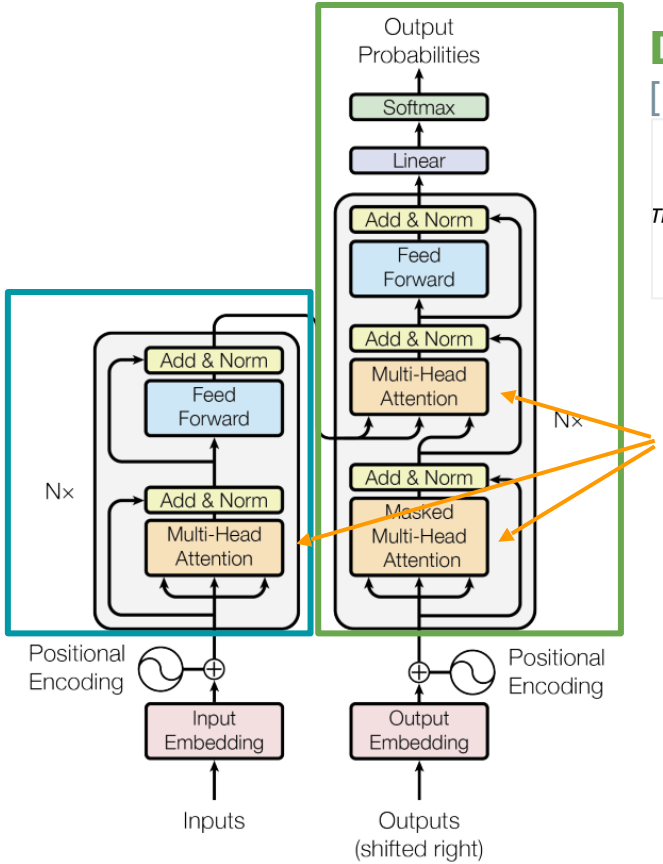

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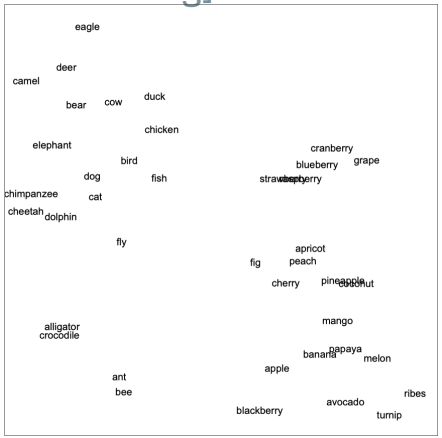

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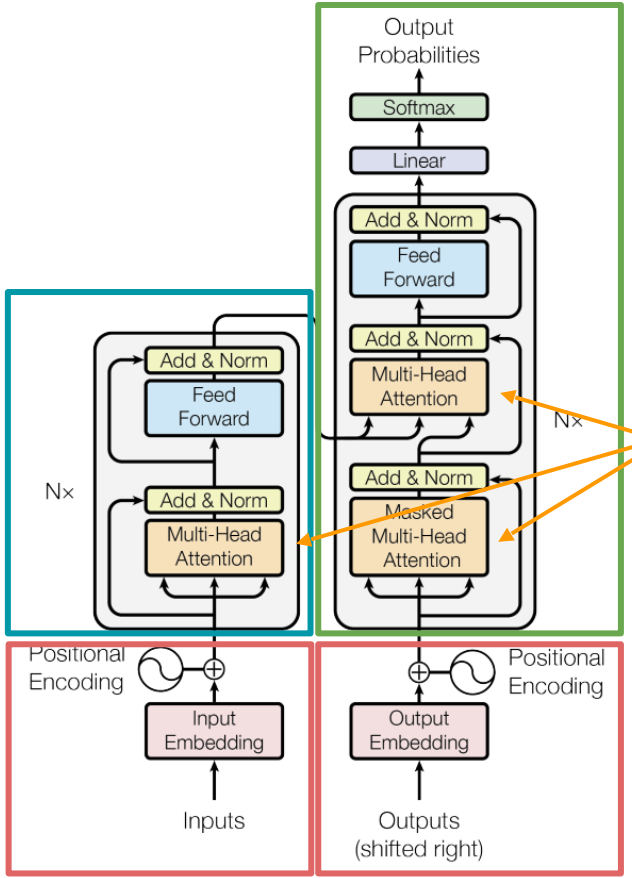

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Text-to-numeric processing

[Token-value + Token-position embeddings]

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Fine-Tuning

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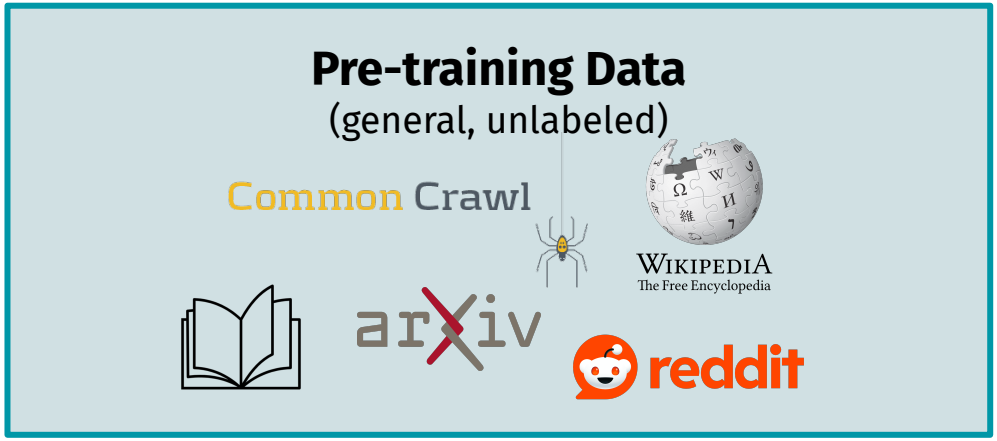

Fine Tuning Data
(specialized, high-quality)

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- **Example use cases for fine-tuning:**
  - *Application areas:* legal documents, medical reports, sports analytics, company data, …
  - *Types of tasks:* custom chatbots, translation, summarization, sentiment analysis, various classification/regression tasks, …

Main approaches for fine-tuning

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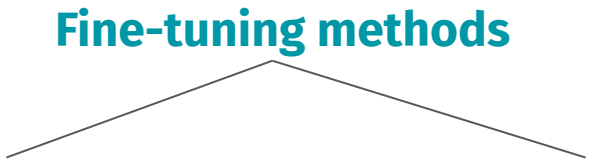

Supervised fine-tuning (SFT)

use labeled data (e.g., prompt-response pairs) from a specific task/domain to adjust the learned weights in the model

Reinforcement learning with human feedback (RLHF)

use human feedback to adjust the weights in the model

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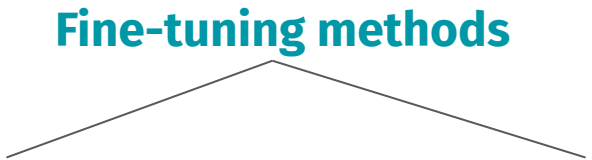

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- What data to use?
- How do we adjust the weights?

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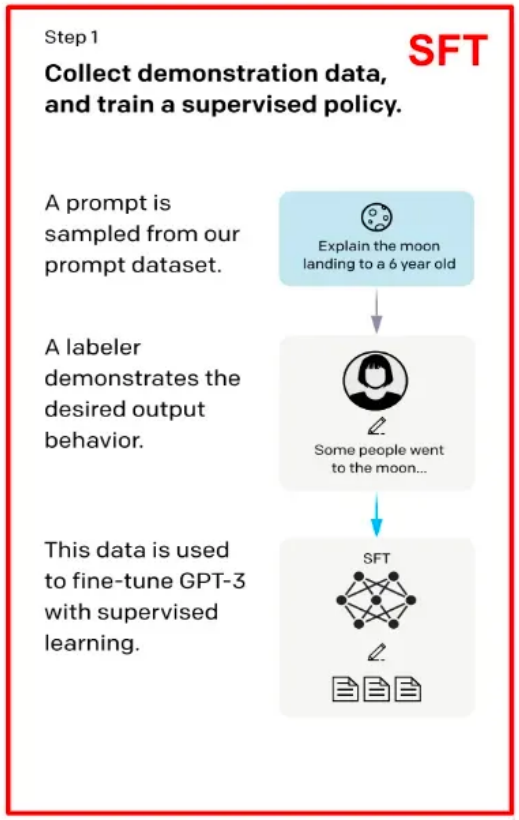

Figure source: Ouyang et al. (2022)

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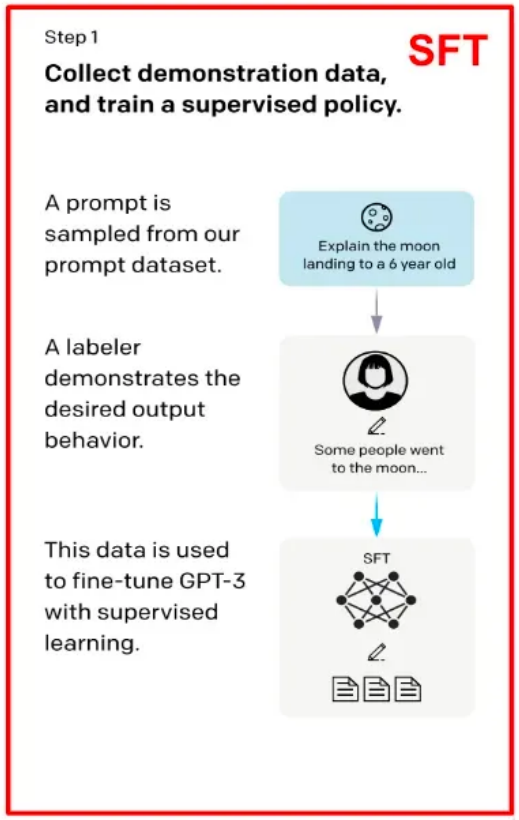

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- Text/sequence classification (e.g., Yelp, movie reviews)

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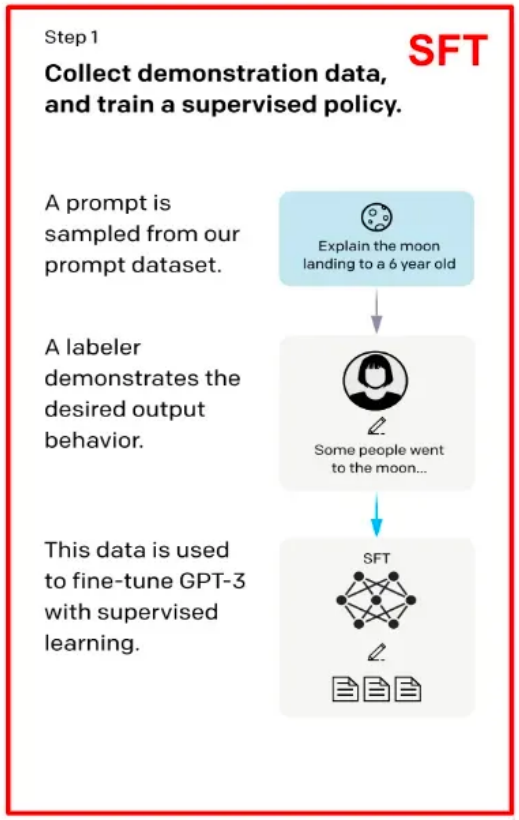

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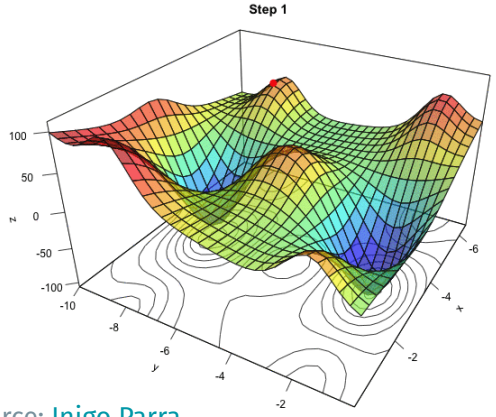

Figure source: Inigo Parra

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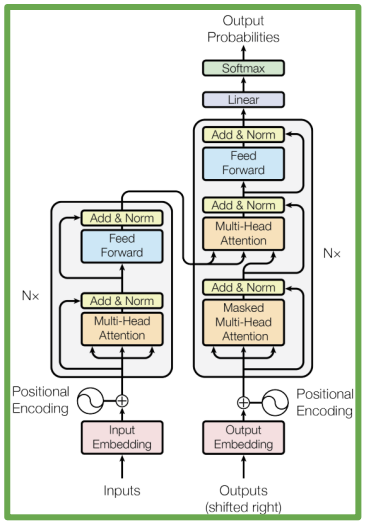

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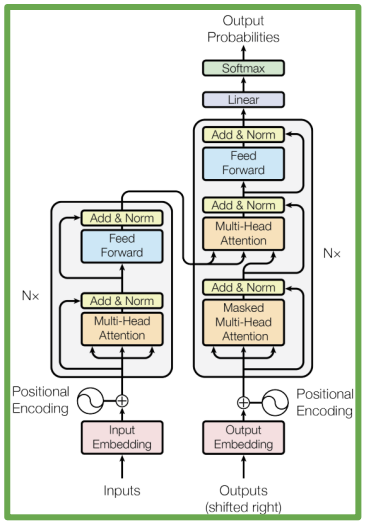

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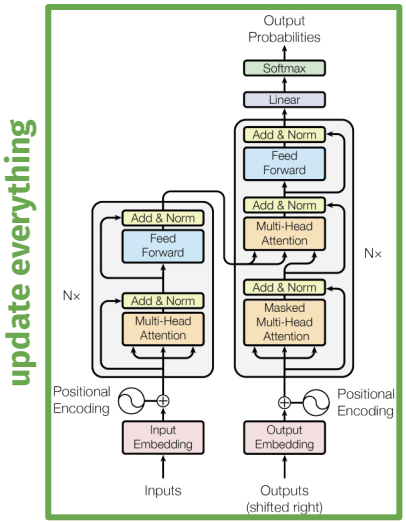

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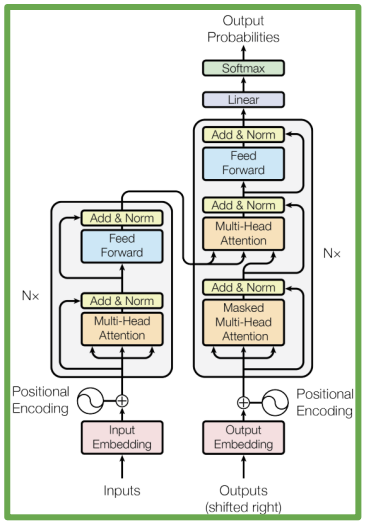

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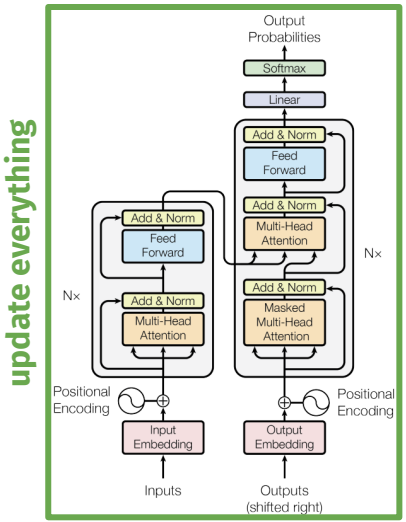

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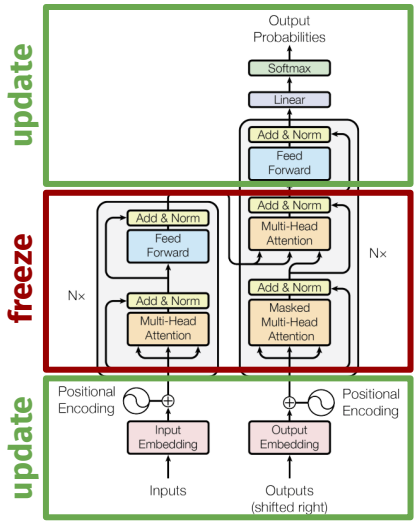

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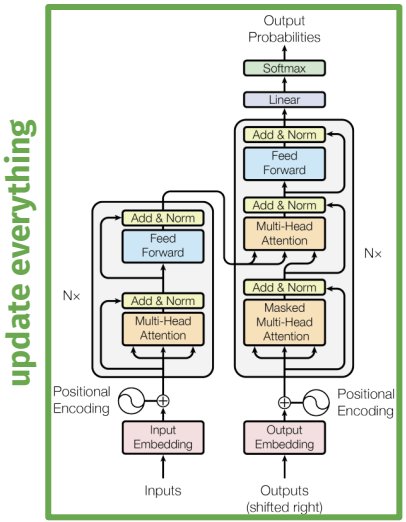

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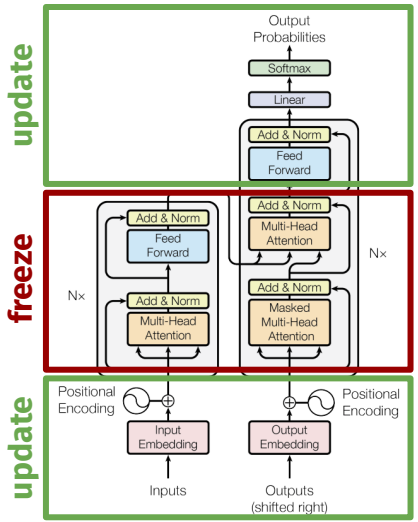

Additive/adapters

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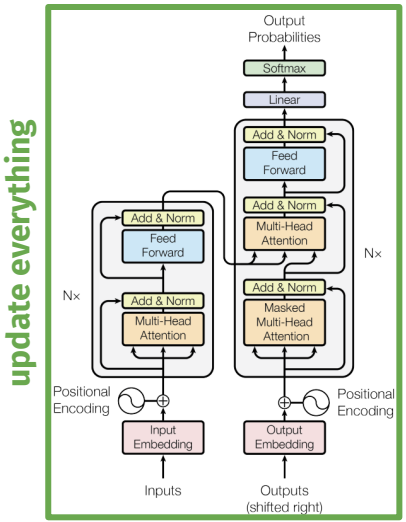

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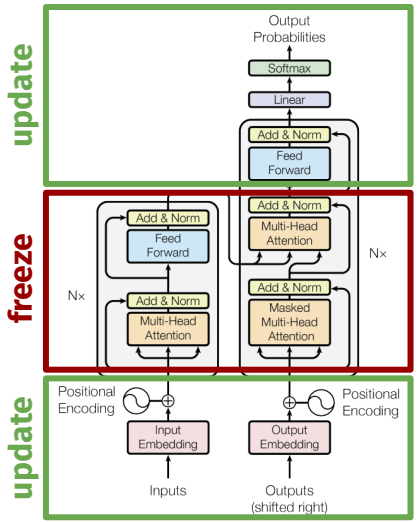

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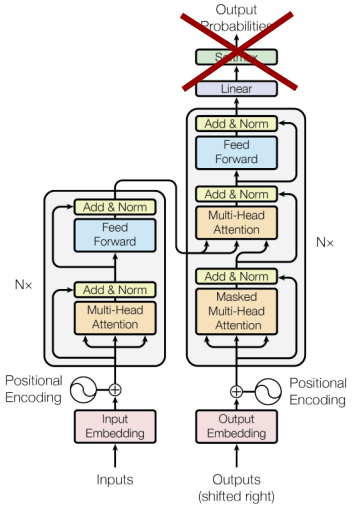

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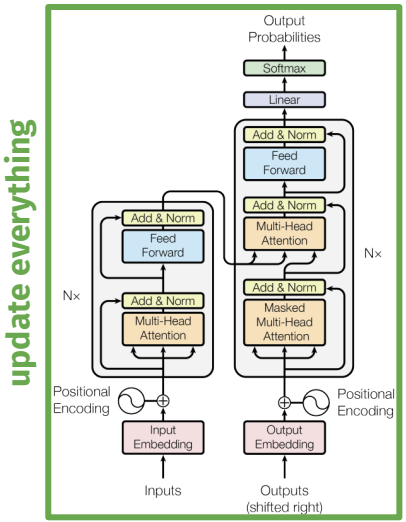

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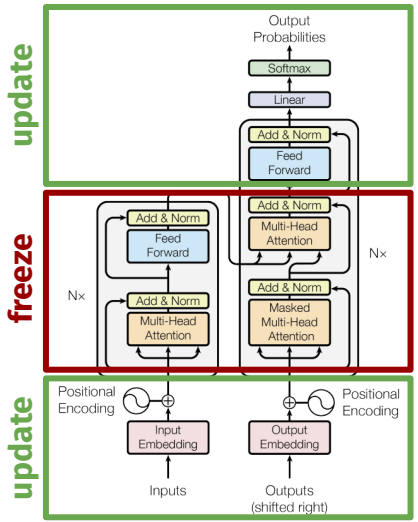

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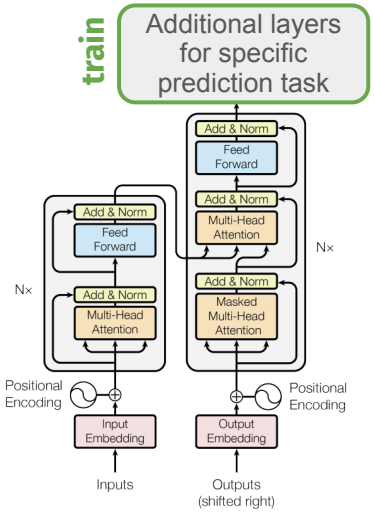

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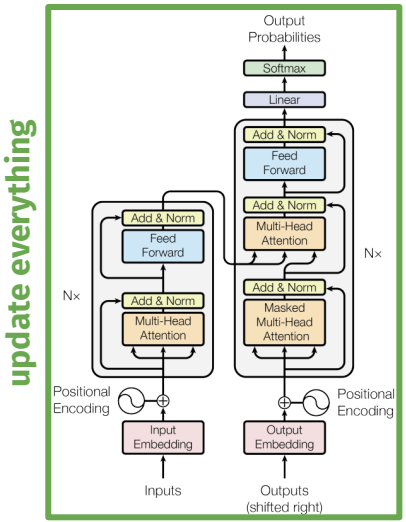

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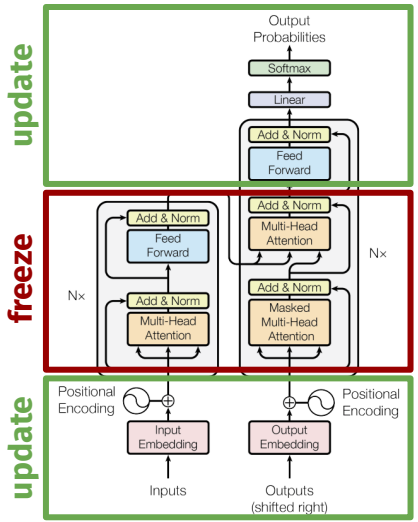

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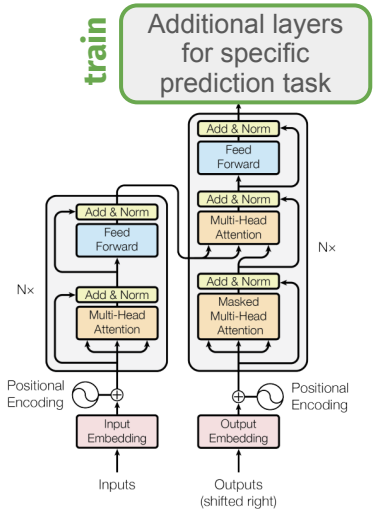

Reparameterization
reparameterize weights to reduce number of parameters that need to be learned/updated

Reparameterized PEFT

Low-Rank Adaptation (LoRA): a popular way to reparameterize weights in SFT

- Reduces number of parameters to train by only allowing for **low-rank** updates to the original network weights (often applied to weights in attention or feed-forward layers)

Figure source: Dasha Herrmannova (2024)

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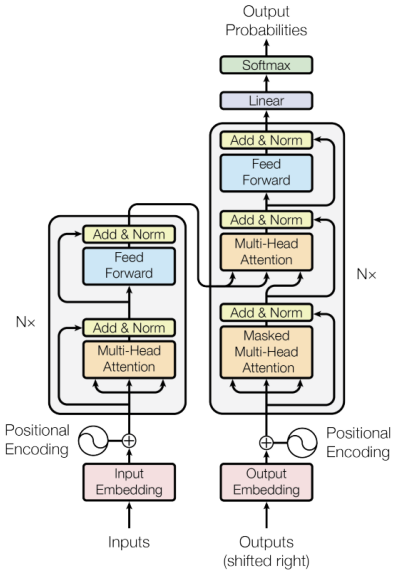

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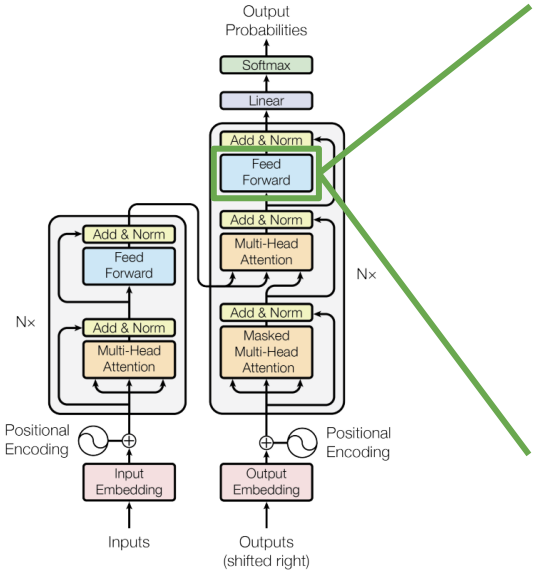

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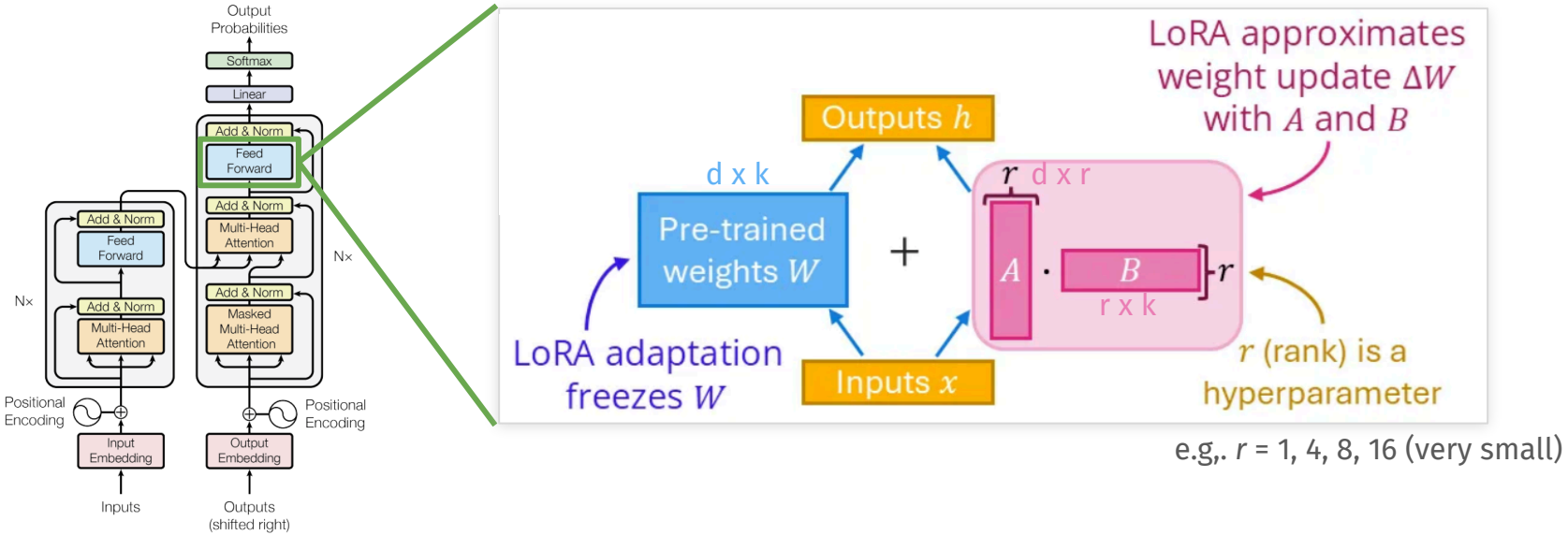

e.g,. r = 1, 4, 8, 16 (very small)

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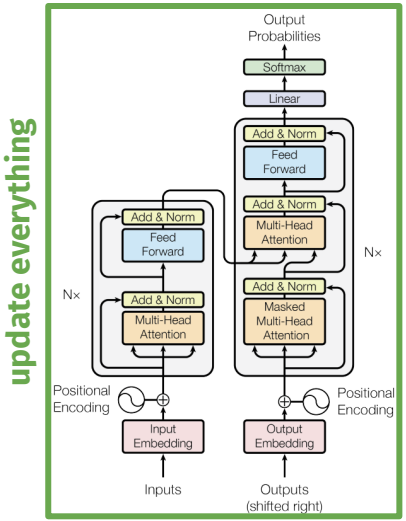
How do we update the model weights when fine-tuning?

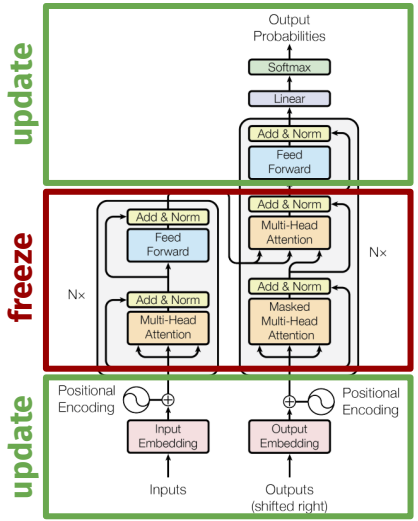
Full fine-tuning
(Update all model parameters)

Downsides: "catastrophic forgetting" (may forget how to do general tasks), requires huge amounts of memory

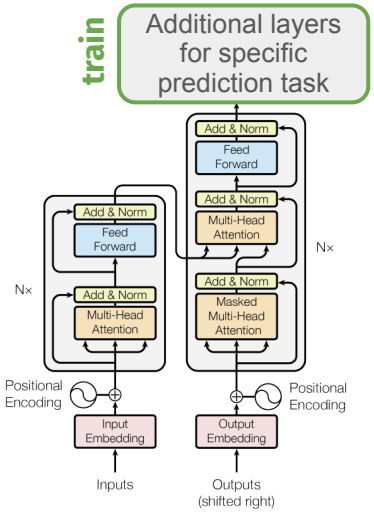


Parameter-efficient fine-tuning (PEFT)
(Partially update model parameters)

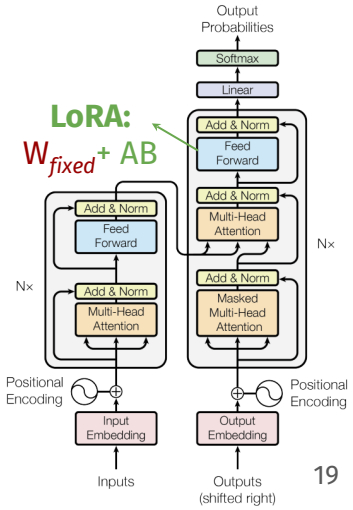
Selective
update subset of original LLM parameters; freeze all others



Additive/adapters
add new trainable components on top of base pre-trained LLM



Reparameterization
reparameterize weights



Supervised fine-tuning in action using **huggingface**

Huggingface: open-source library with pre-trained models

- **Transformers Library**
  - Pre-trained models for NLP tasks (e.g., BERT, GPT, T5, RoBERTa) [https://huggingface.co/models]
  - Easy-to-use APIs for model loading, fine-tuning, and prediction (inference)
- **Datasets Library**
  - Provides easy access to thousands of public datasets
  - Built-in support for data loading, preprocessing, and transformation
- **Tokenizers Library**
  - A fast and efficient library for text tokenization, optimized for performance
  - Supports parallel tokenization
- **Tutorial notebooks:** https://huggingface.co/docs/transformers/main/en/notebooks

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Go to: https://colab.research.google.com/github/tiffanymtang/dsip-s26/blob/main/course_materials/llms/llm_fine_tuning.ipynb

Main approaches for fine-tuning

Supervised fine-tuning (SFT)

use labeled data (e.g., prompt-response pairs) from a specific task/domain to adjust the learned weights in the model

Reinforcement learning with human feedback (RLHF)

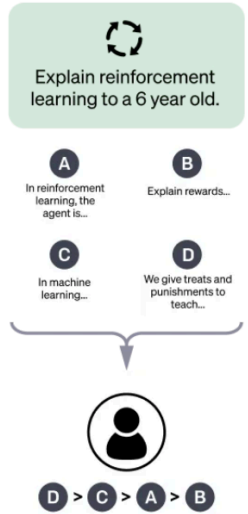
use human feedback to adjust the weights in the model

Reinforcement learning with human feedback

Given pre-trained model:

1. Collect human feedback

A prompt and several model outputs are sampled.



A labeler ranks the outputs from best to worst.

Figure source: Ouyang et al. (2022)

Reinforcement learning with human feedback

Given pre-trained model:

1. Collect human feedback
2. Train reward model to mimic human preferences

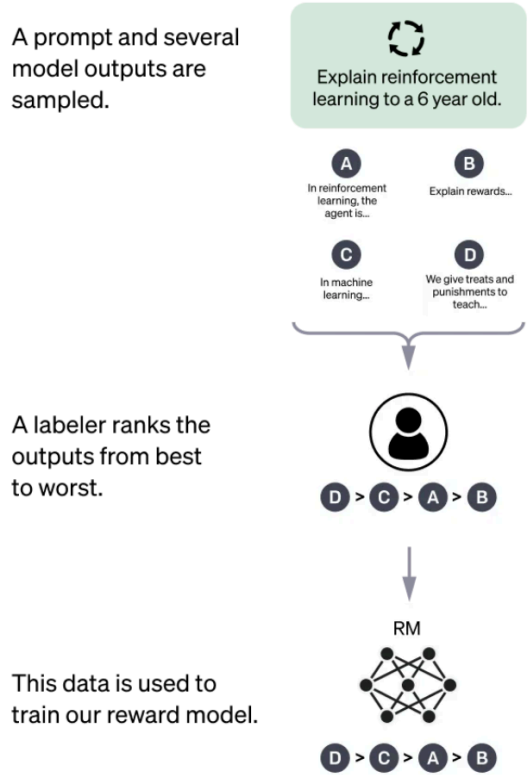


Figure source: Ouyang et al. (2022)

Reinforcement learning with human feedback

Given pre-trained model:

1. Collect human feedback
2. Train reward model to mimic human preferences
3. Fine-tune model using reinforcement learning
    a. Feed training samples through model

A new prompt is sampled from the dataset.

Figure source: Ouyang et al. (2022)

Reinforcement learning with human feedback

Given pre-trained model:

1. Collect human feedback
2. Train reward model to mimic human preferences
3. Fine-tune model using reinforcement learning
    a. Feed training samples through model
    b. Model generates outputs

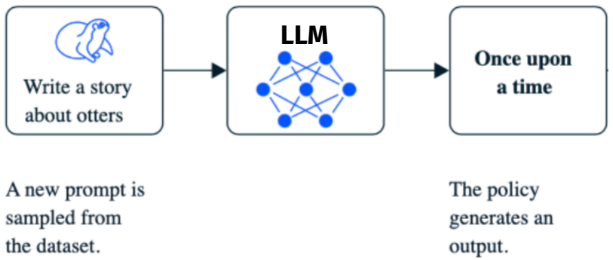


Figure source: Ouyang et al. (2022)

Reinforcement learning with human feedback

Given pre-trained model:

1. Collect human feedback
2. Train reward model to mimic human preferences
3. Fine-tune model using reinforcement learning
    a. Feed training samples through model
    b. Model generates outputs
    c. Outputs get scored by reward model

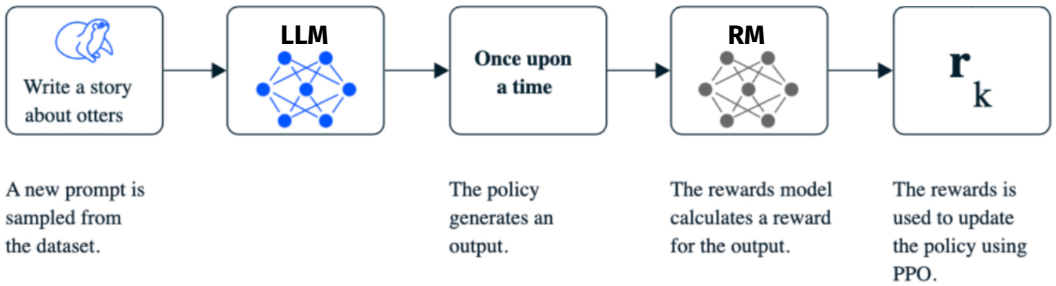


Figure source: Ouyang et al. (2022)

Reinforcement learning with human feedback

Given pre-trained model:

1. Collect human feedback
2. Train reward model to mimic human preferences
3. Fine-tune model using reinforcement learning
    a. Feed training samples through model
    b. Model generates outputs
    c. Outputs get scored by reward model
    d. Update model to maximize reward

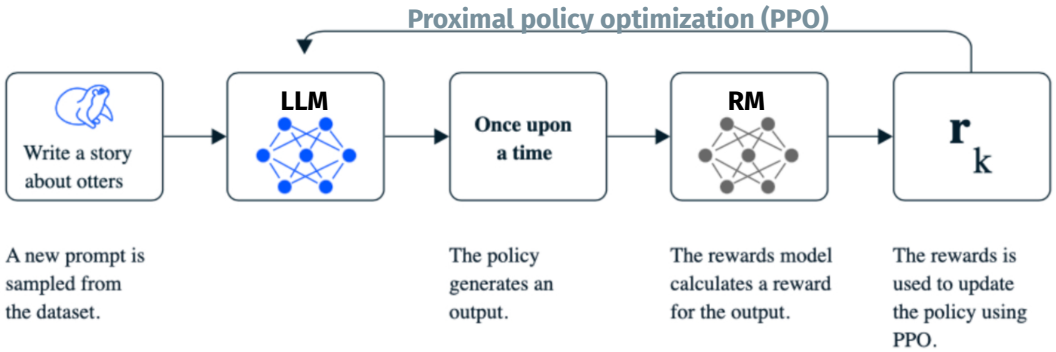


Figure source: Ouyang et al. (2022)

Summary

Summary and Next Time

- **Fine-tuning:** process of further training a language model for a specific task or domain ("specialized") using additional (generally high-quality) data
- **Main approaches for fine-tuning:**
  - *Supervised fine-tuning (SFT):* uses labeled (prompt-response) data
    - Can update weights completely, selectively, additively, or using low-rank adaptations
  - *Reinforcement learning with human feedback (RLHF):* uses human feedback
- Other approaches to improve LLMs: *prompt engineering*, *in-context learning*, and *RAG*