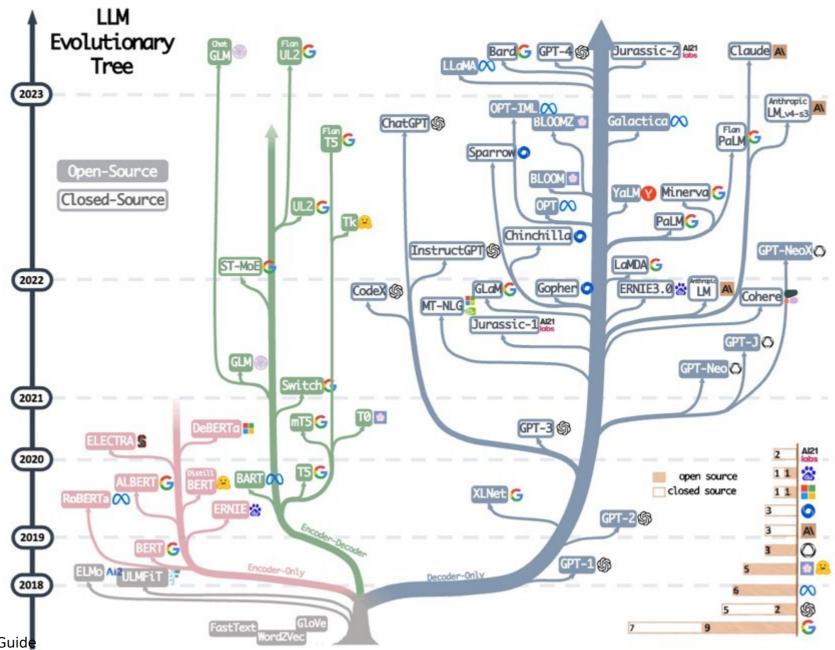
## Fine-Tuning LLMs

Customizing LLMs for your needs

**Ehsan Kamalinejad** 

#### LLMs

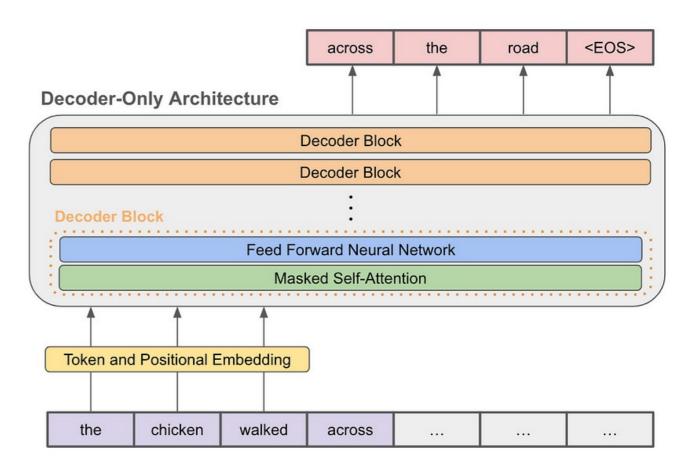
Modern language models are pretrained through selfsupervised learning methods such as MLM or CLM



Source: https://github.com/Mooler0410/LLMsPracticalGuide

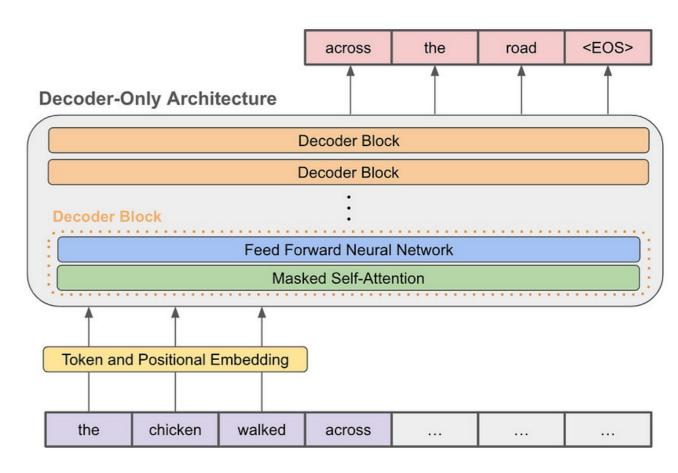
## Pretraining LLMs

 Most of the modern LLMs are pretrained through autoregressive next token prediction.



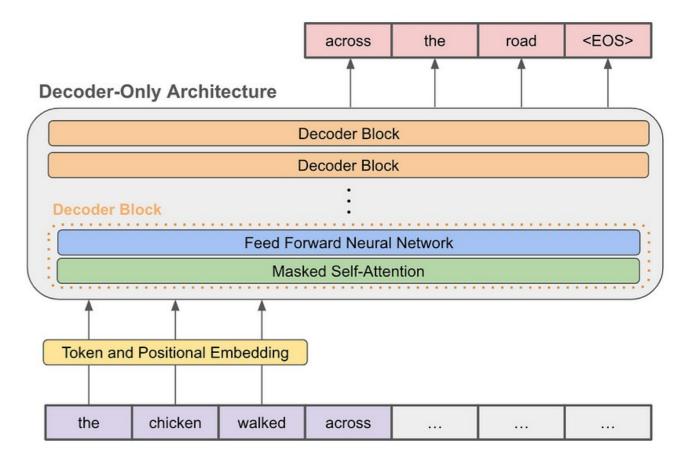
## Pretraining LLMs

- Most of the modern LLMs are pretrained through autoregressive next token prediction.
- This allows to train on any kind of text (language, code, tabular, etc.)
- The whole internet is your playground!



## Pretraining LLMs

- Most of the modern LLMs are pretrained through autoregressive next token prediction.
- This allows to train on any kind of text (language, code, tabular, etc.)
- The whole internet is your playground!
- The task is hard!



#### Foundational Models

- Foundational LLMs are pretrained on large data
- They are versatile and adaptable base for multiple purposes
- In their raw form they do not follow instruction or answer question
- While the knowledge is stored in them, one needs to extract it

Fine-Tuning LLN

To extract the knowledge stored in LLMs, one can do fine-tuning

Two main fine-tuning methods:

- Supervised Fine-Tuning (SFT)
- Reinforcement Learning with Human Feedback (RLHF)

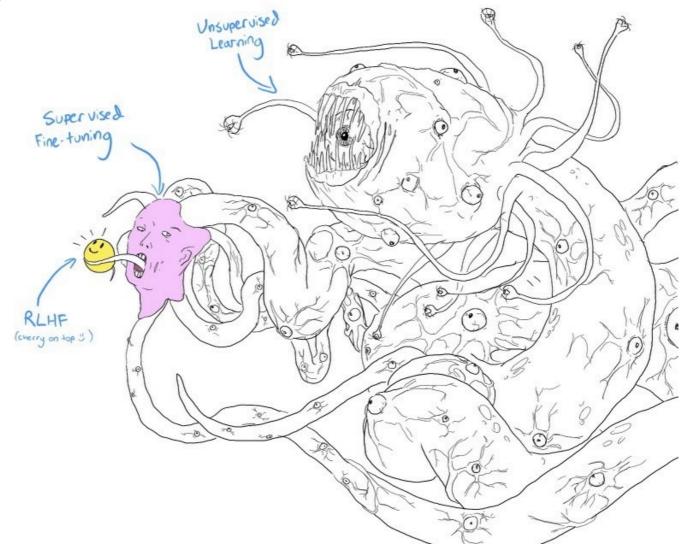
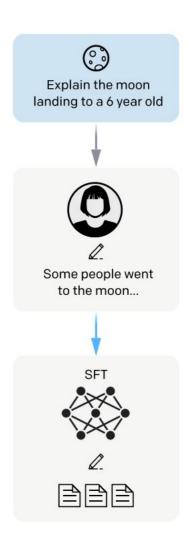


Image: Helen Toner Twitter

## Supervised Fine-Tuning

- Create a diverse prompt dataset compatible with your task
- Sample the prompt dataset
- Give sample prompts to labelers to create the desire output
- Fine-tune the base model with the queryresponse pairs



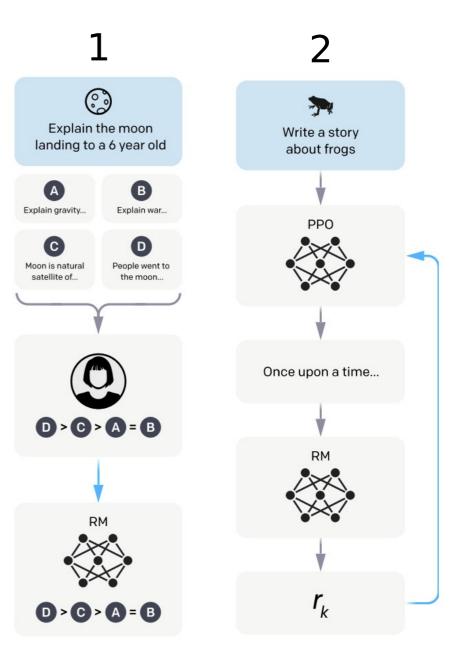
#### **RLHF**

#### 1. Train a reward model:

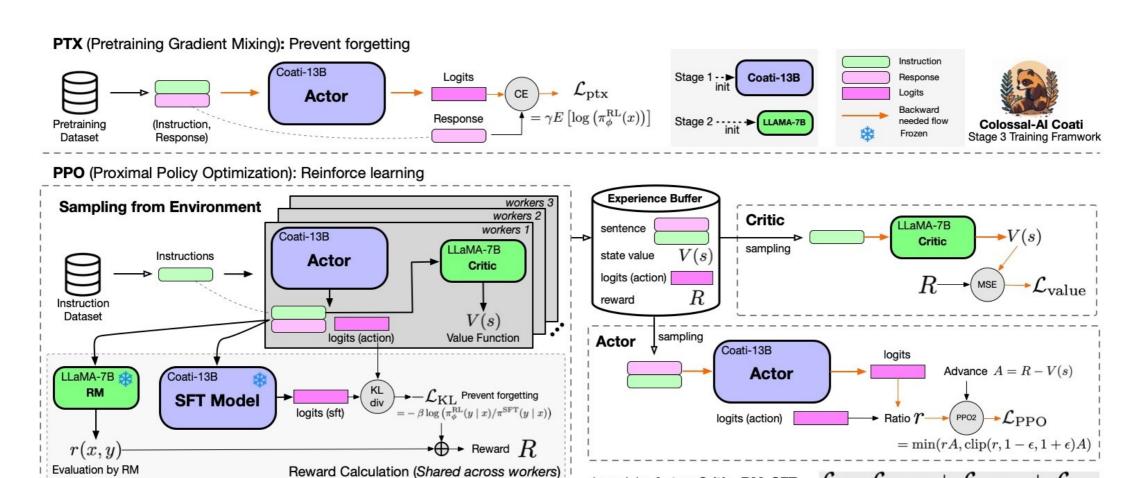
- Collect several responses to a query from the model
- Let the labeler rank the responses according to your definition of a better response
- Train a reward model that can estimate alignment of a response with your desire

#### 2. Train a policy model through PPO

 The reward model guides the base model through reinforcement learning (Proximal Policy Optimization)



#### **RLHF**



4 models: Actor, Critic, RM, SFT

 $\mathcal{L} = \mathcal{L}_{ ext{PPO}} + \mathcal{L}_{ ext{value}} + \mathcal{L}_{ ext{ptx}}$ 

It is harder to label data for SFT vs RLHF

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- RLHF data is collected online while SFT data is collected offline
- RLHF suffers less from "catastrophic forgetting"
- RLHF setup is a lot more complex compared to SFT

### Important Questions

- How much data is needed for SFT or RLHF on top of a foundational model?
- How much improvement one can get by doing domain/problem specialization?
- What are the scaling laws for fine-tuning?
- How effective are methods such as PEFT in fine-tuning?

# Thank you. Questions?