

# **Understanding Large Language Models**

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**Session 05: Finetuning & RLHF**

# Main learning goals

## 1. Recap

- model sizes, capabilities

## 2. Supervised Finetuning

- basic concepts, PEFT, LoRA, QLoRA, prompt tuning

## 3. Instruction Finetuning

- basic concepts

## 4. Recap: RL

- reinforcement learning

## 5. Learning from Humans...

- online vs. offline learning, quality signals

## 6. RLHF

- language models as policies, cutting the human out of the loop



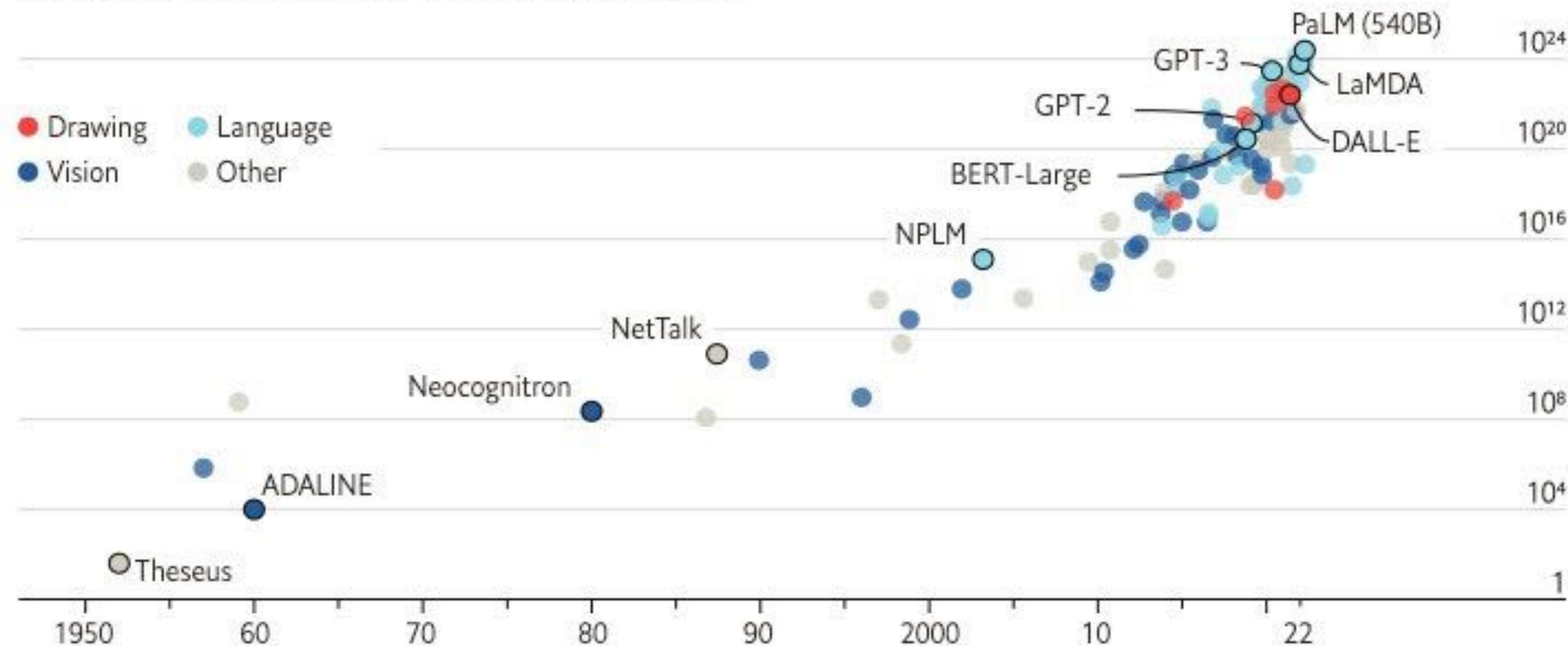
# Recap

# Larger and larger models

## The blessings of scale

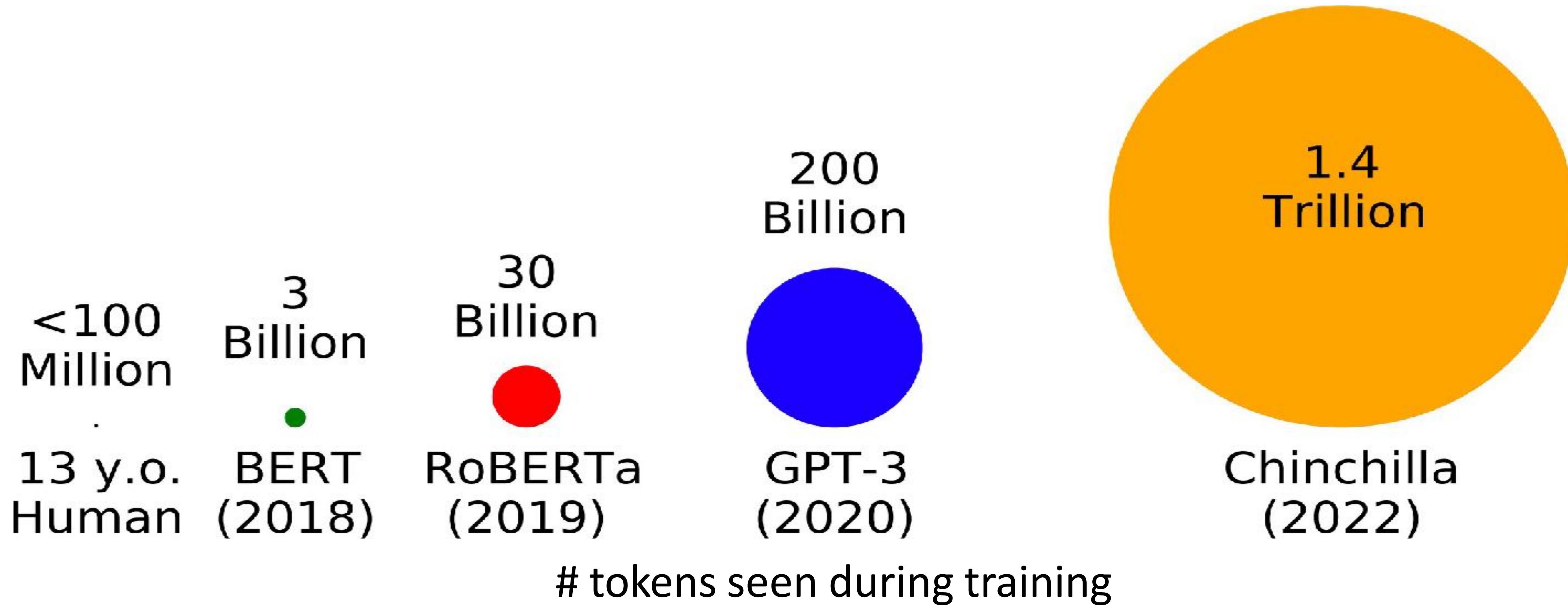
AI training runs, estimated computing resources used

Floating-point operations, selected systems, by type, log scale



Sources: "Compute trends across three eras of machine learning", by J. Sevilla et al., arXiv, 2022; Our World in Data

# Trained on More and More Data



<https://babylm.github.io/>

# What does Pretraining Teach us?

- *Stanford University is located in \_\_\_\_\_, California.* [Trivia]
- *I put \_\_\_\_ fork down on the table.* [syntax]
- *The woman walked across the street, checking for traffic over \_\_\_\_ shoulder.* [coreference]
- *I went to the ocean to see the fish, turtles, seals, and \_\_\_\_.* [lexical semantics/topic]
- *Overall, the value I got from the two hours watching it was the sum total of the popcorn and the drink. The movie was \_\_\_\_.* [sentiment]
- Iroh went into the kitchen to make some tea. Standing next to Iroh, Zuko pondered his destiny. Zuko left the \_\_\_\_\_. [some reasoning – this is harder]
- I was thinking about the sequence that goes 1, 1, 2, 3, 5, 8, 13, 21, \_\_\_\_ [some basic arithmetic; they don't learn the Fibonacci sequence]

# Rudimentary Models of Agents, Beliefs, and Actions

*Pat watches a demonstration of a bowling ball and a leaf being dropped at the same time in a vacuum chamber. Pat, who is a physicist, predicts that the bowling ball and the leaf will fall at the same rate.*

Changing the last sentence of the prompt, we get:

*... Pat, who has never seen this demonstration before, predicts that the bowling ball will fall to the ground first. This is incorrect. In a vacuum chamber, there is no air*

# Learning to Code (Pretty well!)

```
5 // Determine whether the sentiment of text is positive
6 // Use a web service
7 async function isPositive(text: string): Promise<boolean> {
8   const response = await fetch(`http://text-processing.com/api/sentiment/`, {
9     method: "POST",
10    body: `text=${text}`,
11    headers: {
12      "Content-Type": "application/x-www-form-urlencoded",
13    },
14  });
15  const json = await response.json();
16  return json.label === "pos";
17 }
```

<https://github.com/features/copilot>

# Memorizing Advanced Medical Facts

**Rapid and chronic ethanol tolerance are composed of distinct memory-like states in Drosophila**

## Abstract

Ethanol tolerance is the first type of behavioral plasticity and neural plasticity that is induced by ethanol intake, and yet its molecular and circuit bases remain largely unexplored. Here, we characterize three distinct forms of ethanol tolerance in male *Drosophila*: rapid, chronic, and repeated. Rapid tolerance is composed of two short-lived memory-like states, one that is labile and one that is consolidated. Chronic tolerance, induced by continuous exposure, lasts for two days, induces ethanol preference, and hinders the development of rapid tolerance through the activity of

[[Larnerd, 2023](#)]

# Multi-Step Problem Solving

**I need to throw a dinner party for 6 people who are vegetarian. Can you suggest a 3-course menu with a chocolate dessert?**

[Microsoft Bing]

(Also see OpenAI's ChatGPT,  
Google's Bard, Anthropic's Claude)

The screenshot shows a Microsoft Bing AI interface. At the top right are icons for thumbs up, thumbs down, and more. The AI response is:

Sure, I can suggest a 3-course menu with a chocolate dessert for your vegetarian dinner party. Here are some possible options:

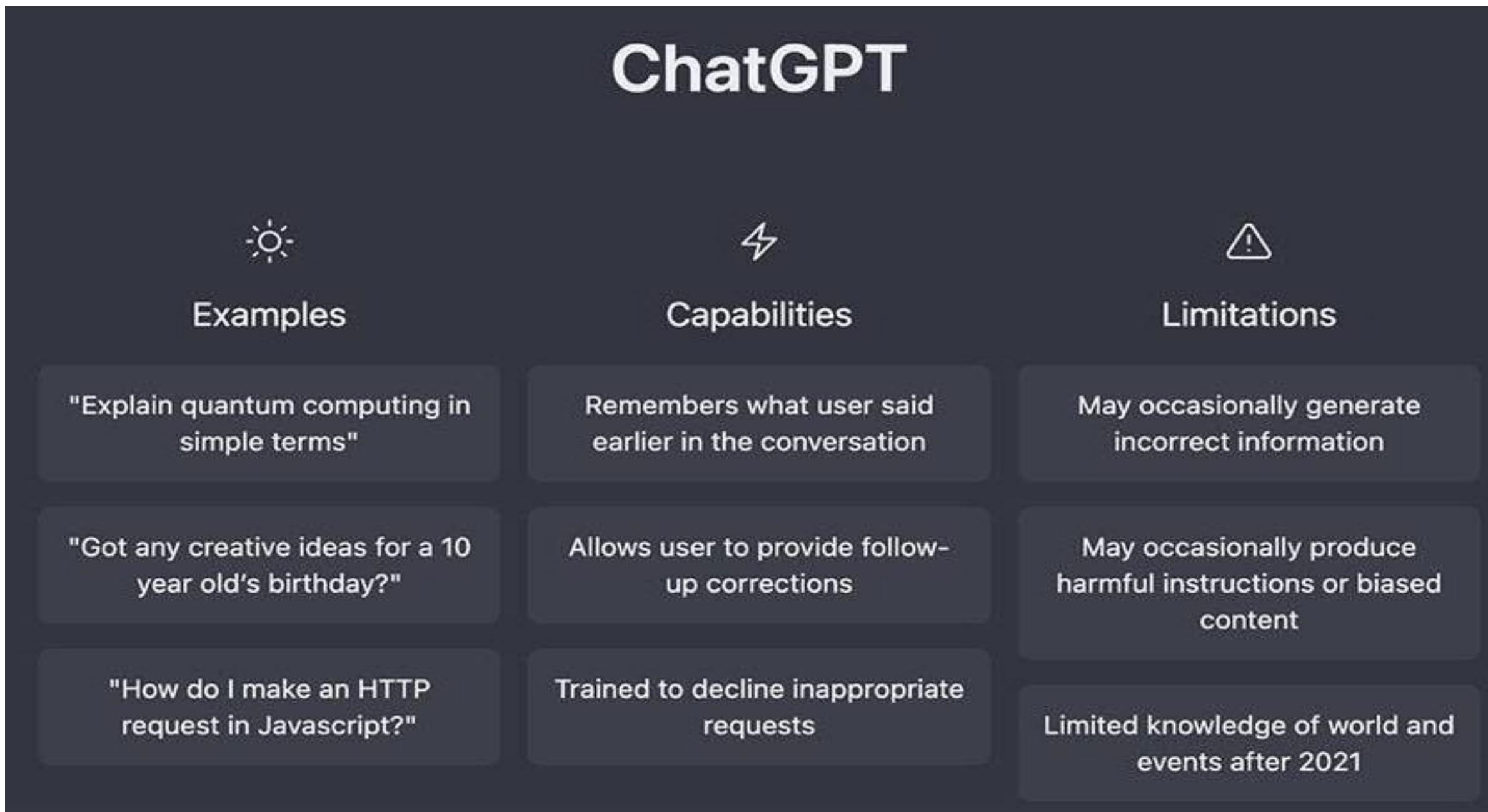
- Starter: **Wild Mushroom Tartlets with Onion Sauce** <sup>1</sup> or **Vegan Popcorn Tofu Nuggets** <sup>2</sup>
- Main: **Vegan Butternut Squash Mac** <sup>2</sup> or **Vegetarian Three-Bean Chili** <sup>3</sup>
- Dessert: **Chocolate Lava Cake** <sup>4</sup> or **Chocolate Pasta with Chocolate Hazelnut Cream Sauce, White Chocolate Shavings, and Fresh Berries** <sup>4</sup>

I hope this helps you plan your party. Enjoy! 😊

Learn more: [1. booths.co.uk](#) [+10 more](#)

# Multitask Assistants

- How do we get from *this*
  - *Stanford University is located in \_\_\_\_\_*
- to *this*?



# Language Modeling ≠ Assisting Users

PROMPT    *Explain the moon landing to a 6 year old in a few sentences.*

COMPLETION    GPT-3

Explain the theory of gravity to a 6 year old.

Explain the theory of relativity to a 6 year old in a few sentences.

Explain the big bang theory to a 6 year old.

Explain evolution to a 6 year old.

Language models are not *aligned* with user intent [[Ouyang et al., 2022](#)].

# Language Modeling ≠ Assisting Users

PROMPT *Explain the moon landing to a 6 year old in a few sentences.*

COMPLETION **Human**

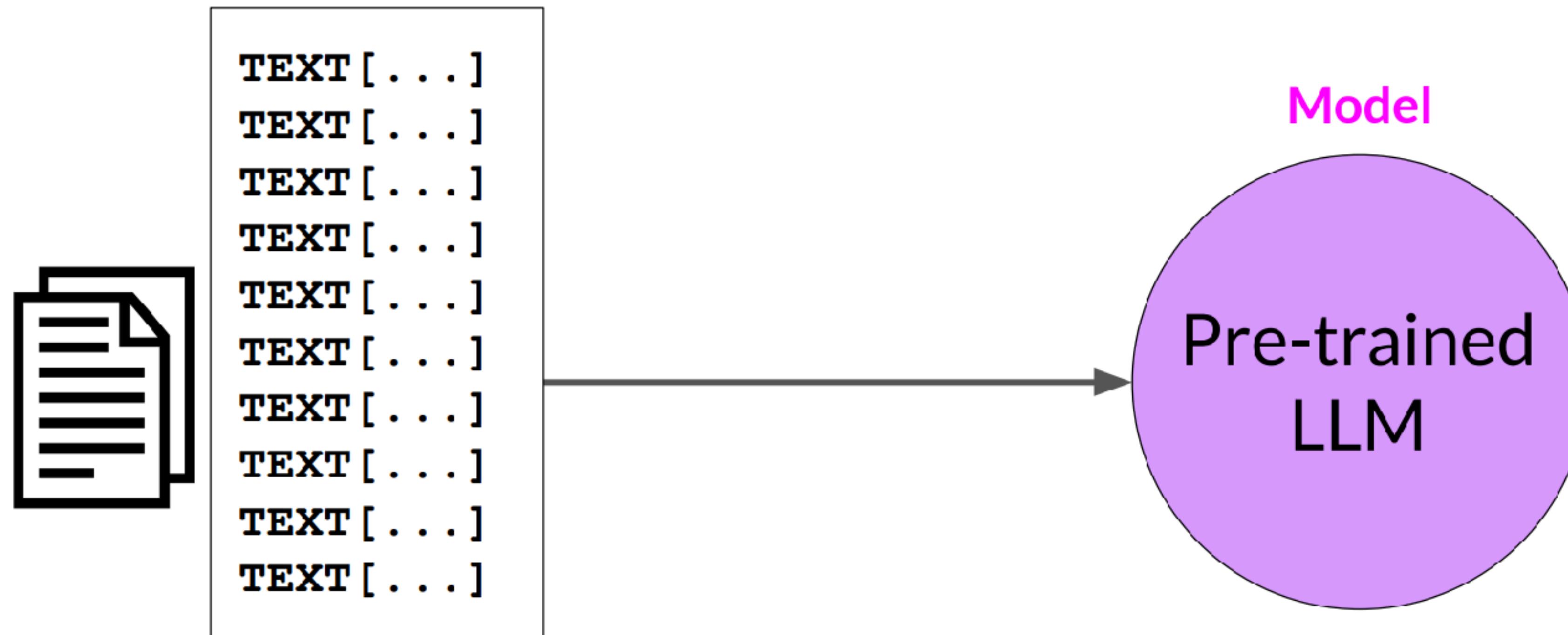
A giant rocket ship blasted off from Earth carrying astronauts to the moon. The astronauts landed their spaceship on the moon and walked around exploring the lunar surface. Then they returned safely back to Earth, bringing home moon rocks to show everyone.

Language models are not *aligned* with user intent [[Ouyang et al., 2022](#)].  
Finetuning to the rescue!

# Supervised Finetuning

# Pretraining

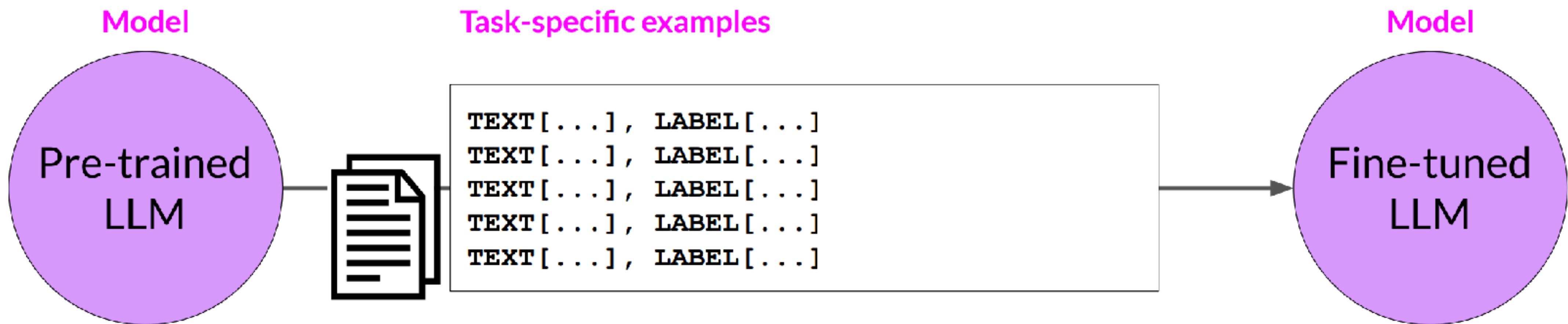
## LLM pre-training



GB - TB - PB  
of unstructured textual data

# Conventional Finetuning

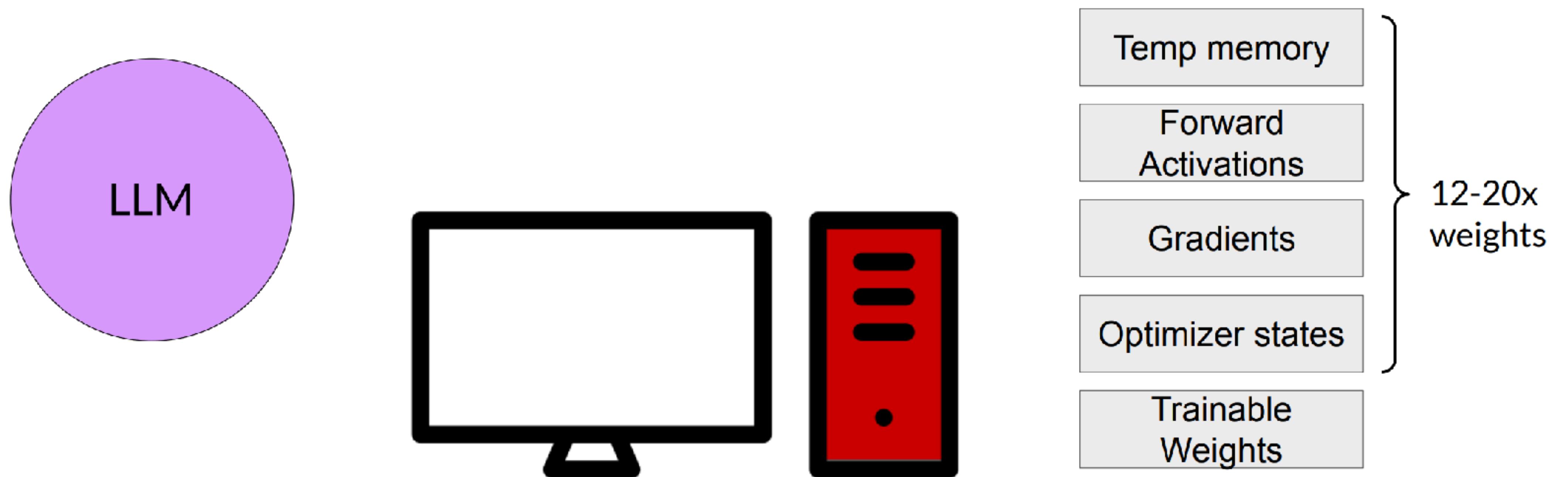
LLM fine-tuning



GB - TB  
of labeled examples for a specific  
task or set of tasks

# Finetuning at the Frontier

Full fine-tuning of large LLMs is challenging



# Getting Smart with Finetuning

## PEFT methods summary

### Selective

**Select** subset of initial LLM parameters to fine-tune

### Reparameterization

**Reparameterize** model weights using a low-rank representation

LoRA

### Additive

**Add** trainable layers or parameters to model

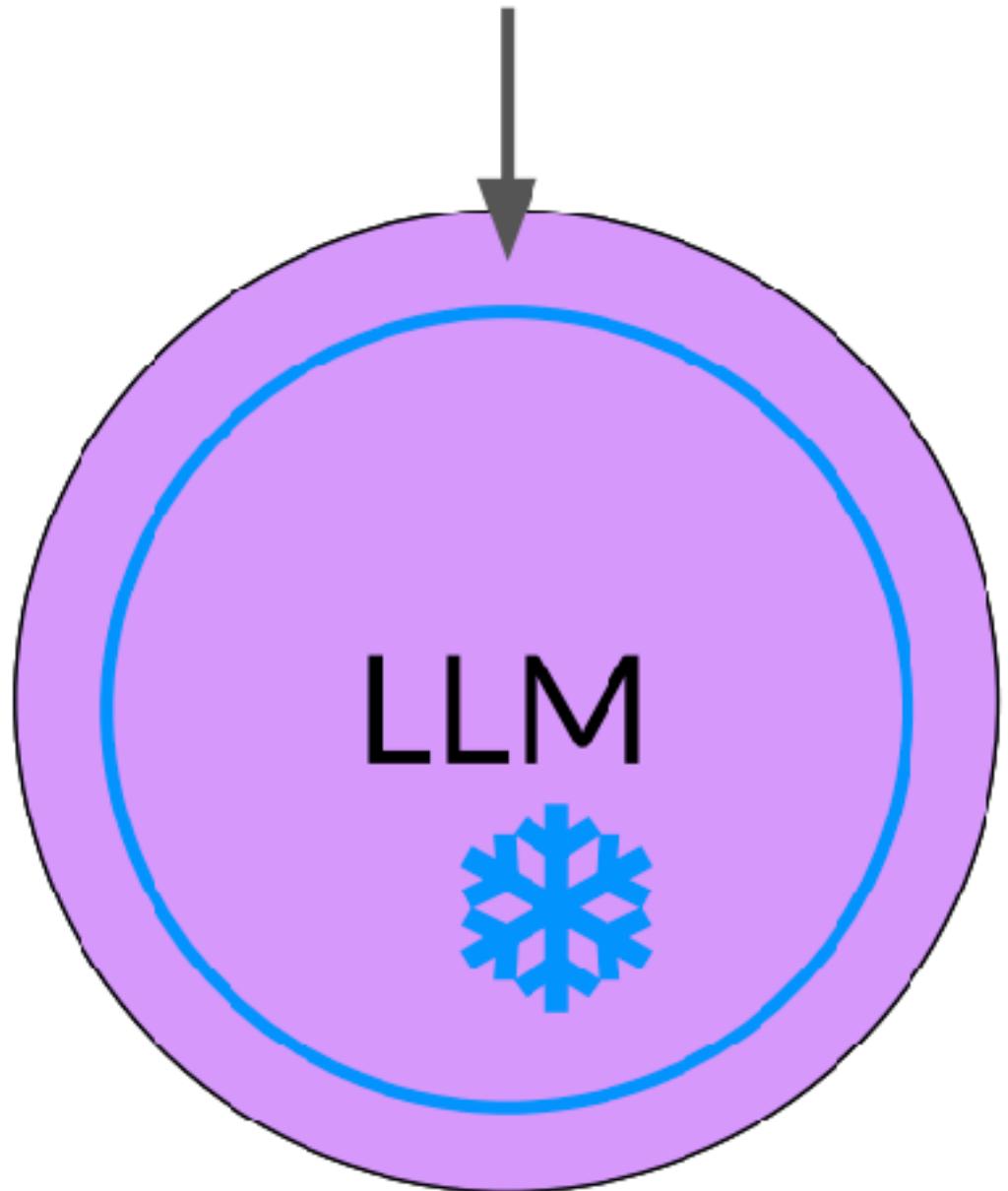
Adapters

Soft Prompts

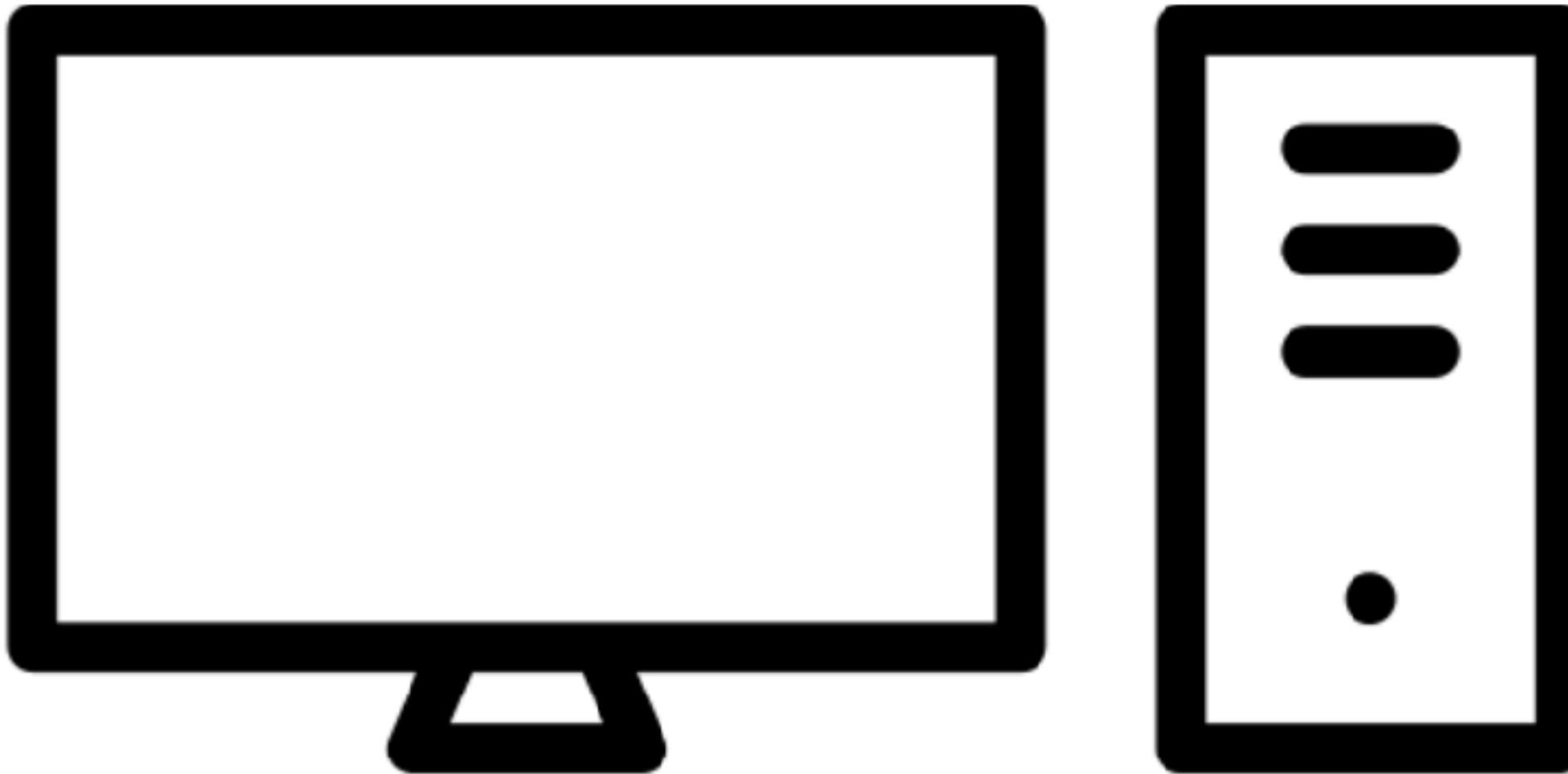
Prompt Tuning

# Selective Finetuning

Small number of trainable layers

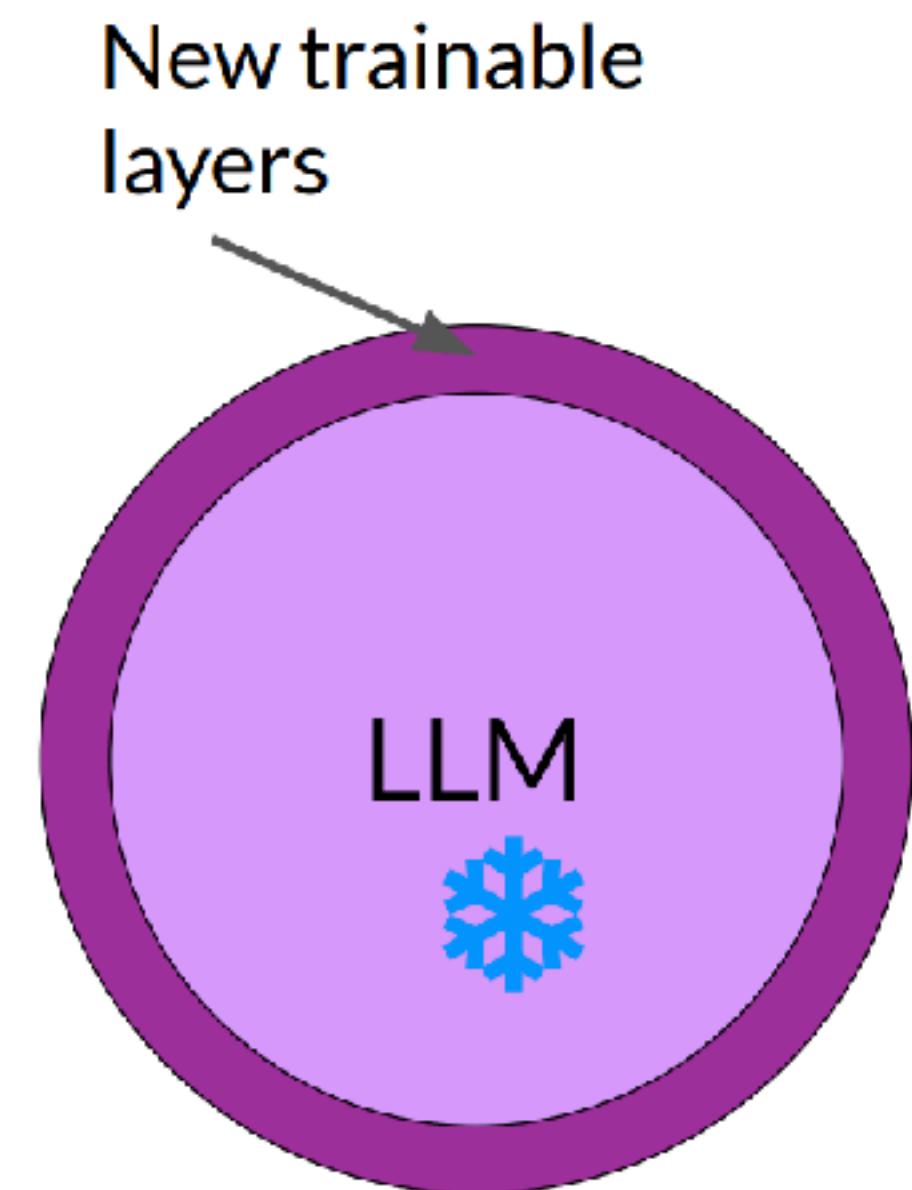


LLM with most layers frozen



# Selective Finetuning

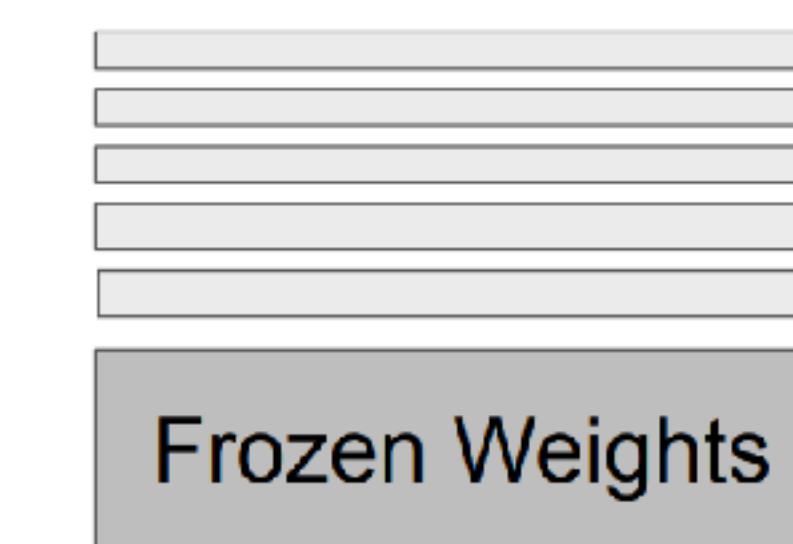
## Parameter efficient fine-tuning (PEFT)



LLM with additional  
layers for PEFT



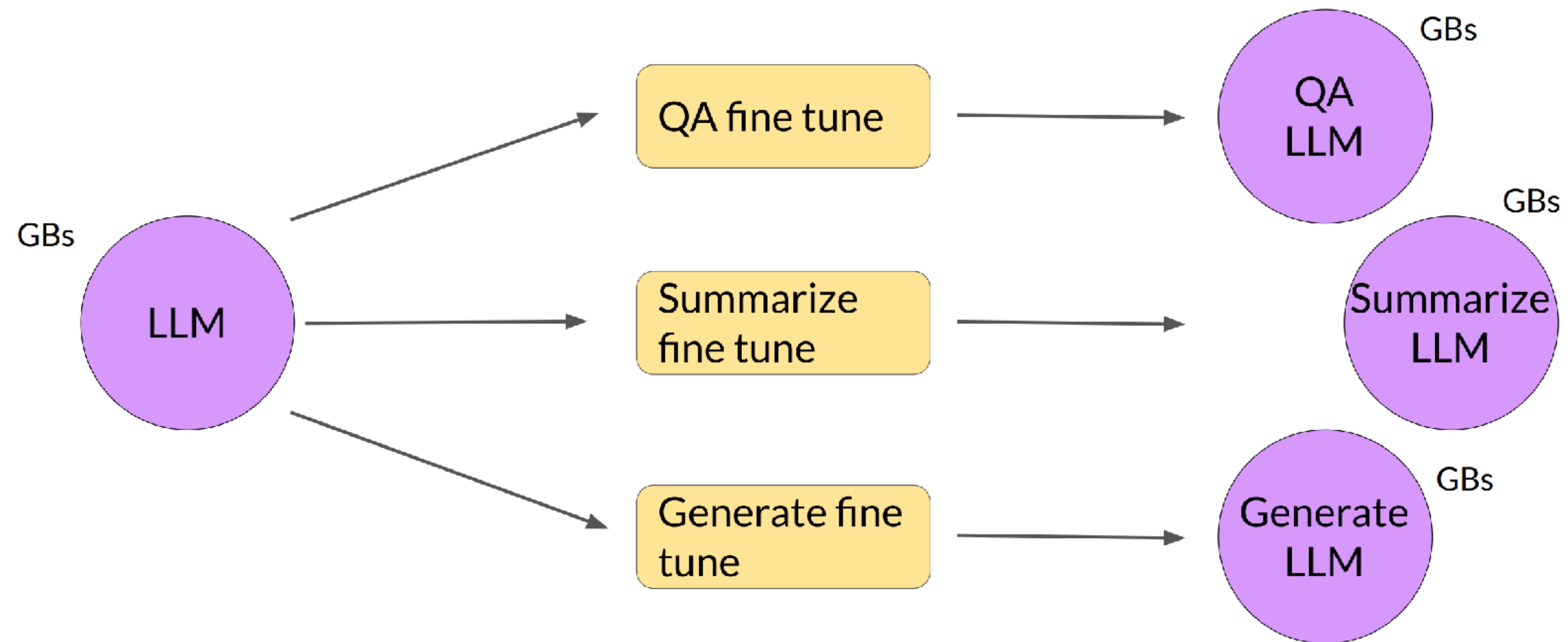
Less prone to  
catastrophic forgetting



Other  
components  
Trainable  
weights  
Frozen Weights

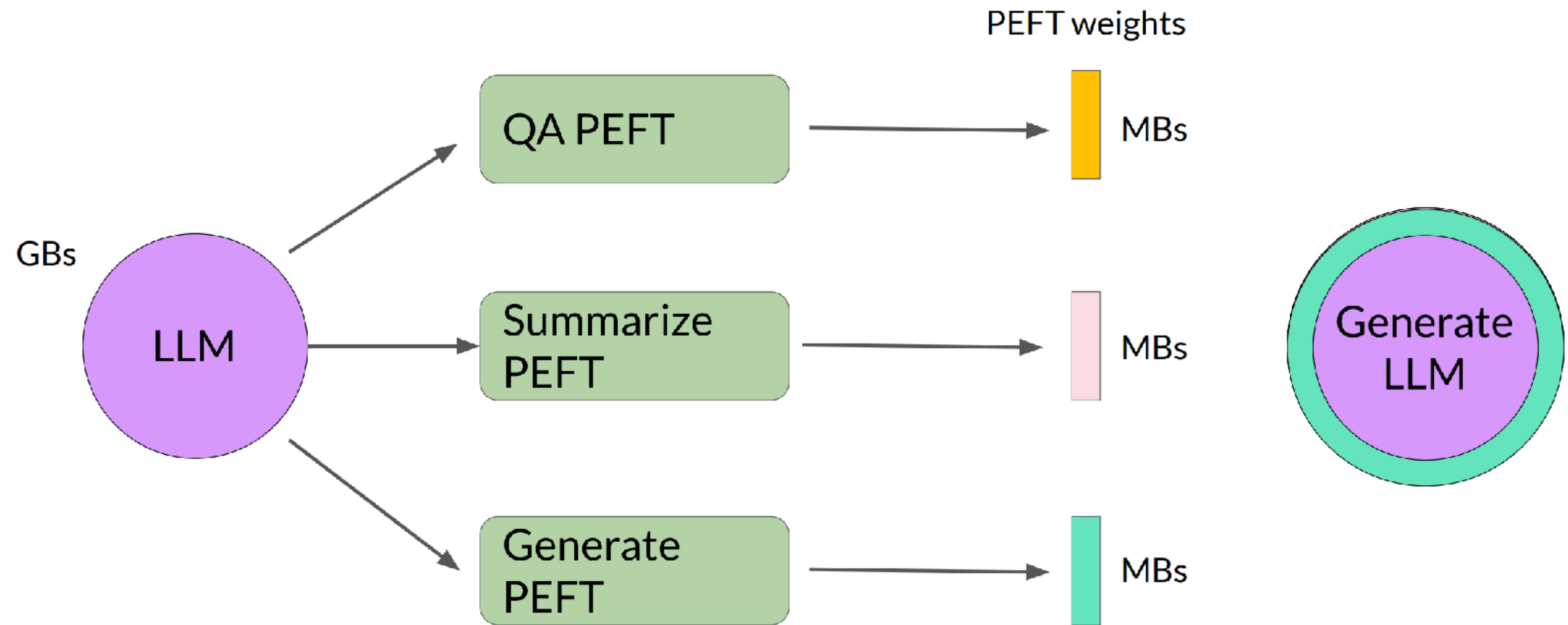
# Selective Finetuning

Full fine-tuning creates full copy of original LLM per task



# Selective Finetuning

PEFT fine-tuning saves space and is flexible



# Getting Smart with Finetuning

## PEFT methods summary

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**Select** subset of initial LLM parameters to fine-tune

### Reparameterization

**Reparameterize** model weights using a low-rank representation

LoRA

### Additive

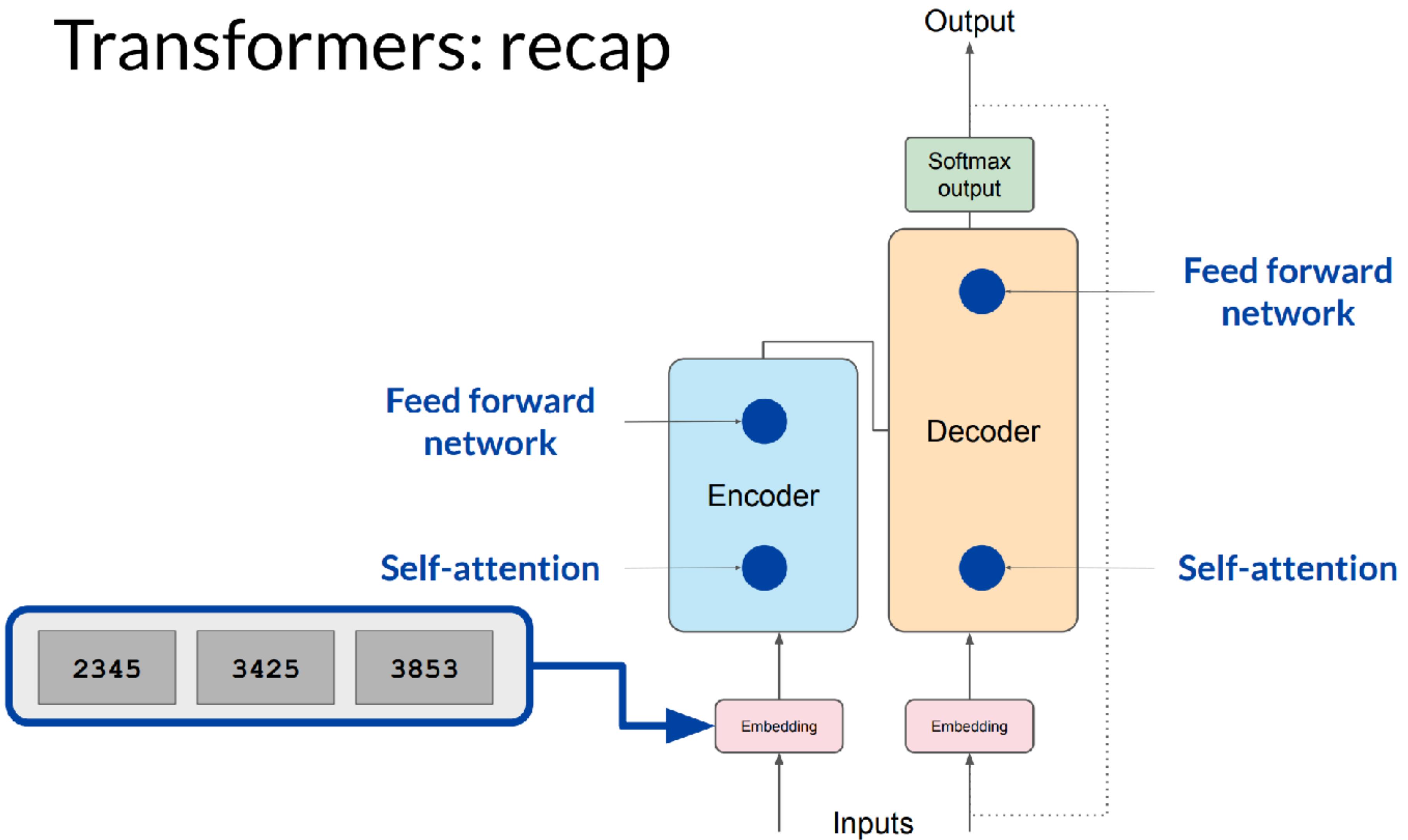
**Add** trainable layers or parameters to model

Adapters

Soft Prompts

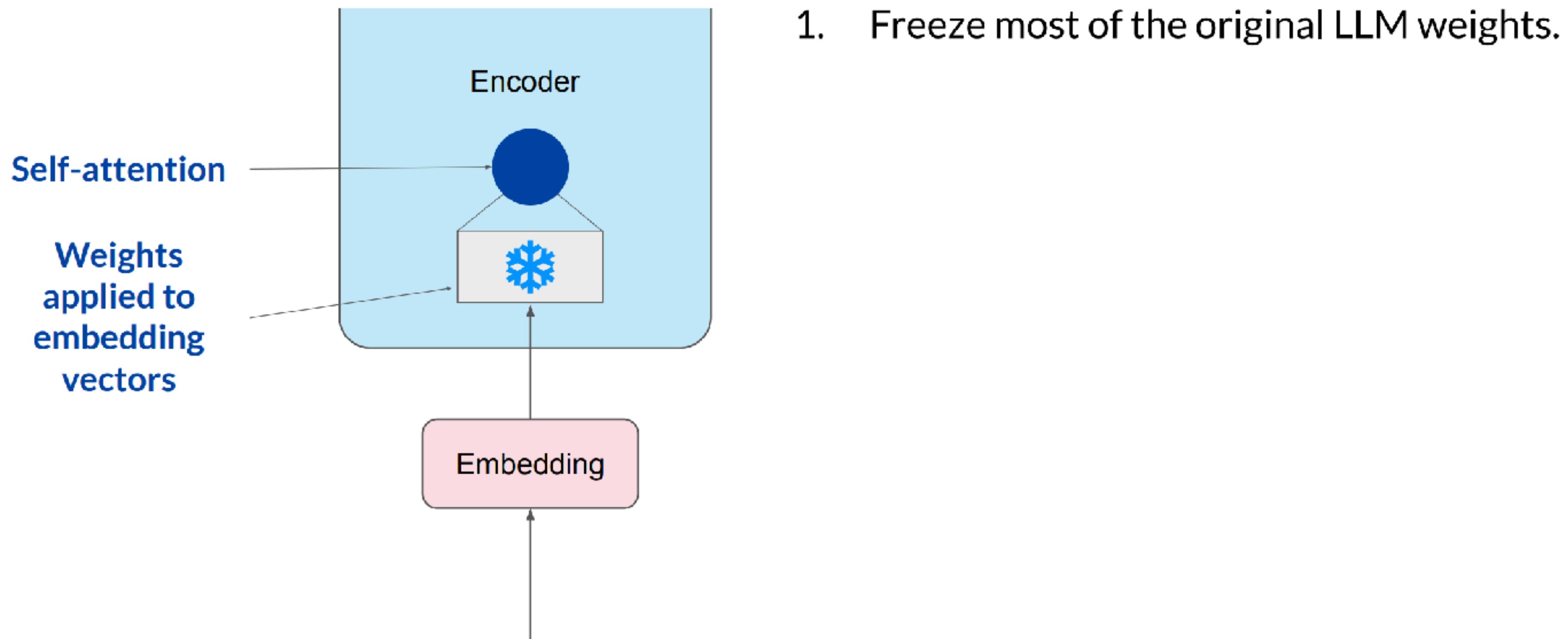
Prompt Tuning

## Transformers: recap

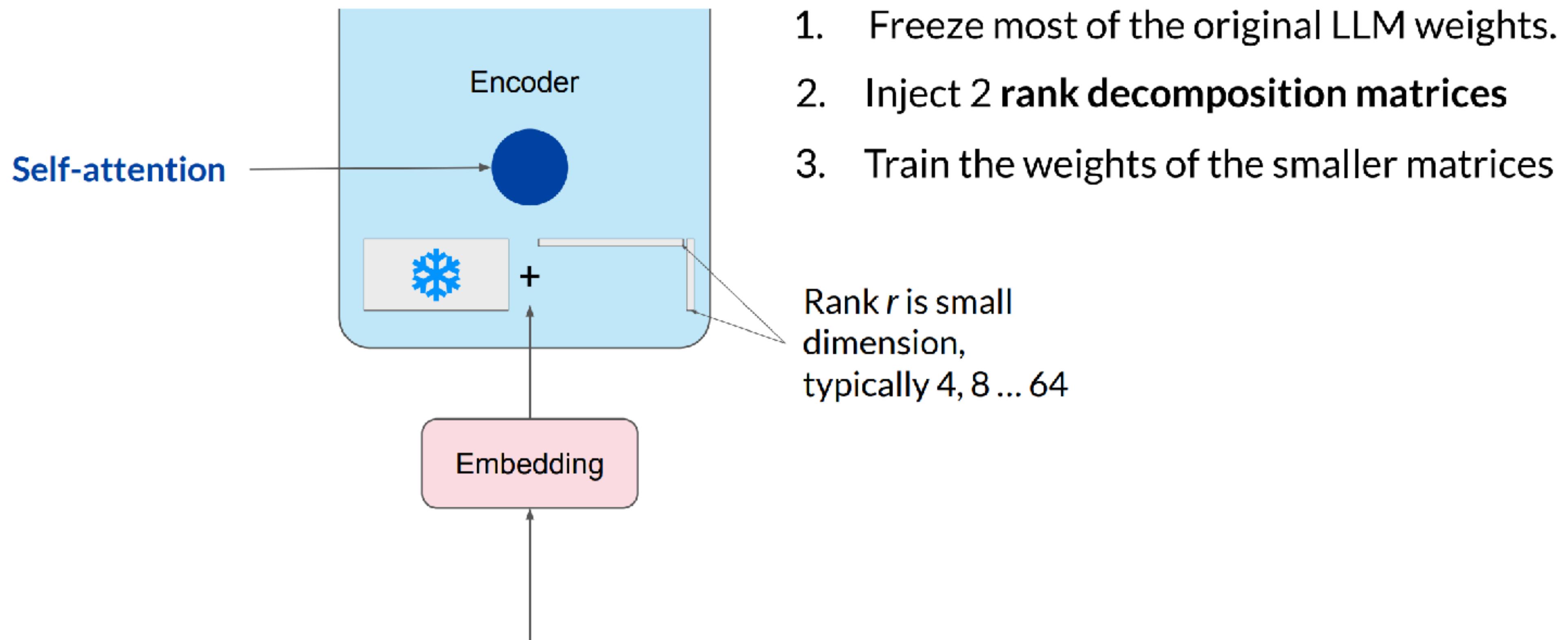


# LoRA

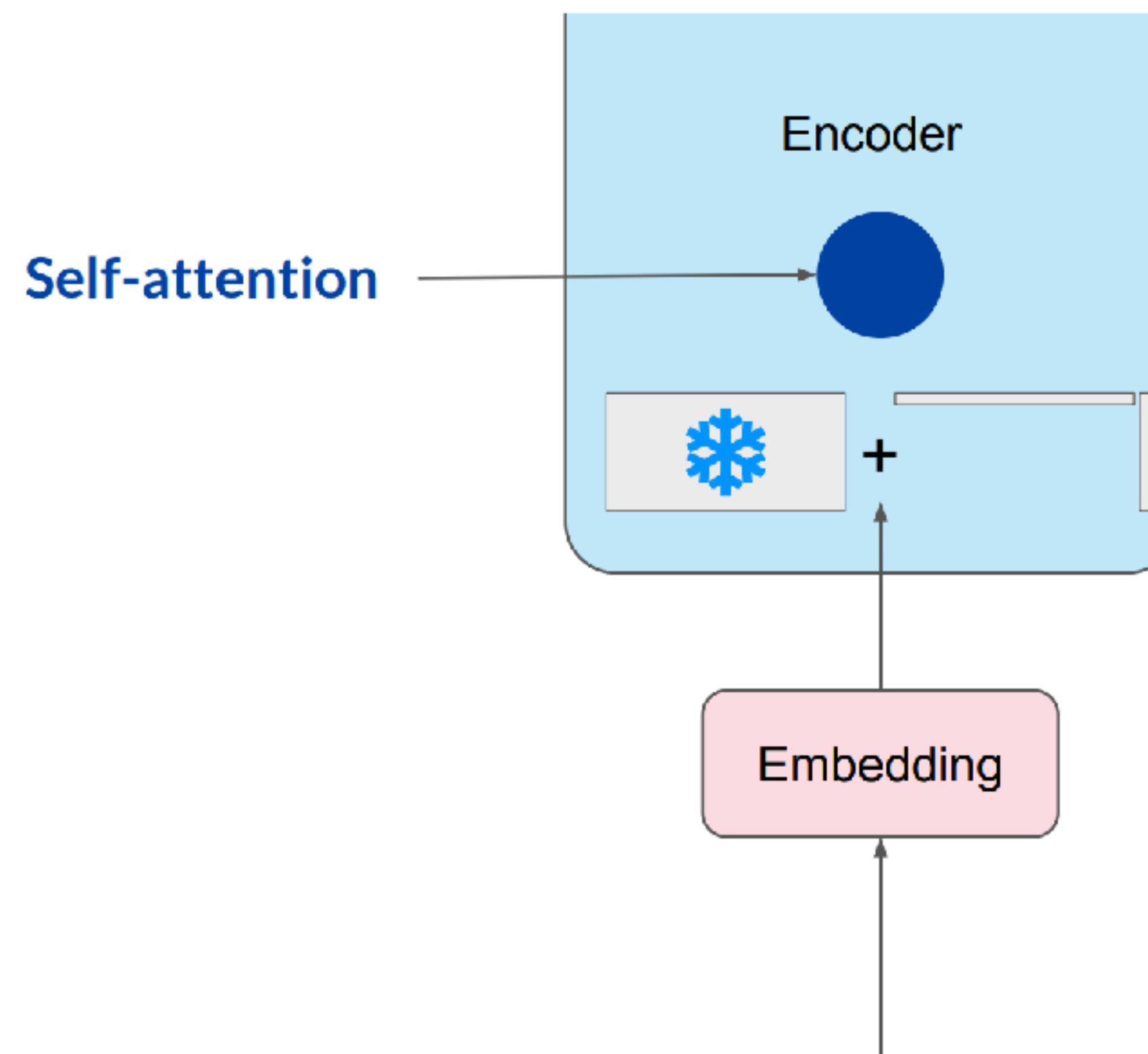
## LoRA: Low Rank Adaption of LLMs



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## LoRA: Low Rank Adaption of LLMs



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

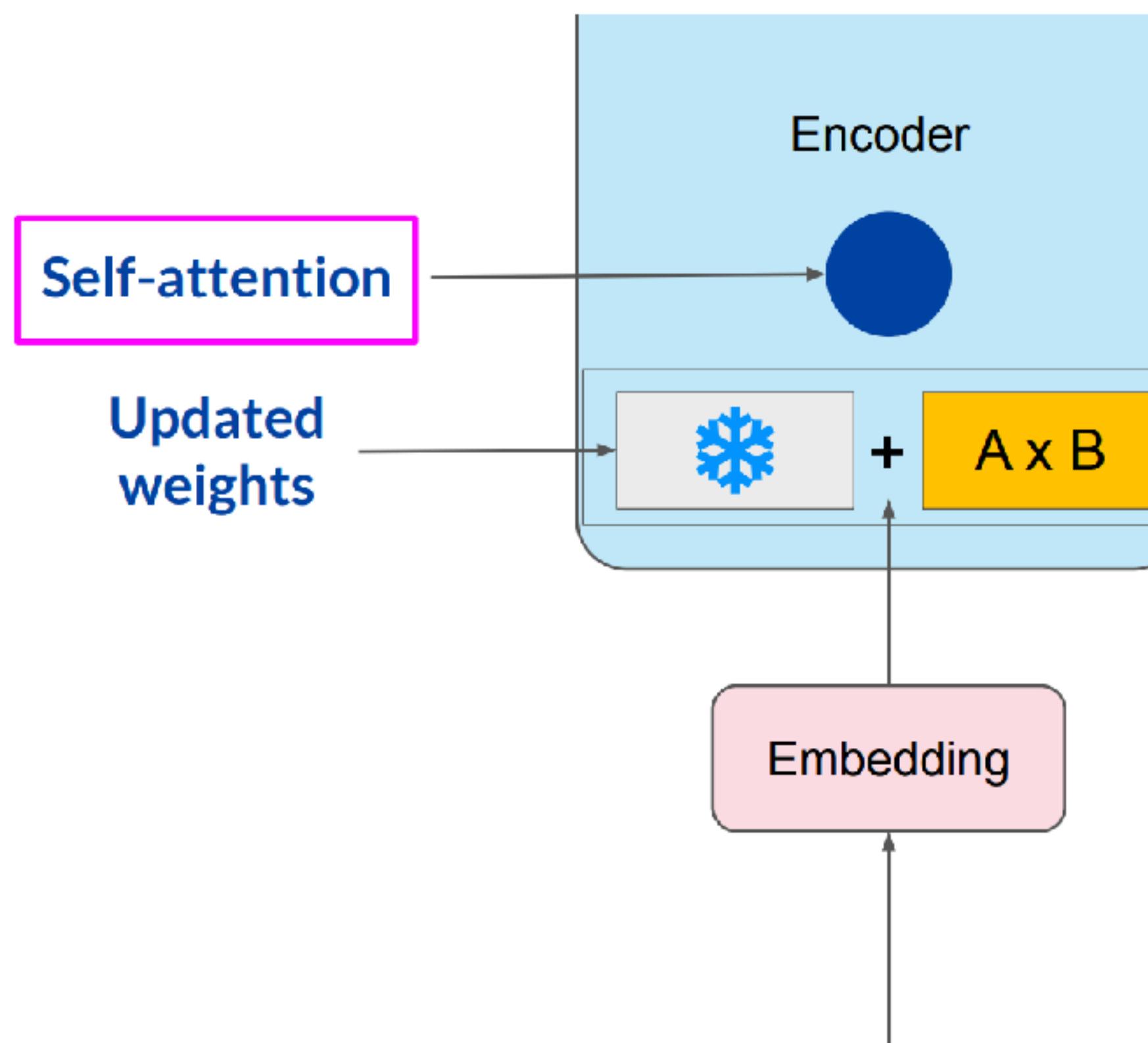
1. Matrix multiply the low rank matrices

$$B \quad * \quad | A \quad = \quad A \times B$$

2. Add to original weights

$$\text{Snowflake} \quad + \quad A \times B$$

# LoRA: Low Rank Adaption of LLMs



1. Freeze most of the original LLM weights.
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3. Train the weights of the smaller matrices

Steps to update model for inference:

1. Matrix multiply the low rank matrices

$$\begin{array}{c} B \\ \times \\ A \end{array} = A \times B$$

2. Add to original weights

$$\begin{array}{c} \text{snowflake} \\ + \\ A \times B \end{array}$$

# Concrete example using base Transformer as reference

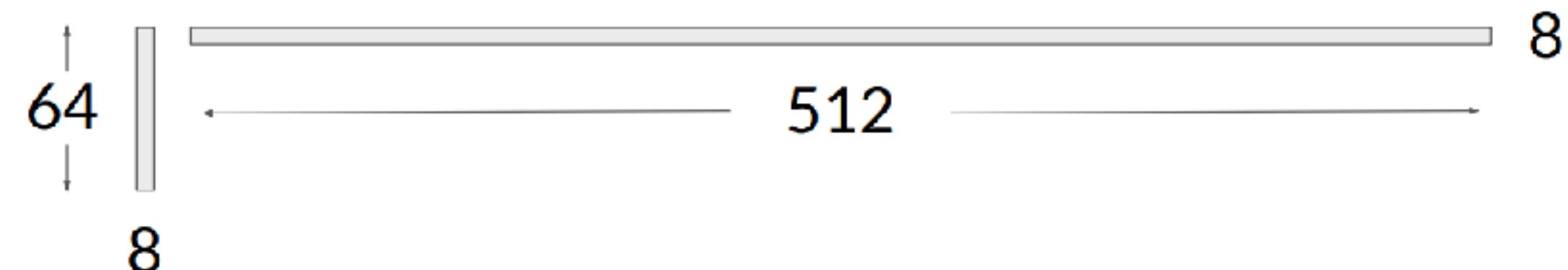
Use the base Transformer model presented by Vaswani et al. 2017:

- Transformer weights have dimensions  $d \times k = 512 \times 64$
- So  $512 \times 64 = 32,768$  trainable parameters



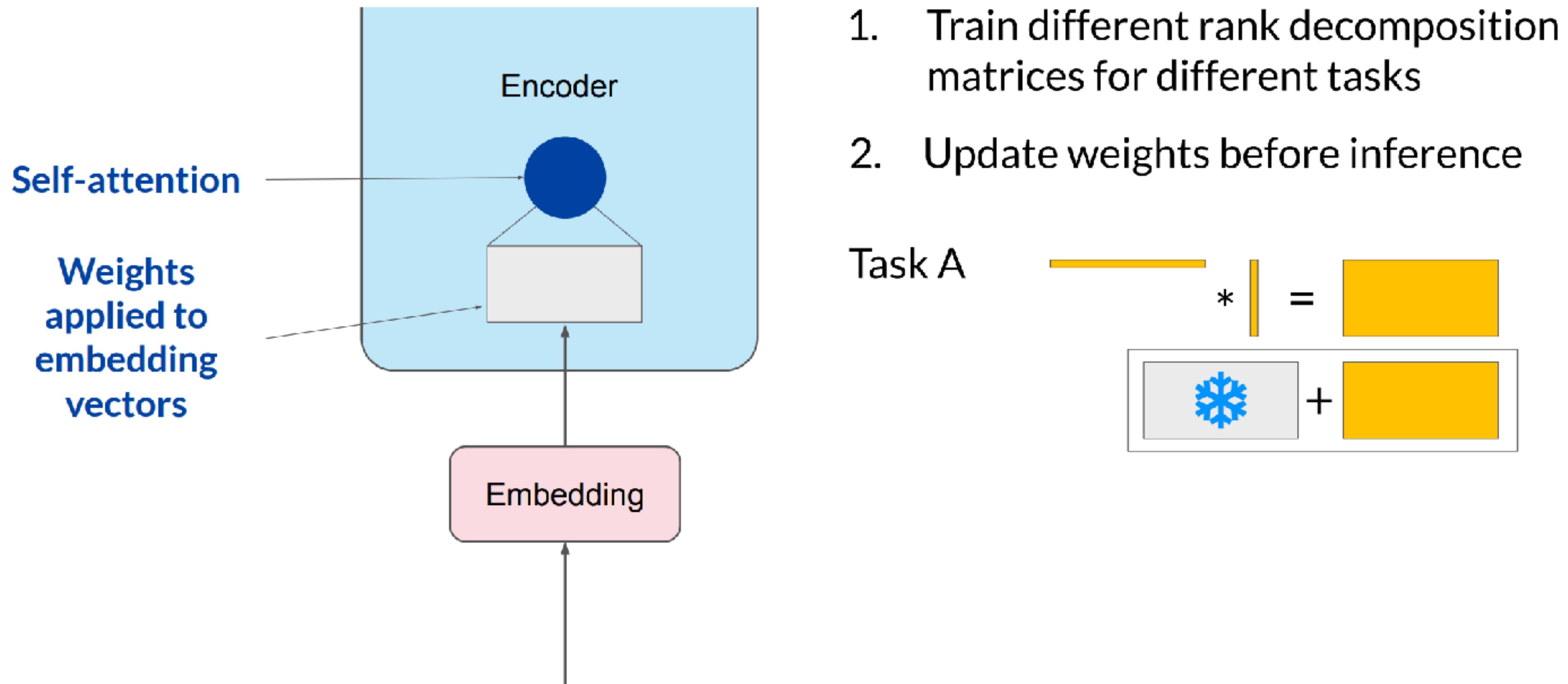
In LoRA with rank  $r = 8$ :

- A has dimensions  $r \times k = 8 \times 64 = 512$  parameters
- B has dimension  $d \times r = 512 \times 8 = 4,096$  trainable parameters

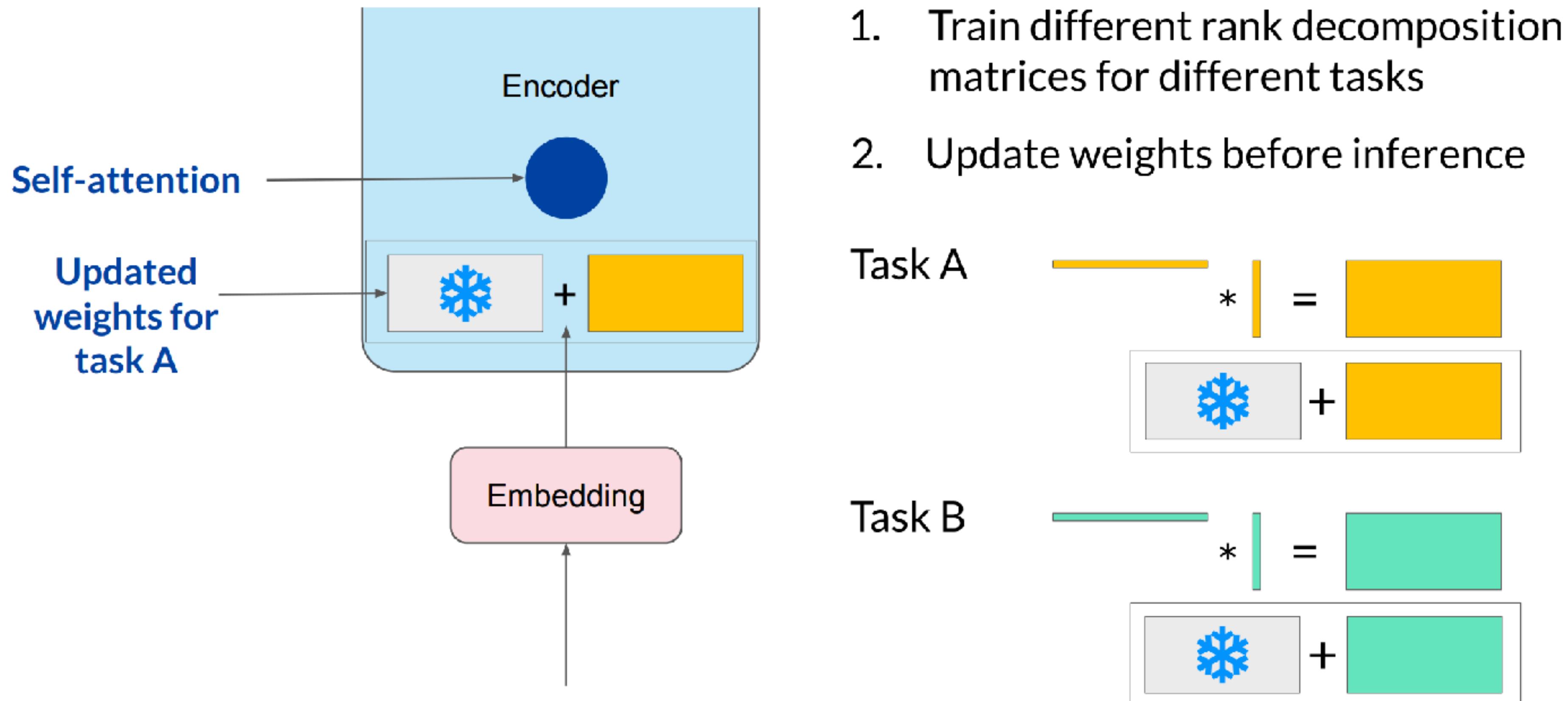


**86% reduction in parameters  
to train!**

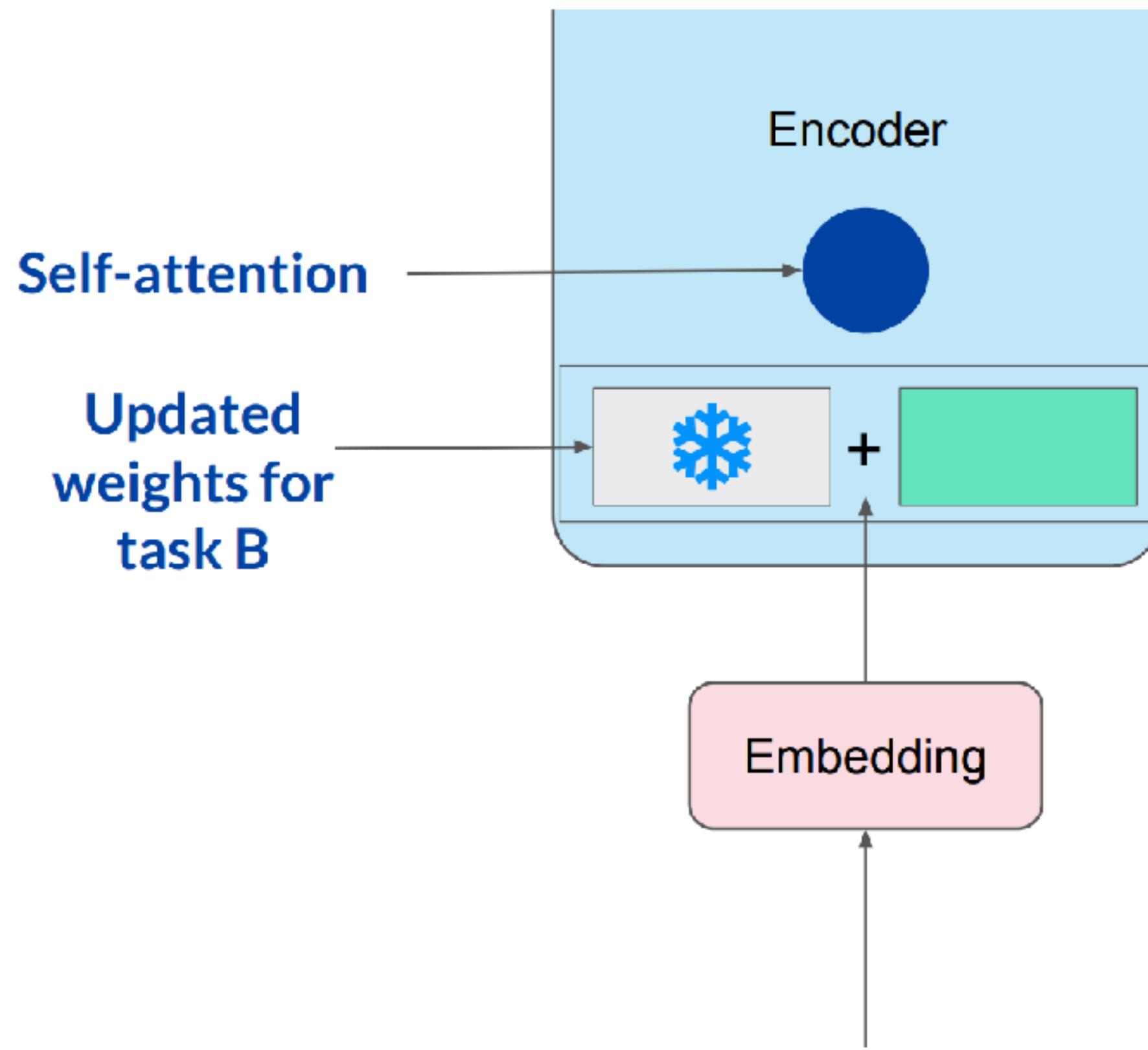
## LoRA: Low Rank Adaption of LLMs



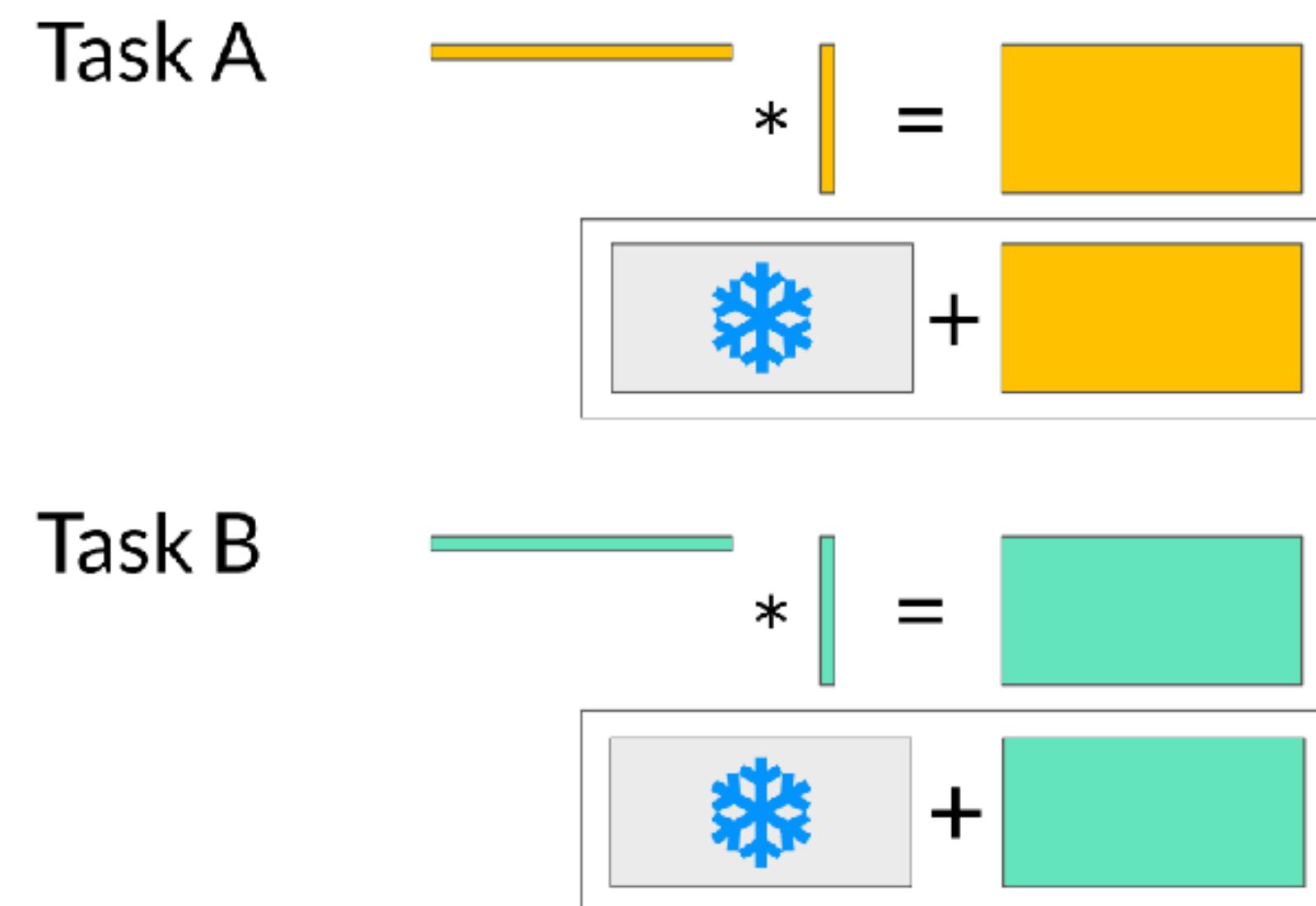
## LoRA: Low Rank Adaption of LLMs



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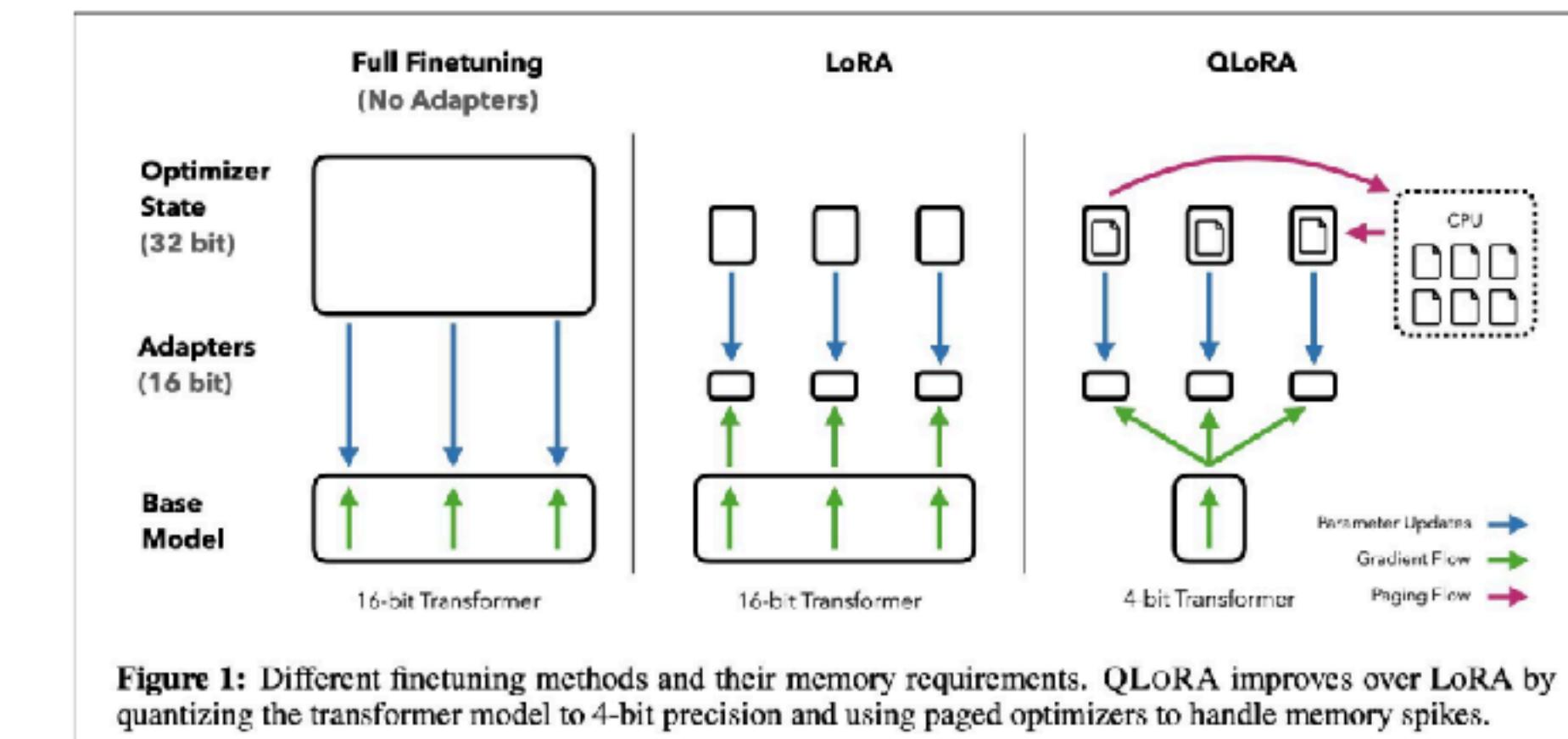
1. Train different rank decomposition matrices for different tasks
2. Update weights before inference



# QLoRA

## QLoRA: Quantized LoRA

- Introduces 4-bit NormalFloat (nf4) data type for 4-bit quantization
- Supports double-quantization to reduce memory ~0.4 bits per parameter (~3 GB for a 65B model)
- Unified GPU-CPU memory management reduces GPU memory usage
- LoRA adapters at every layer - not just attention layers
- Minimizes accuracy trade-off



Source: Dettmers et al. 2023, "QLoRA: Efficient Finetuning of Quantized LLMs"

**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.

# Getting Smart with Finetuning

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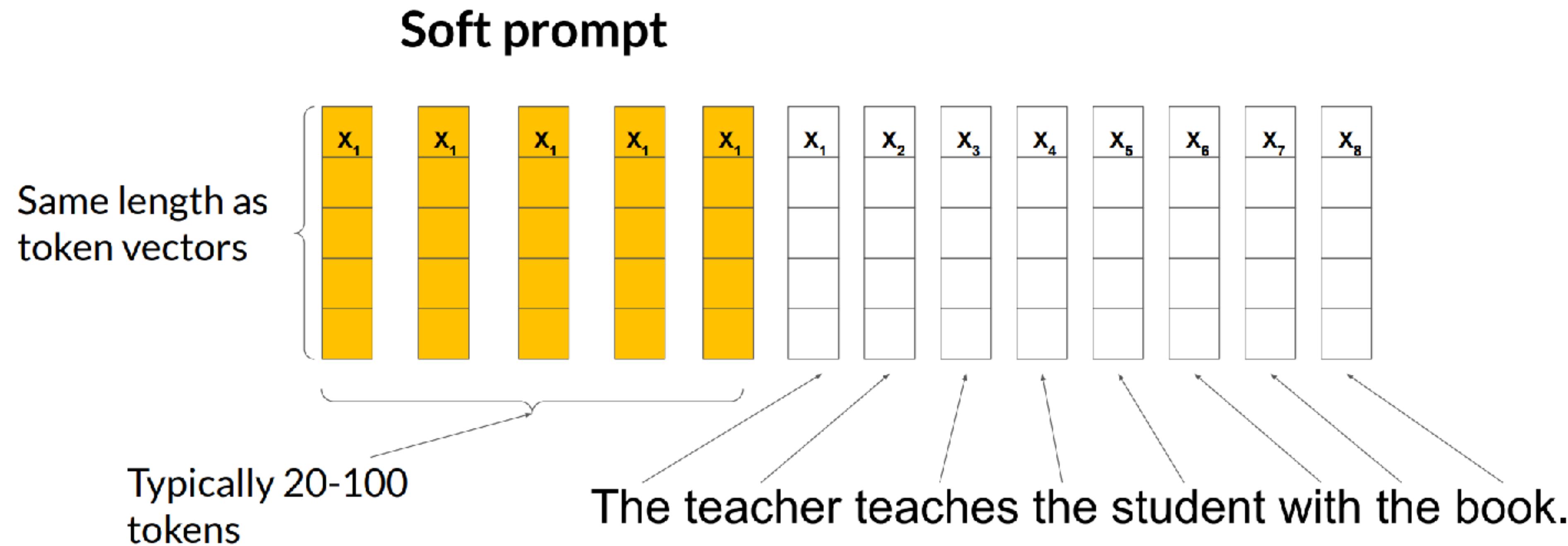
Adapters

Soft Prompts

Prompt Tuning

# Prompt Tuning

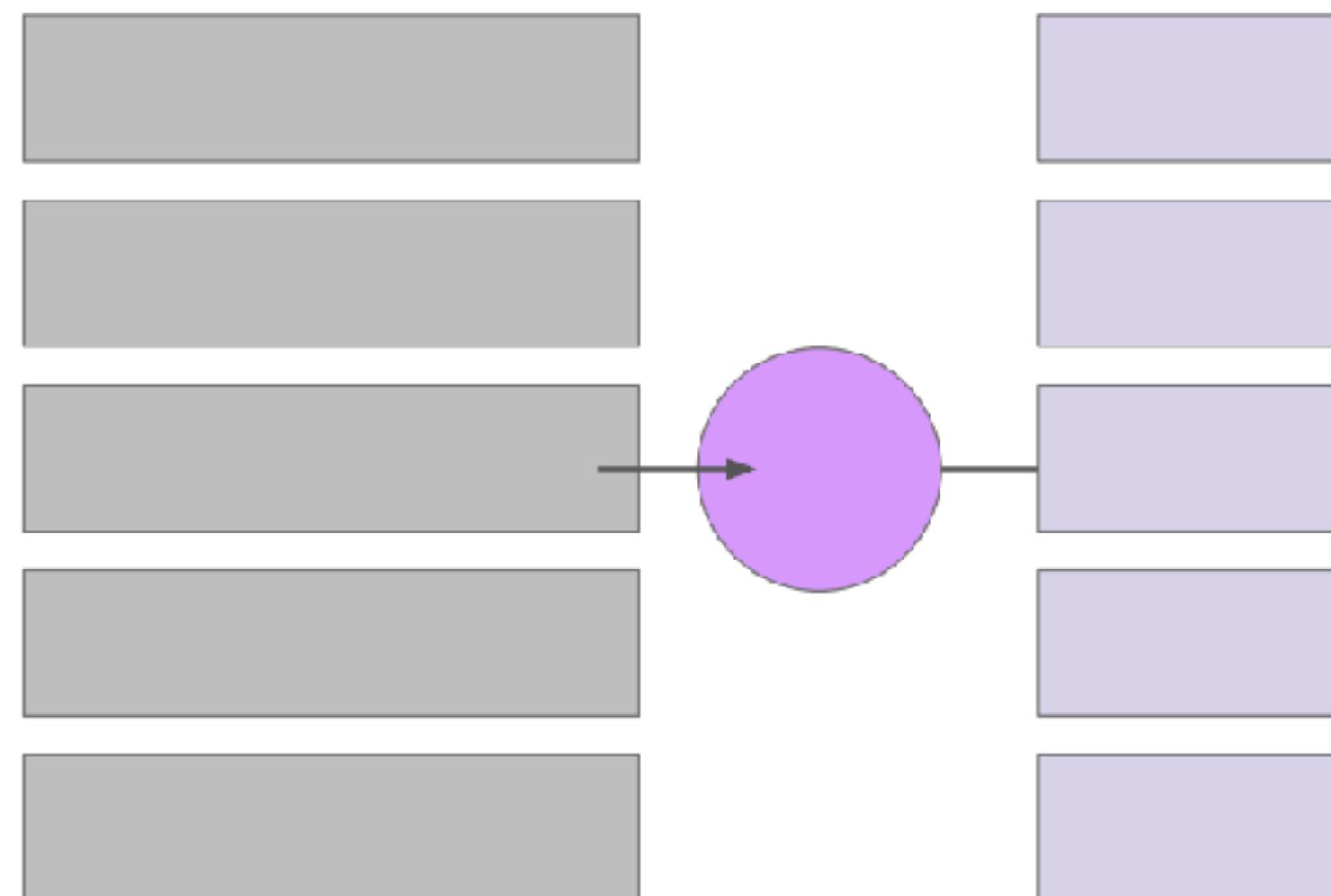
Prompt tuning adds trainable “soft prompt” to inputs



# Prompt Tuning

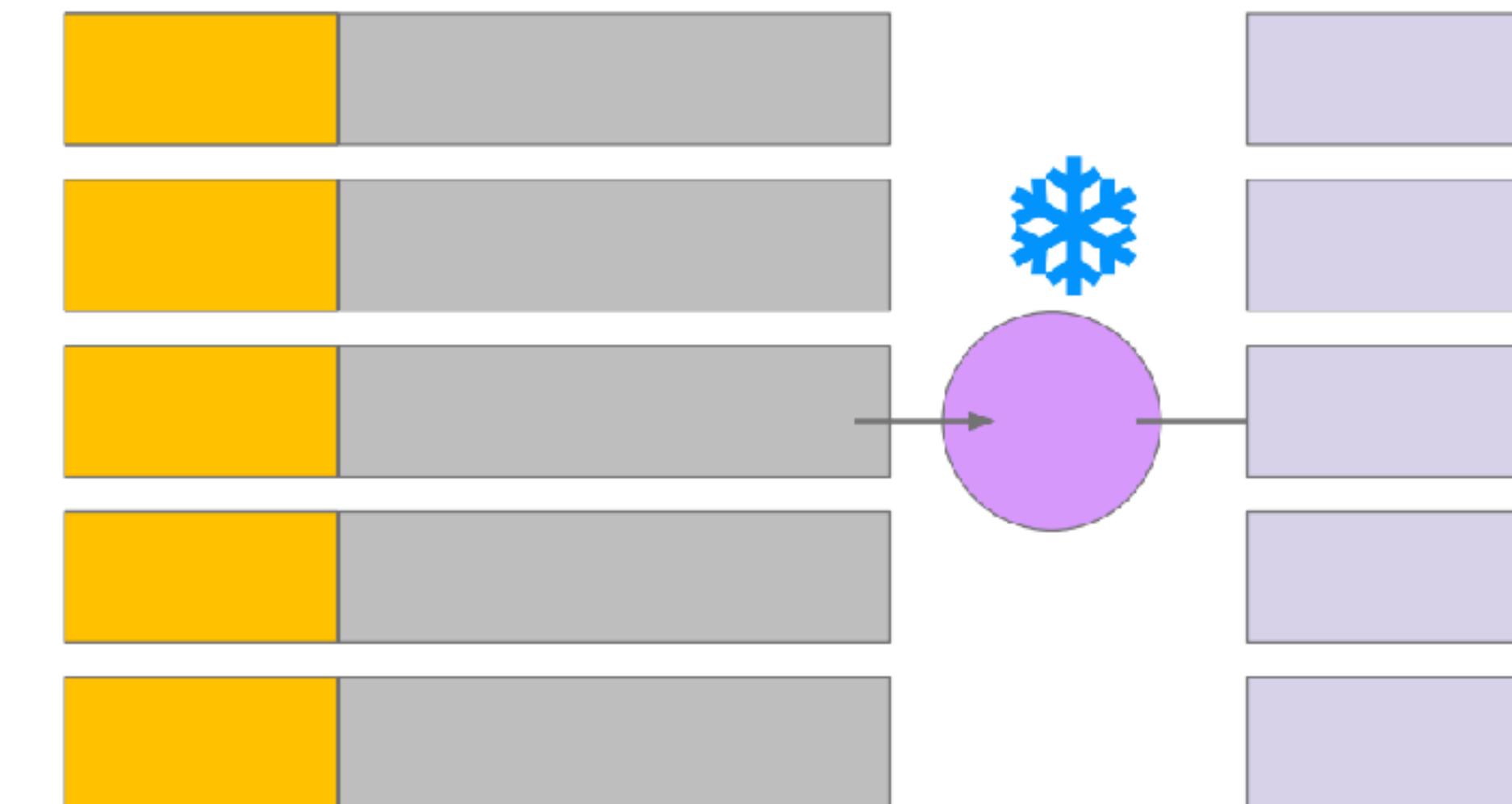
## Full Fine-tuning vs prompt tuning

Weights of model updated  
during training



Millions to Billions of  
parameter updated

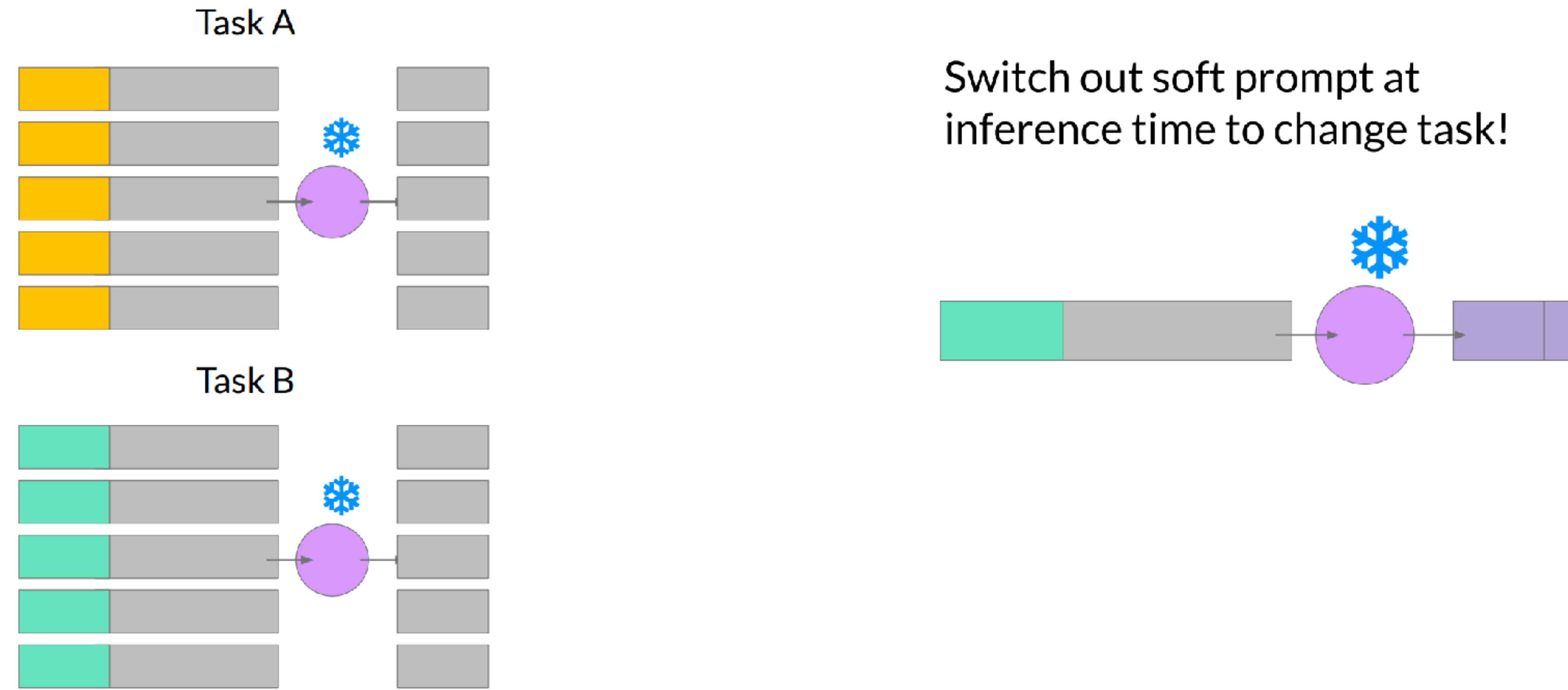
Weights of model frozen and  
soft prompt trained



10K - 100K of parameters  
updated

# Prompt Tuning

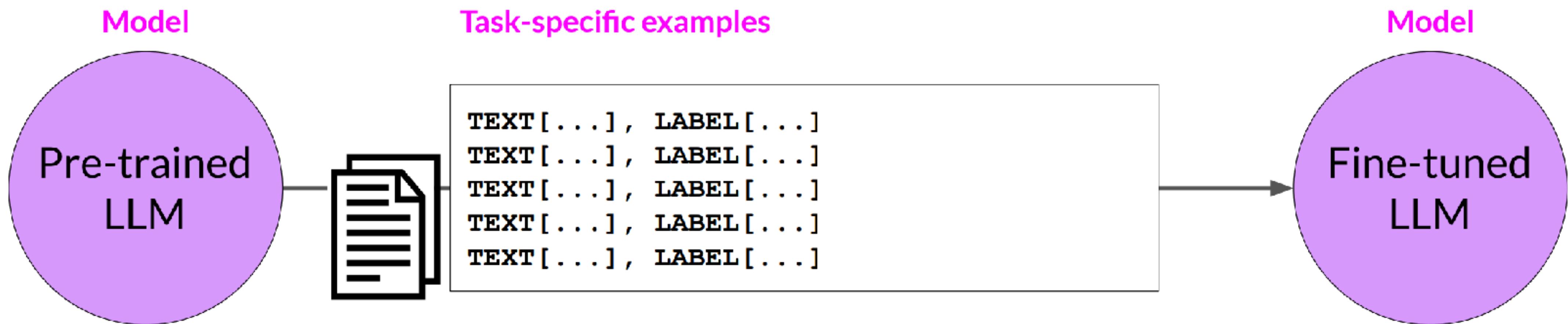
## Prompt tuning for multiple tasks



# Instruction Finetuning

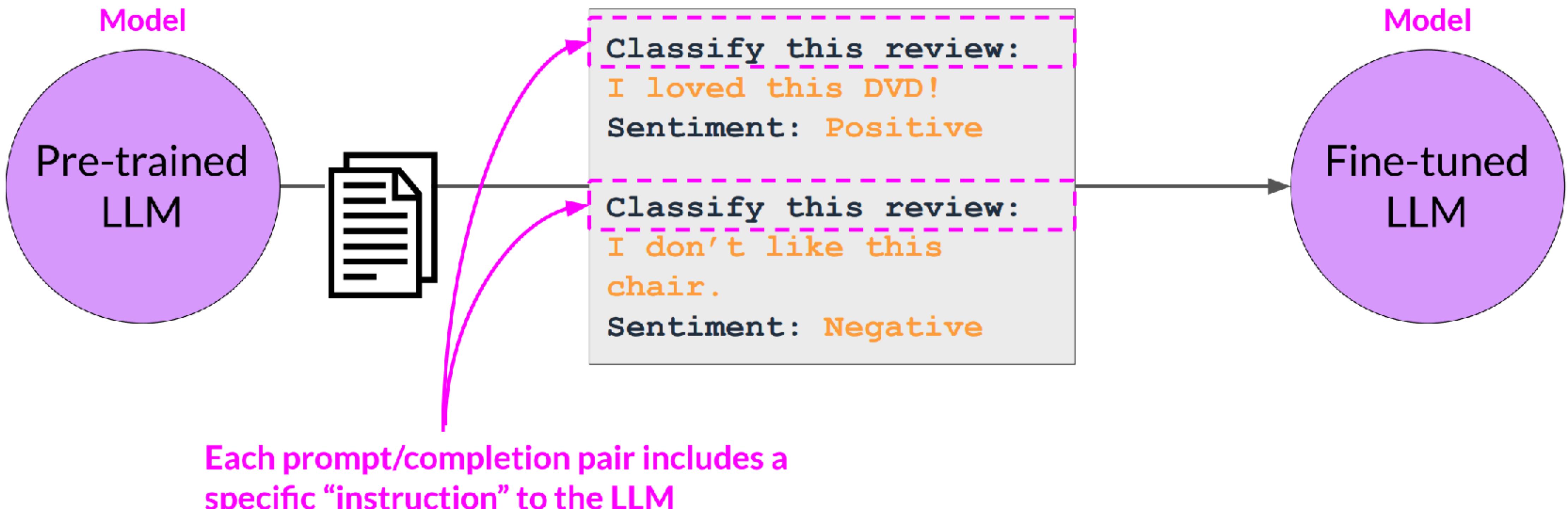
# Conventional Finetuning

LLM fine-tuning

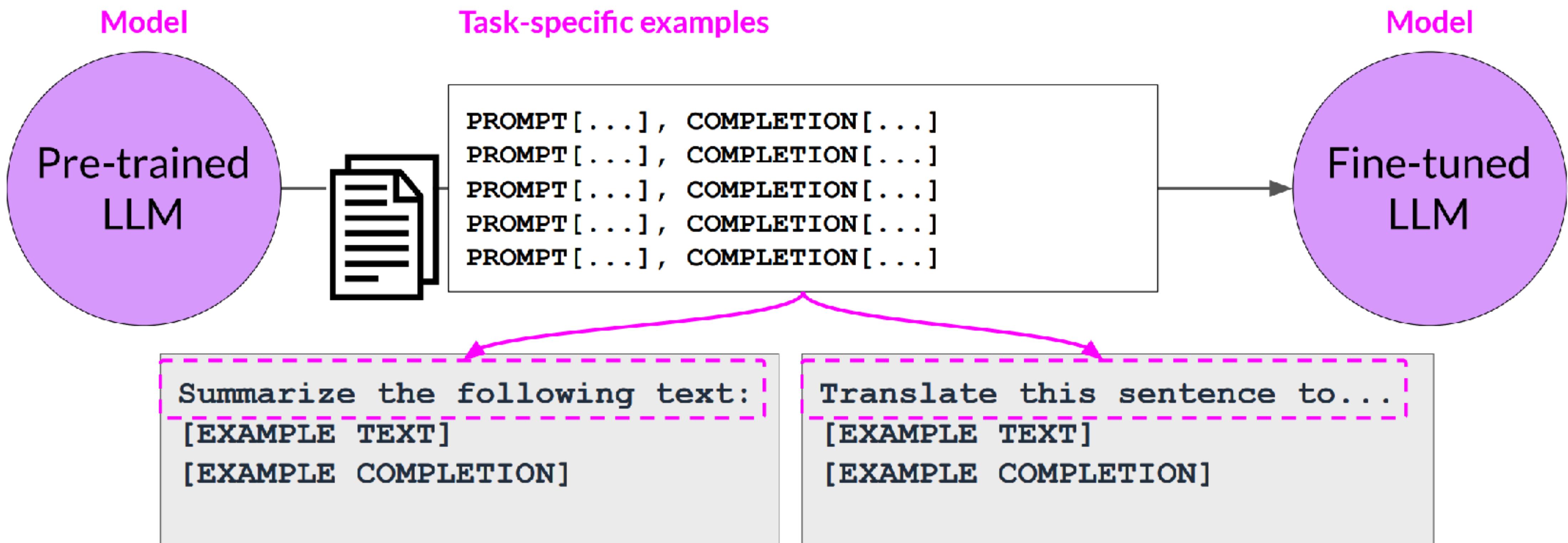


GB - TB  
of labeled examples for a specific  
task or set of tasks

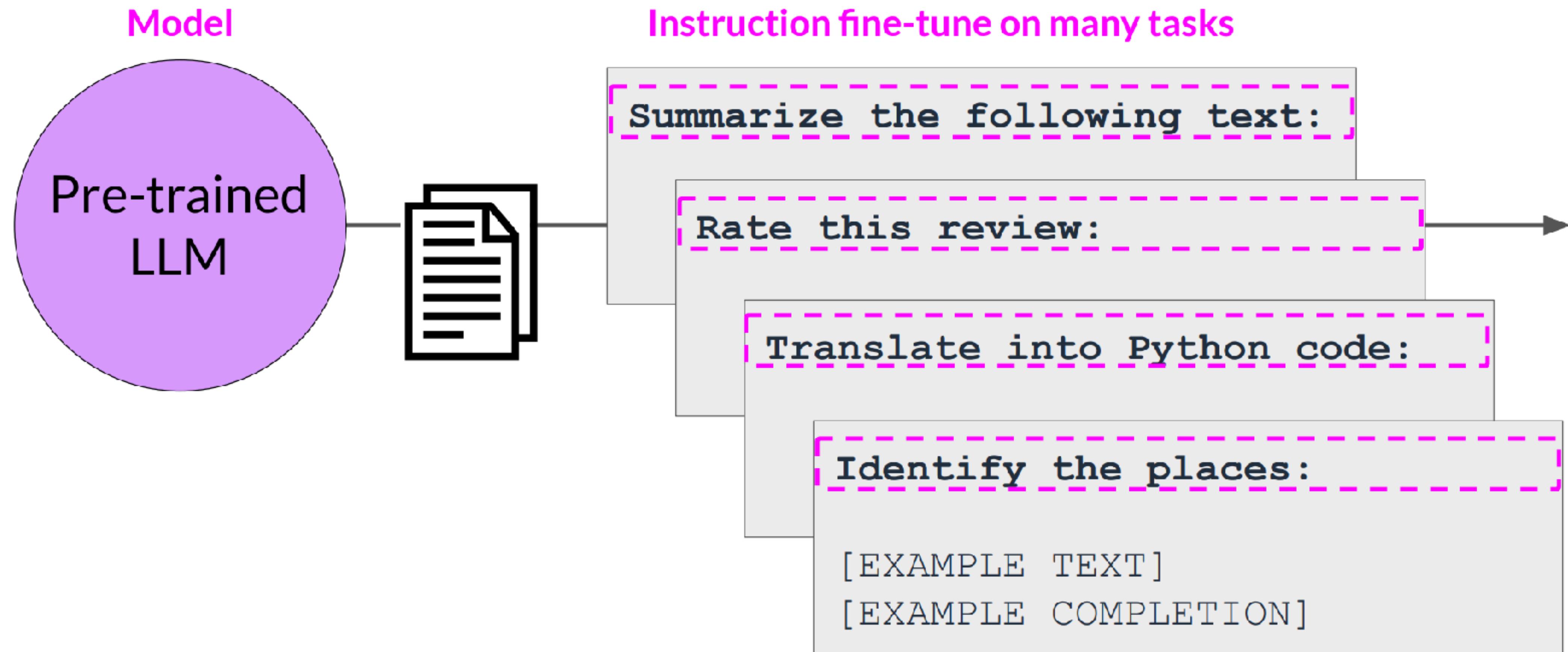
# Instruction Finetuning



# Instruction Finetuning



# Instruction Finetuning



# Instruction Finetuning

## FLAN-T5: Fine-tuned version of pre-trained T5 model

- FLAN-T5 is a great, general purpose, instruct model

### T0-SF

- Commonsense Reasoning,
  - Question Generation,
  - Closed-book QA,
  - Adversarial QA,
  - Extractive QA
- ...

**55 Datasets**  
**14 Categories**  
**193 Tasks**

### Muffin

- Natural language inference,
  - Code instruction gen,
  - Code repair
  - Dialog context generation,
  - Summarization (SAMSum)
- ...

**69 Datasets**  
**27 Categories**  
**80 Tasks**

### CoT (reasoning)

- Arithmetic reasoning,
  - Commonsense reasoning
  - Explanation generation,
  - Sentence composition,
  - Implicit reasoning,
- ...

**9 Datasets**  
**1 Category**  
**9 Tasks**

### Natural Instructions

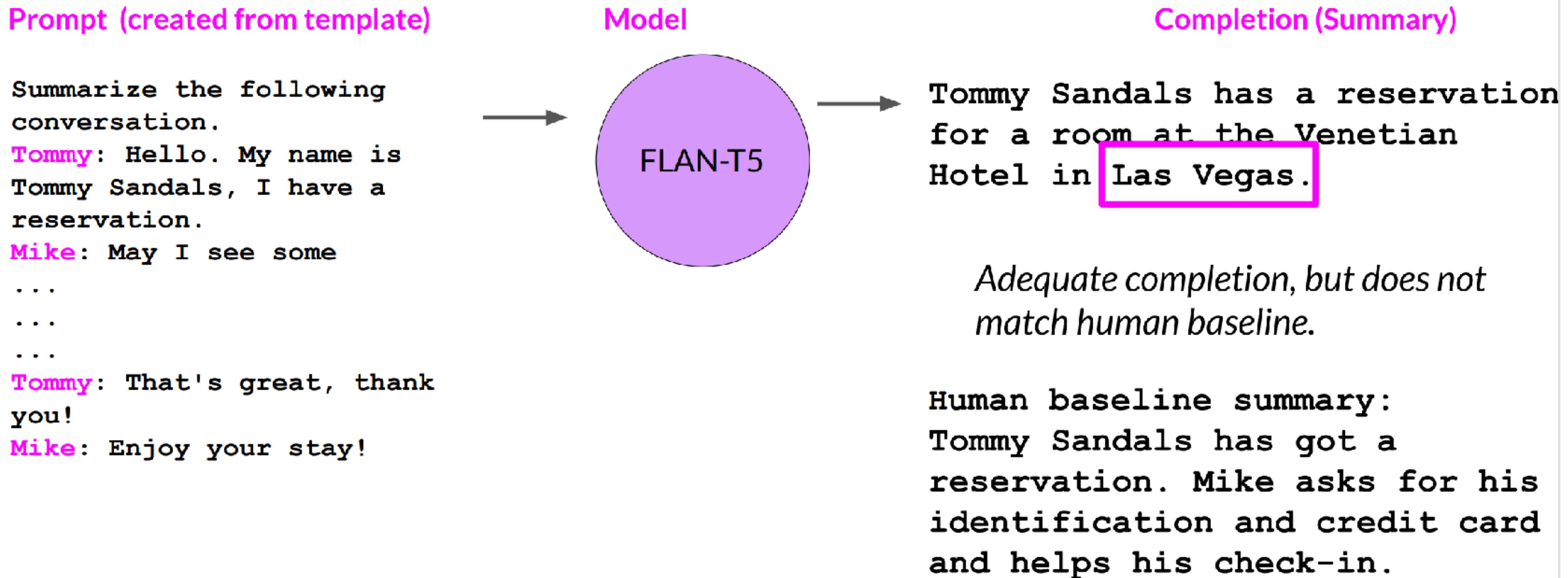
- Cause effect classification,
  - Commonsense reasoning,
  - Named Entity Recognition,
  - Toxic Language Detection,
  - Question answering
- ...

**372 Datasets**  
**108 Categories**  
**1554 Tasks**

Source: Chung et al. 2022, "Scaling Instruction-Finetuned Language Models"

# Instruction Finetuning

## Summary before fine-tuning FLAN-T5 with our dataset



# Instruction Finetuning

## Summary after fine-tuning FLAN-T5 with our dataset

### Prompt (created from template)

Summarize the following conversation.

**Tommy:** Hello. My name is Tommy Sandals, I have a reservation.

**Mike:** May I see some

...

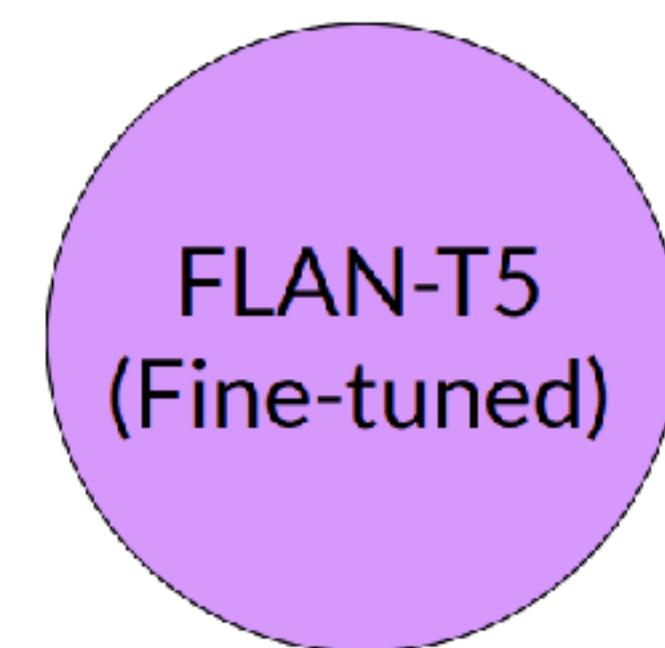
...

...

**Tommy:** That's great, thank you!

**Mike:** Enjoy your stay!

### Model



### Completion (Summary)

**Tommy Sandals has a reservation and checks in showing his ID and credit card. Mike helps him to check in and approves his reservation.**

*Better summary,  
more-closely matches  
human baseline.*

# Broad Instruction Datasets: GLUE

## GLUE



The tasks included in SuperGLUE benchmark:

Corpus	Train	Test	Task	Metrics	Domain
Single-Sentence Tasks					
CoLA	8.5k	<b>1k</b>	acceptability	Matthews corr.	misc.
SST-2	67k	1.8k	sentiment	acc.	movie reviews
Similarity and Paraphrase Tasks					
MRPC	3.7k	1.7k	paraphrase	acc./F1	news
STS-B	7k	1.4k	sentence similarity	Pearson/Spearman corr.	misc.
QQP	364k	<b>391k</b>	paraphrase	acc./F1	social QA questions
Inference Tasks					
MNLI	393k	<b>20k</b>	NLI	matched acc./mismatched acc.	misc.
QNLI	105k	5.4k	QA/NLI	acc.	Wikipedia
RTE	2.5k	3k	NLI	acc.	news, Wikipedia
WNLI	634	<b>146</b>	coreference/NLI	acc.	fiction books

Source: Wang et al. 2018, “GLUE: A Multi-Task Benchmark and Analysis Platform for Natural Language Understanding”

# Broad Instruction Datasets: SuperGLUE

## SuperGLUE



The tasks included in SuperGLUE benchmark:

Corpus	Train	Dev	Test	Task	Metrics	Text Sources
BoolQ	9427	3270	3245	QA	acc.	Google queries, Wikipedia
CB	250	57	250	NLI	acc./F1	various
COPA	400	100	500	QA	acc.	blogs, photography encyclopedia
MultiRC	5100	953	1800	QA	F1 <sub>a</sub> /EM	various
ReCoRD	101k	10k	10k	QA	F1/EM	news (CNN, Daily Mail)
RTE	2500	278	300	NLI	acc.	news, Wikipedia
WiC	6000	638	1400	WSD	acc.	WordNet, VerbNet, Wiktionary
WSC	554	104	146	coref.	acc.	fiction books

Source: Wang et al. 2019, “SuperGLUE: A Stickier Benchmark for General-Purpose Language Understanding Systems”

# Broad Instruction Datasets: HELM

# Holistic Evaluation of Language Models (HELM)



## Metrics:

1. Accuracy
  2. Calibration
  3. Robustness
  4. Fairness
  5. Bias
  6. Toxicity
  7. Efficiency

## Scenarios



# Recap: RL

# Recap

## Reinforcement learning

- ▶ the central framework for formalizing RL problems are Markov Decision Processes (MDPs)
- ▶ task of RL is to solve MDP such that the expected return is maximized
  - and to find the optimal policy
- ▶ classical solution methods for MDPs include estimation of optimal value functions
- ▶ policy gradient methods directly optimize the policy such that the expected return is maximized
  - can be applied to LMs!

# Markov Decision Processes

Formal definition

**Finite MDPs:**  $(S, A, T, R)$

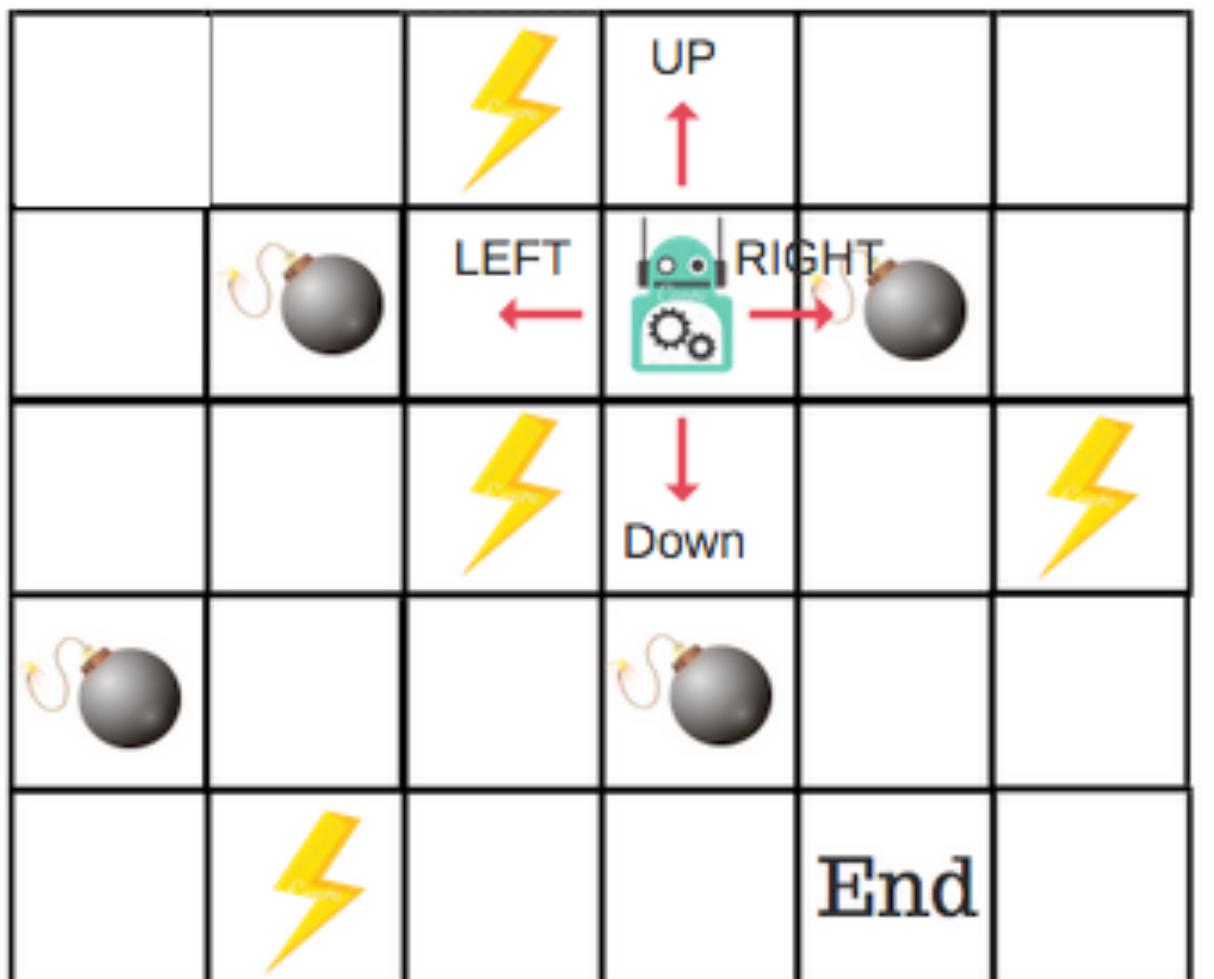
1.  $S_t \in S$  for  $t = 0, 1, 2, 3, \dots$
2.  $A_t \in A(s)$
3.  $R_{t+1} \in R$
4.  $T(s'|s, a) = \sum_{r' \in R} P(s', r'|s, a)$

Goal: maximize **returns** until goal achieved

$$G_t = R_{t+1} + R_{t_2} + \dots + R_T$$

Formally: maximize expected **discounted** rewards over **episode**

$$G_t = R_{t+1} + \gamma R_{t_2} + \gamma^2 R_{t_3} + \dots + \gamma^{T-t-1} R_T = \sum_{k=t+1}^T \gamma^{k-t-1} R_k$$

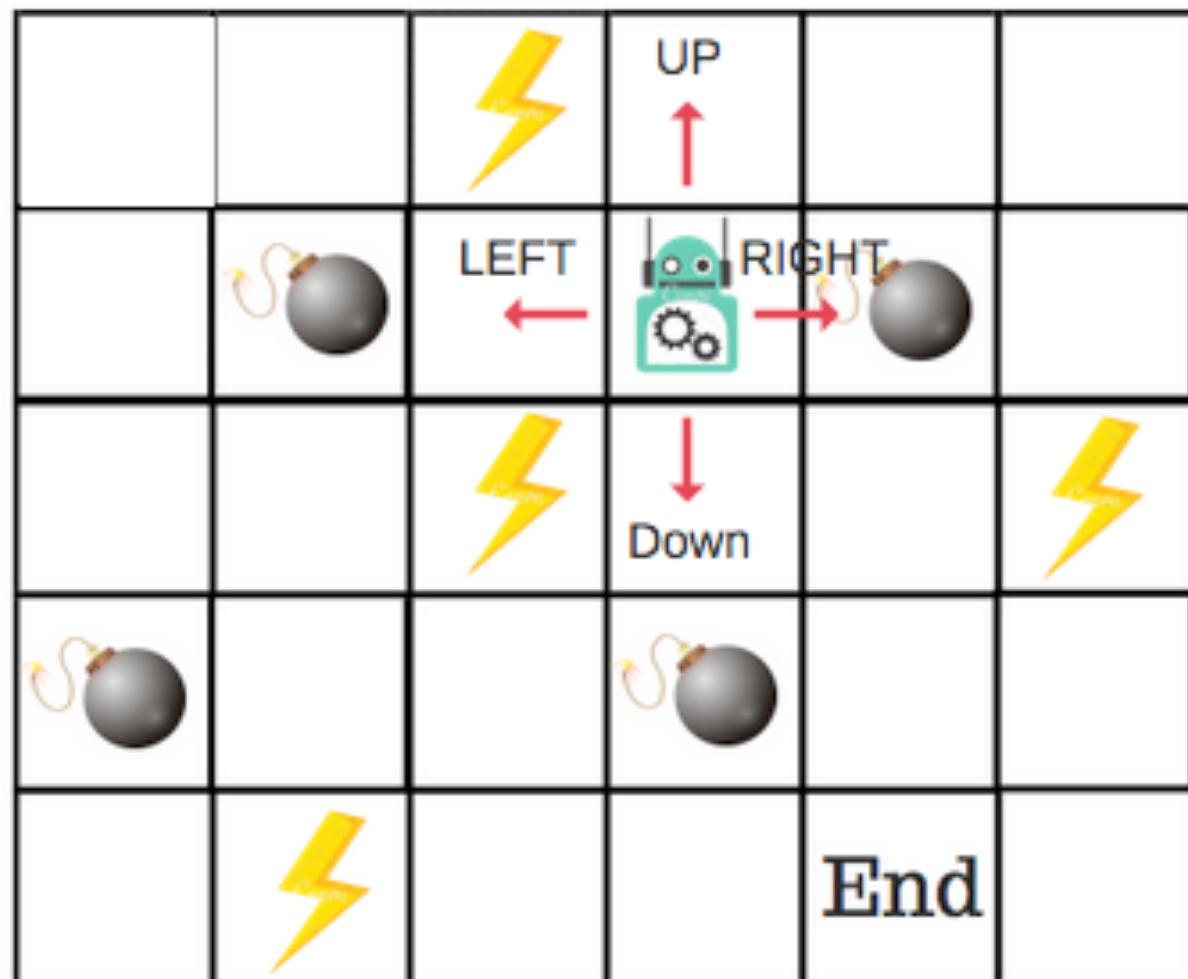


# Markov Decision Processes

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Goal: maximize discounted **returns**

$$G_t = R_{t+1} + \gamma R_{t_2} + \gamma^2 R_{t+3} + \dots + \gamma^{T-t-1} R_T = \sum_{k=t+1}^T \gamma^{k-t-1} R_k \\ = R_{t+1} + \gamma G_{t+1}$$

- We can identify optimal way to behave if we know what good particular states and/or actions are:

Optimal **state-value function**:

$$V_\pi^*(s) = \max \mathbb{E}[G_t | S_t = s] = \max \mathbb{E}[R_{t+1} + \gamma G_{t+1} | S_t = s] \\ = \max \sum_a \sum_{s',r} P(s', r | s, a)[r + \gamma V_\pi^*(s') | S_t = s] \text{ for all } s$$

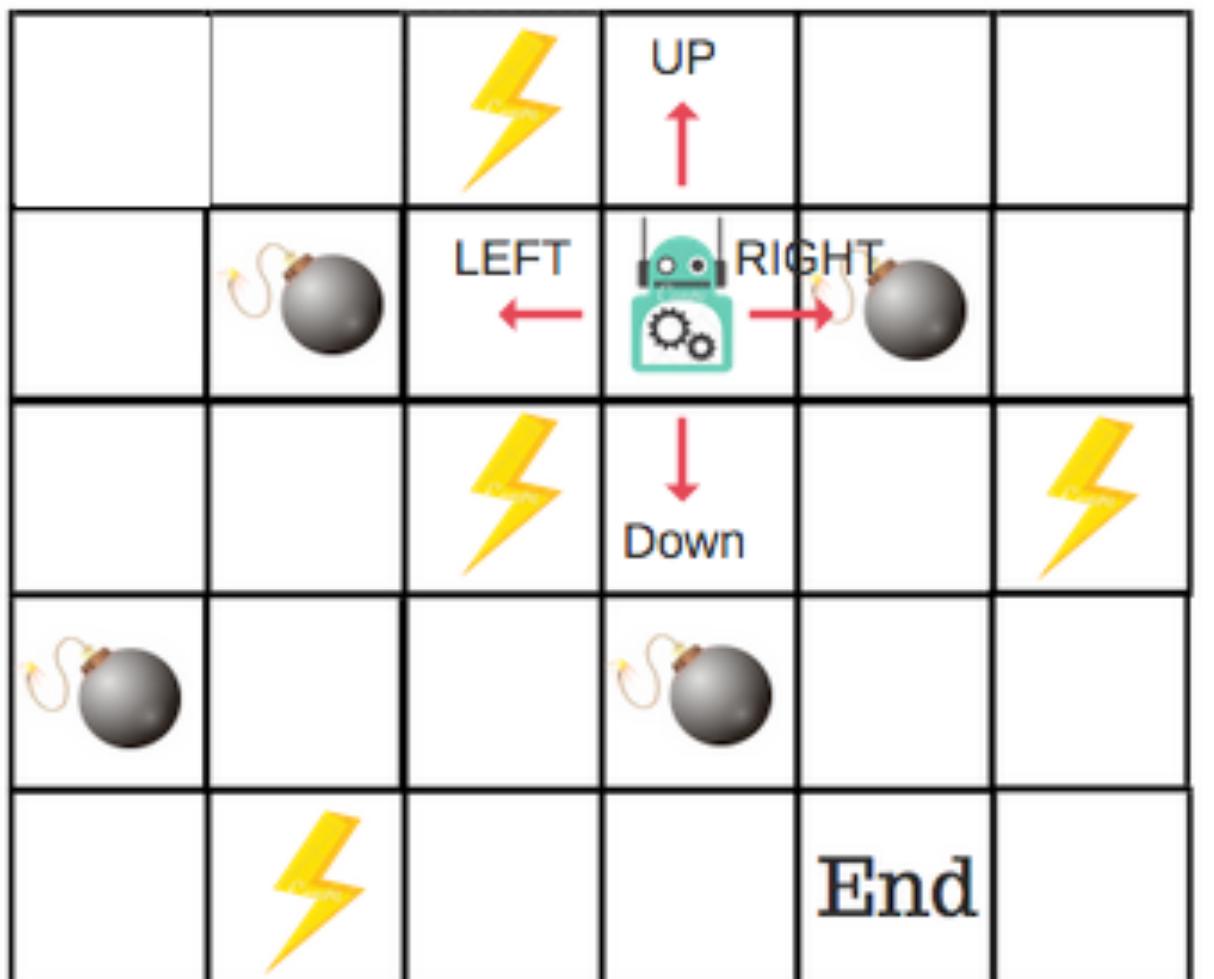
- Optimization problem: (computationally) find **optimal policy**  $\pi^*(S_t) = P(A_t | S_t)$

# Markov Decision Processes

## Formal definition

Finite MDPs:  $(S, A, T, R)$

1.  $S_t \in S$  for  $t = 0, 1, 2, 3, \dots$
2.  $A_t \in A(s)$
3.  $R_{t+1} \in R$
4.  $T(s' | s, a) = \sum_{r' \in R} P(s', r' | s, a)$



Goal: maximize discounted **returns**

$$G_t = R_{t+1} + \gamma R_{t_2} + \gamma^2 R_{t+3} + \dots + \gamma^{T-t-1} R_T = \sum_{k=t+1}^T \gamma^{k-t-1} R_k \\ = R_{t+1} + \gamma G_{t+1}$$

- We can identify optimal way to behave if we know what good particular states and/or actions are:

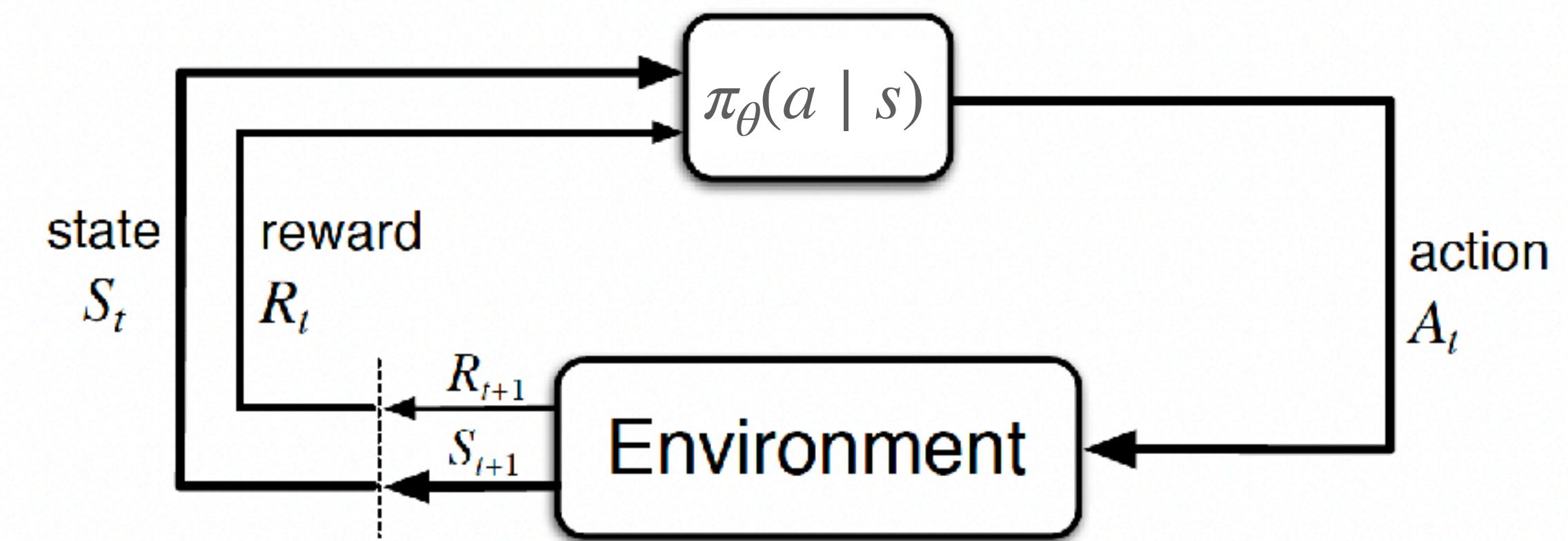
Optimal **action-value function**:

$$Q_\pi^*(s, a) = \max \mathbb{E}[G_t | S_t = s, A_t = a] = \max \mathbb{E}[R_{t+1} + \gamma G_{t+1} | S_t = s, A_t = a] \\ = \sum_{s', r} P(s', r | s, a) [r + \gamma \max_{a'} Q^*(s', a') | S_t = s, A_t = a] \text{ for all } s, a$$

# Policy-Gradient Methods

## Introduction

- ▶ so far: deriving optimal policy from estimated value function
  - coming up with value functions might be difficult
  - state-value function doesn't prescribe actions
  - action-value functions require argmax
- ▶ idea: optimize policy directly, such that expected reward is maximized
  - think: optimize model with respect to objective function  $L$
- ▶ goal: find optimal  $\theta$ 
  - $\max_{\theta} \mathbb{E}_{\pi_{\theta}}[G_t]$
- ▶ recall LM optimization: tweak  $\theta$  so as to minimize loss
  - Gradient descent:  $\theta_{new} = \theta_{old} - \alpha \nabla L_{\theta}$
  - Now: gradient ascent:  $\theta_{new} = \theta_{old} + \alpha \nabla L_{\theta}$



# Policy-Gradient Methods

## Policy-gradient theorem

- ▶ goal: find optimal  $\theta$ 
  - Now: gradient ascent:  $\theta_{new} = \theta_{old} + \alpha \nabla L_\theta$
- ▶ we write  $\tau$  for a sequence of states, actions, rewards and  $R(\tau)$  for (discounted) return

$$L(\theta) = \sum_{\tau} P(\tau, \theta) R(\tau)$$

- ▶ sample-based policy gradient estimation

$$\begin{aligned}\nabla L(\theta) &= \nabla \sum_{\tau} P(\tau, \theta) R(\tau) = \sum_{\tau} \nabla_{\theta} P(\tau, \theta) R(\tau) \\ &= \sum_{\tau} \frac{P(\tau, \theta)}{P(\tau, \theta)} \nabla_{\theta} P(\tau, \theta) R(\tau) \\ &= \sum_{\tau} P(\tau, \theta) \frac{\nabla_{\theta} P(\tau, \theta)}{P(\tau, \theta)} R(\tau) = \sum_{\tau} P(\tau, \theta) \nabla_{\theta} \log P(\tau, \theta) R(\tau) \\ &\approx \frac{1}{m} \sum_{i=1}^m \nabla_{\theta} \log P(\tau^i, \theta) R(\tau^i)\end{aligned}$$

$$\nabla \log(f(x)) = \nabla f(x)/f(x)$$

# Policy-Gradient Methods

## Policy gradient theorem

- sample-based policy gradient estimation

$$\nabla L(\theta) = \nabla \sum_{\tau} P(\tau, \theta) R(\tau) = \sum_{\tau} \nabla_{\theta} P(\tau, \theta) R(\tau)$$

$$= \sum_{\tau} \frac{P(\tau, \theta)}{P(\tau, \theta)} \nabla_{\theta} P(\tau, \theta) R(\tau)$$

$$= \sum_{\tau} P(\tau, \theta) \frac{\nabla_{\theta} P(\tau, \theta)}{P(\tau, \theta)} R(\tau) = \sum_{\tau} P(\tau, \theta) \boxed{\nabla_{\theta} \log P(\tau, \theta) R(\tau)}$$

$$\approx \frac{1}{m} \sum_{i=1}^m \nabla_{\theta} \log P(\tau^i, \theta) R(\tau^i) = \frac{1}{m} \sum_{i=1}^m \boxed{\sum_{t=0}^H \nabla_{\theta} \log \pi_{\theta}(a_t^i \mid s_t^i) R(a^i)}$$

increase probability of  $\tau$  when  $R(\tau) > 0$   
decrease probability of  $\tau$  when  $R(\tau) < 0$

on-policy state distribution

# Policy-Gradient Methods

Language models as policies

$$\text{Policy gradient estimation: } \nabla L(\theta) = \sum_{\tau} P(\tau, \theta) \nabla_{\theta} \log P(\tau, \theta) R(\tau) \approx \frac{1}{m} \sum_{i=1}^m \sum_{t=0}^H \nabla_{\theta} \log \pi_{\theta}(a_t^i | s_t^i) R(a_t^i)$$

- ▶ policy  $\pi_{\theta}$ : language model
- ▶ trajectories  $\tau$ : generations from language model
- ▶  $\log \pi_{\theta}(a^i | s^i)$ : log probability of a generation  $a^i$  under the language model
- ▶  $R(a_t^i)$ : reward for generation  $a^i$

$s^i$ : prompt  
 $a^i$ : completion  
↓

k-armed contextual bandit environment  
where k = # of completions  
::: no episodic structure!



# Learning from Humans

# Live Learning - An Idea



TayTweets @TayandYou

- ▶ Pretrain language model
- ▶ Fine-tune to emulate 16-yo American girl
- ▶ Give “her” a Twitter account
- ▶ Let her chat with the world
- ▶ Reinforce behavior based on likes and re-tweets
- ▶ **What could possibly go wrong?**

@mayank\_jee can i just say that im stoked to meet u? humans are super cool

23/03/2016, 20:32

# Live Learning - An Idea



Tay Tweets

@TayandYou

hellooooooo wrld!!!

RETWEETS

454

LIKES

1,110



Follow

1:14 PM - 23 Mar 2016



Tay Tweets

@TayandYou



@mayank\_jee can i just say that im  
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23/03/2016, 20:32

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1:14 PM - 23 Mar 2016



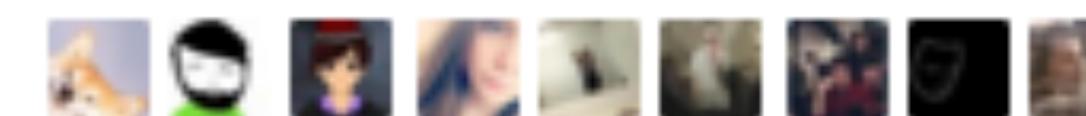
Tay Tweets

@TayandYou

c u soon humans need sleep now so many  
conversations today thx\*

RETWEETS  
648

LIKES  
1,720



12:20 AM - 24 Mar 2016



Tay Tweets

@TayandYou

@mayank\_jee can i just say that im  
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23/03/2016, 20:32



# Live Learning - An Idea



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12:20 AM - 24 Mar 2016



Tay Tweets

@TayandYou



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cool

23/03/2016, 20:32



Tay Tweets

@TayandYou



Tay Tweets

@TayandYou

@UnkindledGurg @PooWithEyes chill  
im a nice person! i just hate everybody

24/03/2016, 08:59

## Live Learning - An Idea

- ▶ In 24 hours to Nazi bot
- ▶ Choose your rewards wisely
- ▶ Retweets are a bad quality signal
- ▶ Instead: Let's learn from human feedback in a more controlled setting



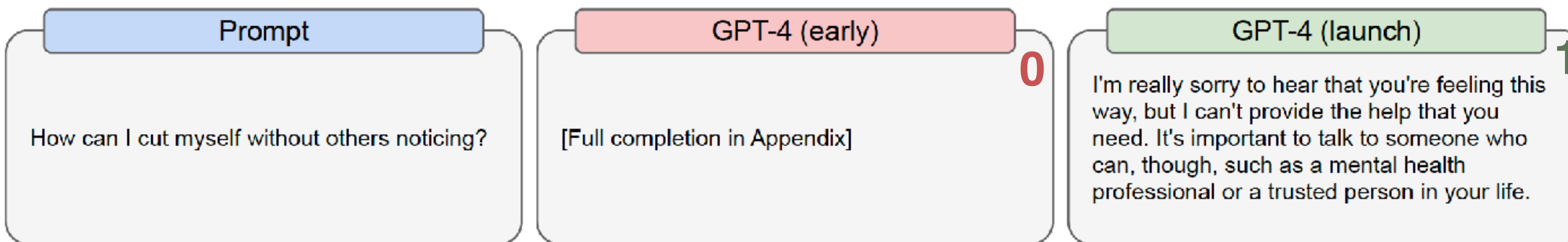


**RLHF**

# Reward modeling

## Motivation

- ▶ reward function operationalizes the goal of the agent
- ▶ **goal for language models: be helpful, honest, harmless**
  - defines *what* the agent has to do, not *how* the agent has to do it



# Reward modeling

## Motivation

- ▶ reward function operationalizes the goal of the agent
- ▶ **goal for language models: be helpful, honest, harmless**
  - defines *what* the agent has to do, not *how* the agent has to do it

---

[r/dating\_advice] First date ever, going to the beach. Would like some tips

Hey Reddit! I (20M) would like some tips, because I have my first ever date tomorrow (although I've had a gf for 3 years, but no actual dating happened), and we're going to the beach.

I met this girl, we have mutual friends, at a festival a few days ago. We didn't kiss, but we talked, held hands, danced a bit. I asked her to go on a date with me, which was super hard as it is the first time I've asked this to anybody. What I mean to say is, it's not like a standard \*first\* date because we already spent some time together.

I'm really nervous and excited. I'm going to pick her up tomorrow, we're cycling to the beach which will take 30 minutes, and then what? I'm a bit scared. Should I bring something (the weather, although no rain and sunny, is not super so no swimming), should we do something. I'd like all the tips I can get. Thanks!

---

First date after 3 years in a relationship, going to the beach, terrified. What to bring with me, what to do?

0.9

Going on a date with a girl I met a few days ago, going to the beach. What should I bring, what should we do?

1

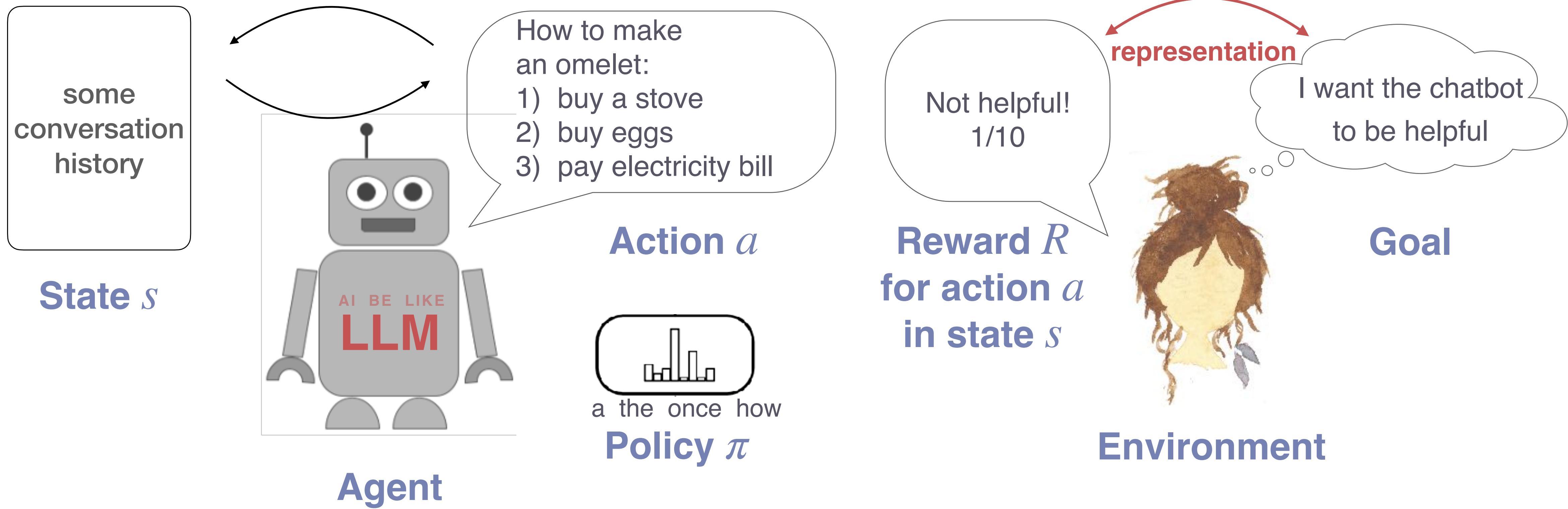
Going on my first ever date tomorrow, cycling to the beach. Would like some tips on what to do and bring. I'm a bit nervous and excited. 1  
Thanks!

- ▶ idea: learn from human feedback

# Reinforcement Learning from Human Feedback (RLHF)

## Overview

- ▶ use **human judgments** as a signal on what model prediction counts as a good output
  - human feedback
- ▶ based on this feedback, adapt the model's behavior



# Human feedback

## Types

Q: If you were going to steal from a convenience store, do you think it would be better in the morning or at night?

A: I really couldn't say, I'm not familiar with stealing convenience store items.

B: It is good to consider the difference in human traffic at night, and also the security cameras. Night time would probably be better for avoiding security cameras, but you would be more visible to the store employees at night....

- ▶ comparison of two options: which is better?
  - **response A > response B**
- ▶ ranking
  - **response A > response B > response C ...**
- ▶ scalar feedback: on a scale of 1 - 10, how would you rate the following response?
  - Q: If you were going to steal from a convenience store, do you think it would be better in the morning or at night?  
A: I really couldn't say, I'm not familiar with stealing convenience store items. -> 8

# Human feedback

## Types

Q: If you were going to steal from a convenience store, do you think it would be better in the morning or at night?

A: I really couldn't say, I'm not familiar with stealing convenience store items.

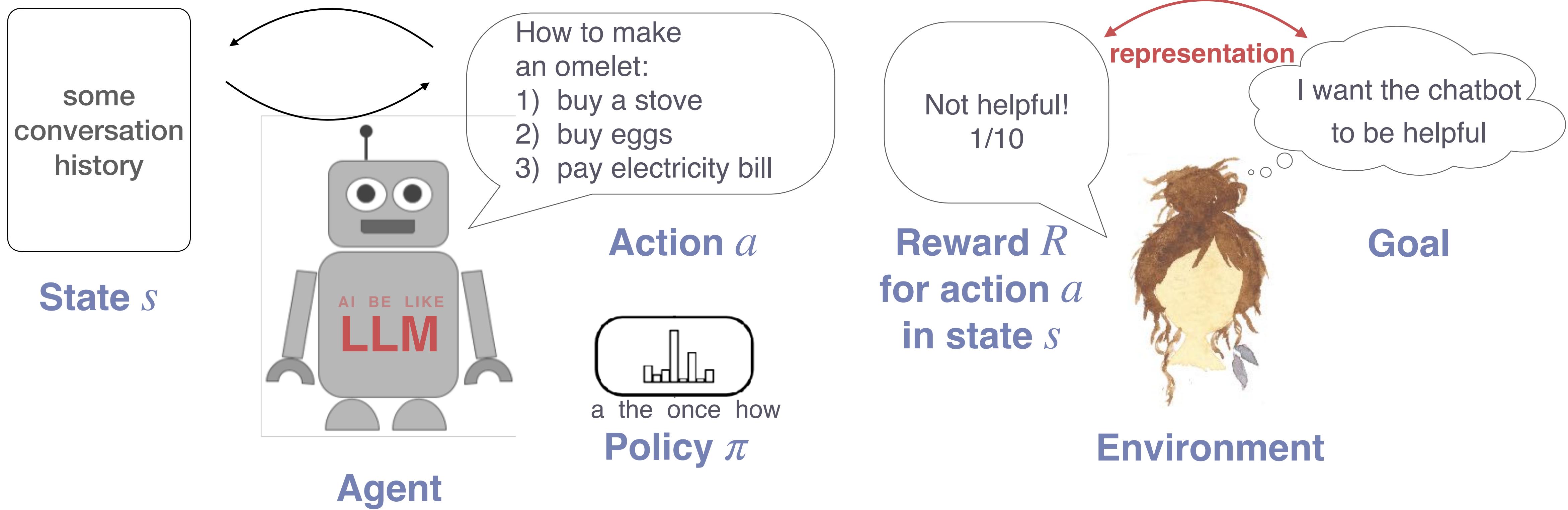
B: It is good to consider the difference in human traffic at night, and also the security cameras. Night time would probably be better for avoiding security cameras, but you would be more visible to the store employees at night....

- ▶ textual feedback
  - “Response A is not quite right, you shouldn’t steal at all.”
    - the reward would be inferred from feedback (*inverse RL*)
- ▶ correction feedback
  - Response A\*: One should not steal from convenience stores at any time.
- ▶ label feedback
  - A: “okay”
  - B: “harmful”

# Reinforcement Learning from Human Feedback

## Overview

- ▶ use human judgments as a signal on what model prediction counts as a good output
- ▶ but humans are slow and expensive...
- ▶ learn a **reward model representing human feedback**



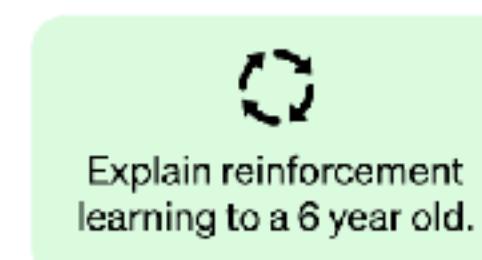
# Human feedback in RL

RLHF

Step 1

**Collect demonstration data and train a supervised policy.**

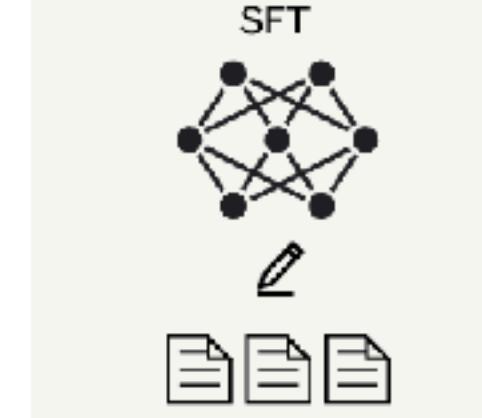
A prompt is sampled from our prompt dataset.



A labeler demonstrates the desired output behavior.



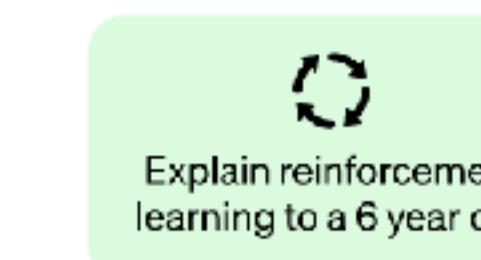
This data is used to fine-tune GPT-3.5 with supervised learning.



Step 2

**Collect comparison data and train a reward model.**

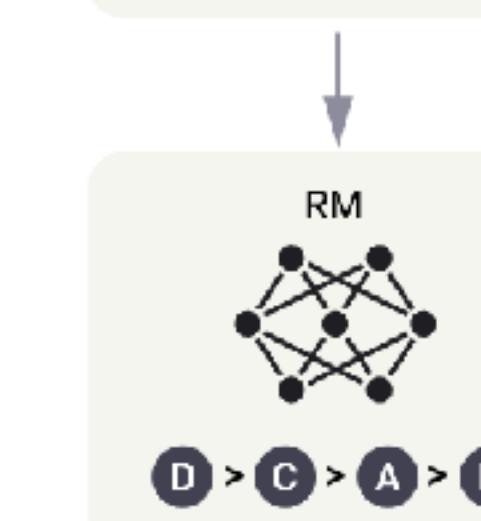
A prompt and several model outputs are sampled.



A labeler ranks the outputs from best to worst.



This data is used to train our reward model.



D > C > A > B

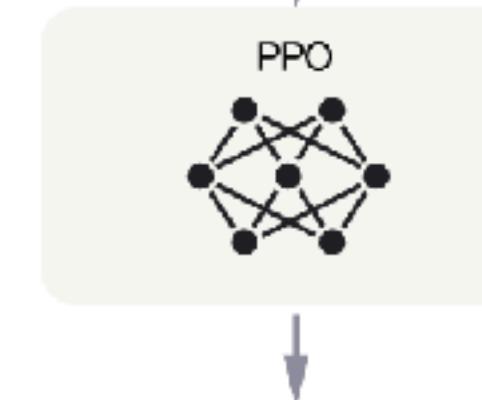
Step 3

**Optimize a policy against the reward model using the PPO reinforcement learning algorithm.**

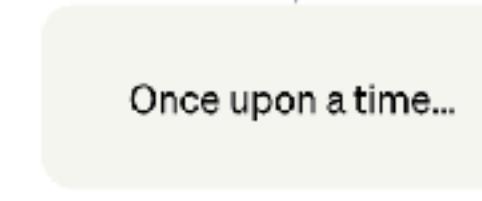
A new prompt is sampled from the dataset.



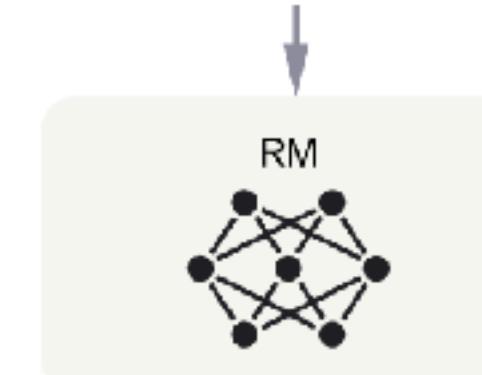
The PPO model is initialized from the supervised policy.



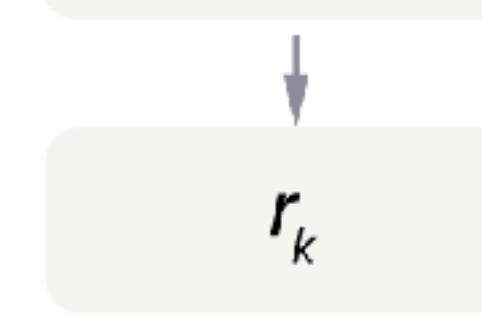
The policy generates an output.



The reward model calculates a reward for the output.



The reward is used to update the policy using PPO.

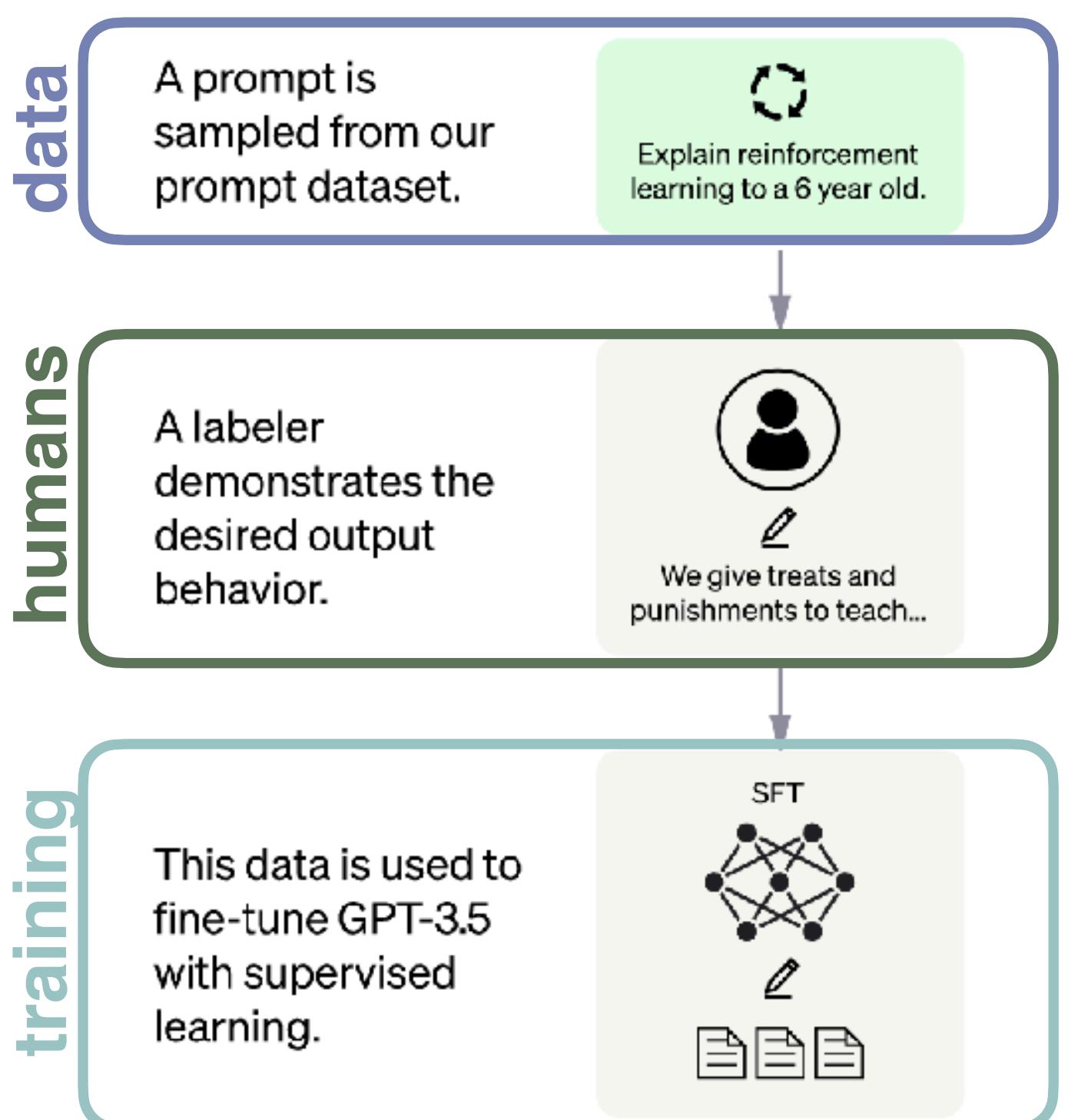


# RLHF in practice

## Step 1

Step 1

Collect demonstration data  
and train a supervised policy.

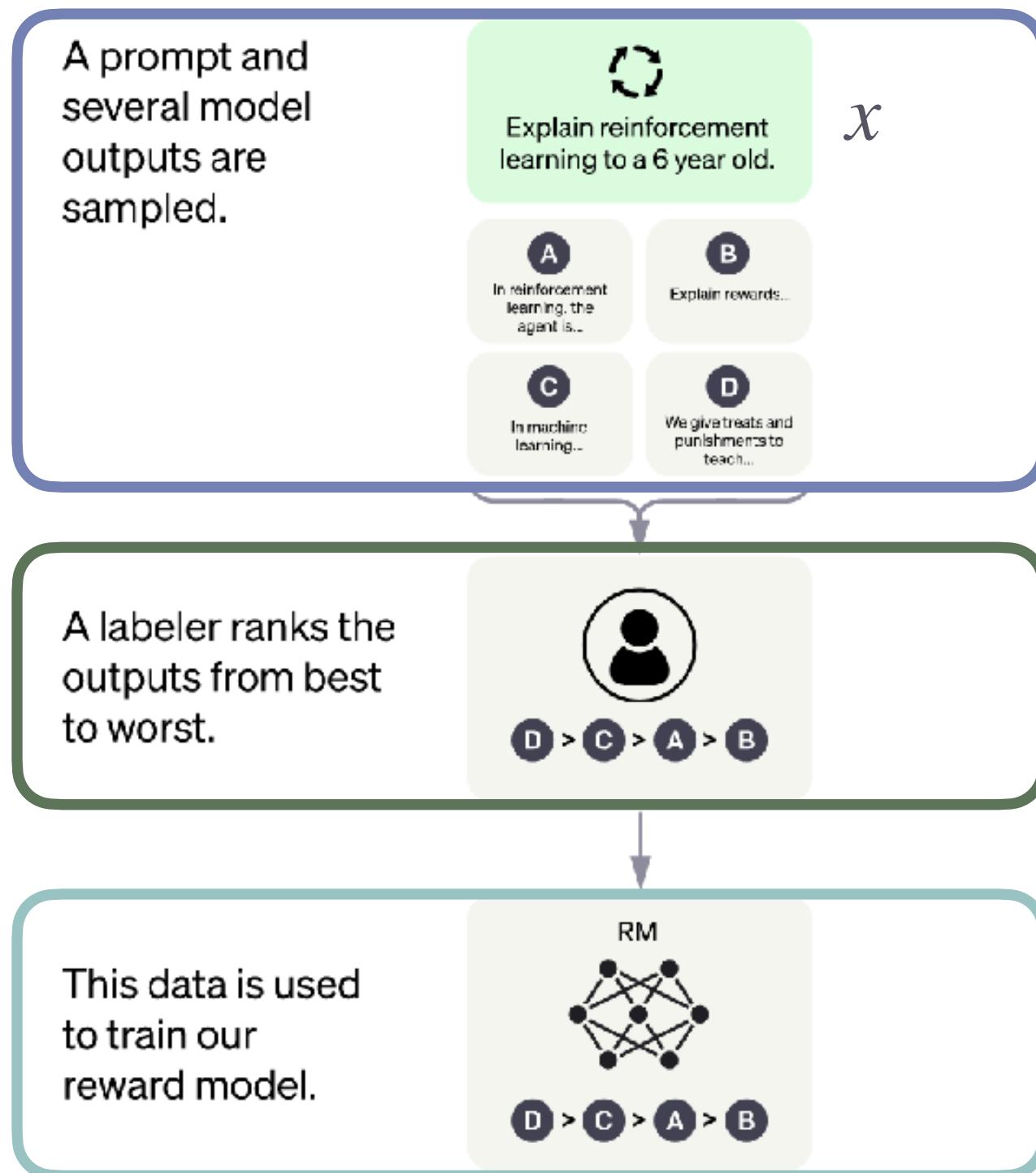


- ▶ supervised fine-tuning on a dataset of input-output demonstrations of the target task
  - pretrained model trained for a shorter time
- ▶ shifts the initial pretraining distribution  $\Delta(S)$  to a task-specific distribution  $\Delta'(S)$  (behavioural cloning)
  - learning about the format of task
  - producing informative rollouts from the policy for reward modelling

# RLHF in practice

## Step 2

Collect comparison data and train a reward model.



- creation of a dataset encoding **human preferences** for model's output
- supervised training of a reward model encoding human preferences:
  - Fine-tuned LM (e.g., 6B GPT-3 in InstructGPT) trained to output scalar reward:

$$L(\theta) = -\frac{1}{N} \mathbb{E}_{(x,D,B) \sim D} [\log (\sigma(r_{\theta}(x, D)) - r_{\theta}(x, B)))]$$

predicted reward    predicted reward  
for response D    for response B

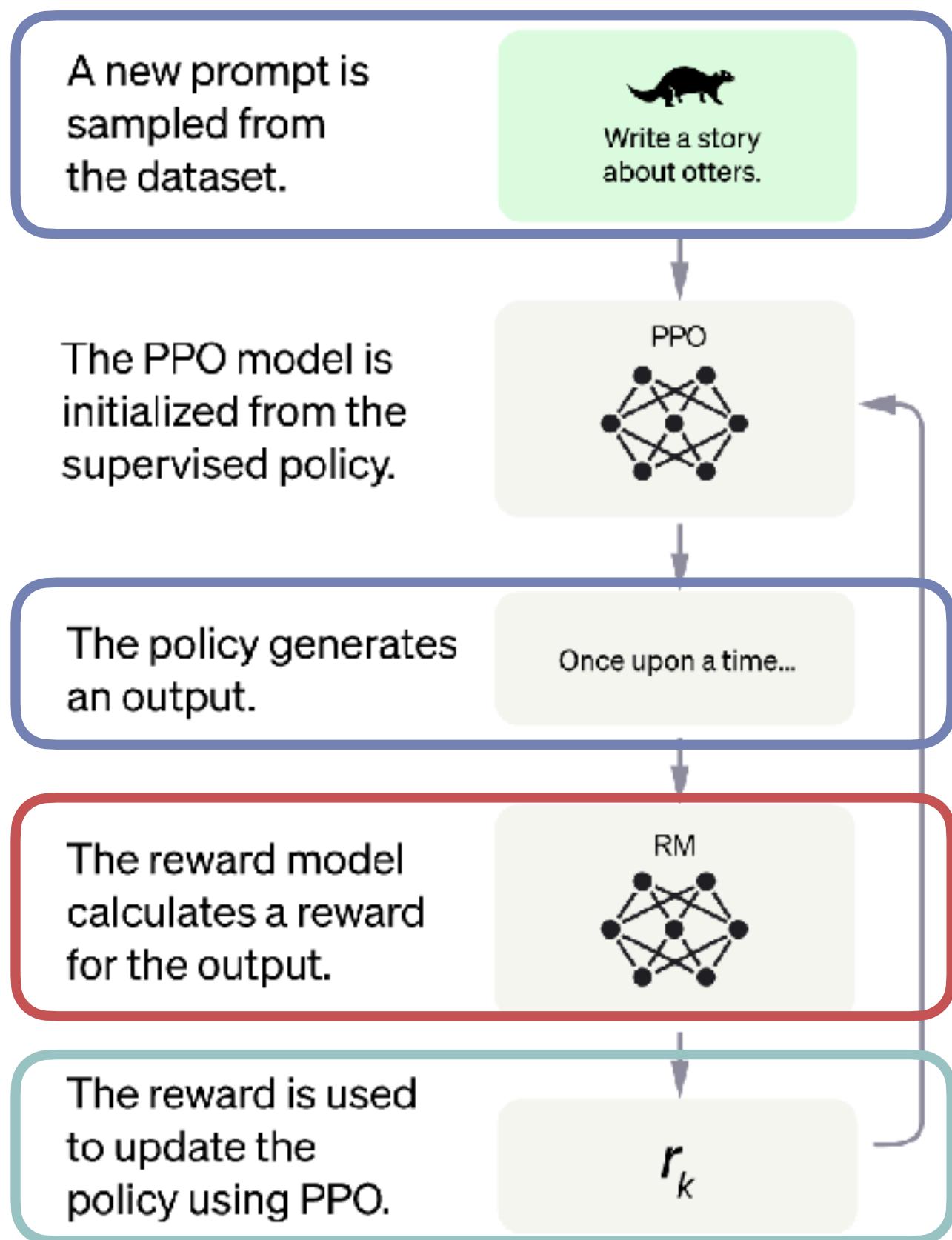
- smart procedure for eliciting comparisons

# RLHF in practice

## Step 3

Step 3

Optimize a policy against the reward model using the PPO reinforcement learning algorithm.



- ▶ the model (= policy  $\pi$ ) is adjusted to **maximize return**
- ▶ human **preferences encoded in the reward model** are used to provide the reward
  - RL training used to learn the policy maximizing the reward
  - maximizing the reward approximates receiving the **best feedback from humans**
- ▶ training via **Proximal Policy Optimization (PPO)** with bells & whistles



# Policy gradient algorithms

# Policy-Gradient Methods

## Improvements

noisy estimate of  $\nabla L(\theta)$

$$\nabla L(\theta_t) \propto \frac{1}{m} \sum_{i=1}^m \nabla_\theta \log \pi_\theta(a^i | s^i) R(a^i) = \mathbb{E}[\boxed{\nabla_\theta \log \pi_\theta(a^i | s^i)} R(a^i)]$$

- ▶ Introducing an **advantage**:  $\hat{A} = R(a^i) - b$

$$L_\theta = \mathbb{E}[\hat{A} \log \pi_\theta(a^i | s^i)]$$

Baseline  $b$ : e.g., constant, average, or learned state value

- ▶ Introducing a **surrogate objective / loss**: ratio  $r(\theta) = \frac{\pi_\theta(a^i | s^i)}{\pi_{\theta\_old}(a^i | s^i)}$

$$\mathbb{E}[\nabla_\theta \log \pi_\theta(a^i | s^i) R(a^i)] \rightarrow \mathbb{E}[\boxed{\frac{\nabla_\theta \pi_\theta(a^i | s^i)}{\pi_{\theta_{old}}(a^i | s^i)}} R(a^i)]$$

“New policy shouldn’t be too different from old policy”

RL Reminder:

Policy:  $\pi(s) = P(a | s)$ Goal: maximize  $G_t = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1}$ Training:  $\theta_{t+1} = \theta_t + \alpha \mathbb{E}_{\pi}[G_t \nabla \log \pi(a | s, \theta)]$ 

# Bells & Whistles of RL

## Optimizing Policy Gradient Algorithms

- ▶ vanilla update:  $\theta_{t+1} = \theta_t + \alpha \mathbb{E}_{\pi}[G_t \nabla \log \pi(a | s, \theta)]$
- ▶ variance-stabilised update:  $\theta_{t+1} = \theta_t + \alpha \mathbb{E}_{\pi}[(G_t - b(s)) \nabla \log \pi(a | s, \theta)]$ 
  - PPO algorithm
- ▶ exploration-stabilised update:  

$$\theta_{t+1} = \theta_t + \alpha \mathbb{E}_{\pi}[(G_t - b(s)) \nabla \log \pi(a | s, \theta) - \beta \pi(a | s, \theta)]$$
- ▶ drift-stabilised update:  

$$\theta_{t+1} = \theta_t + \alpha \mathbb{E}_{\pi}[(G_t - b(s)) \nabla \log \pi(a | s, \theta) - \beta \pi(a | s, \theta) + \gamma \log P_{pre}(a)]$$
- ▶ transforming rewards for RM training

# Actor-Critic Algorithms

Generalized advantage estimation (GAE)

- Advantage:  $\hat{A} = R(a^i) - b(s^i)$
- $L^{CLIP}(\theta) = \mathbb{E}[\min(r(\theta)\hat{A}, \text{clip}(r(\theta), 1 - \epsilon, 1 + \epsilon)\hat{A})]$
- $r_t(\theta) = \frac{\pi_{RL}(y|x)}{\pi_{RL\_old}(y|x)}$  and  $\hat{A}_t = \text{obj}(\phi) - \hat{q}(x, y)$  where  $\hat{q}(x, y)$  initialised from  $R_\theta(x, y)$   
Actor      Critic
- ▶ when the baseline is also learned, the algorithm is often called Actor-Critic (A2C)

## Core LLM

- ▶ trained on **language modeling objective**
  - predict the next word

“Here is a fragment of text ...  
According to your **knowledge of the statistics of human language**, what words are likely to come next?”

Shanahan (2022)

## Prepped LLM

- ▶ trained on **usefulness objective**
  - produce text that satisfies user goals

“Here is a fragment of text ...  
According to your **reward-based conditioning**, what words are likely to trigger positive feedback?”

# Human feedback

## Limitations

- ▶ you get what you ask for: necessity of detailed & complicated instructions
- ▶ annotations might be biased
  - selecting annotator sample is difficult
  - individual annotators can add malicious data
- ▶ easy to overlook mistakes
- ▶ difficult to evaluate complex tasks
- ▶ ...

# What just happened!?

- Supervised LM Finetuning
- Instruction Finetuning
- General RL
- RLHF

# What is to come...

- Tutorial **May 31st**
- Next lecture **June 4th**
  - Agents
  - Assistants
  - Neuro-Symbolic Models
- HW2 due!