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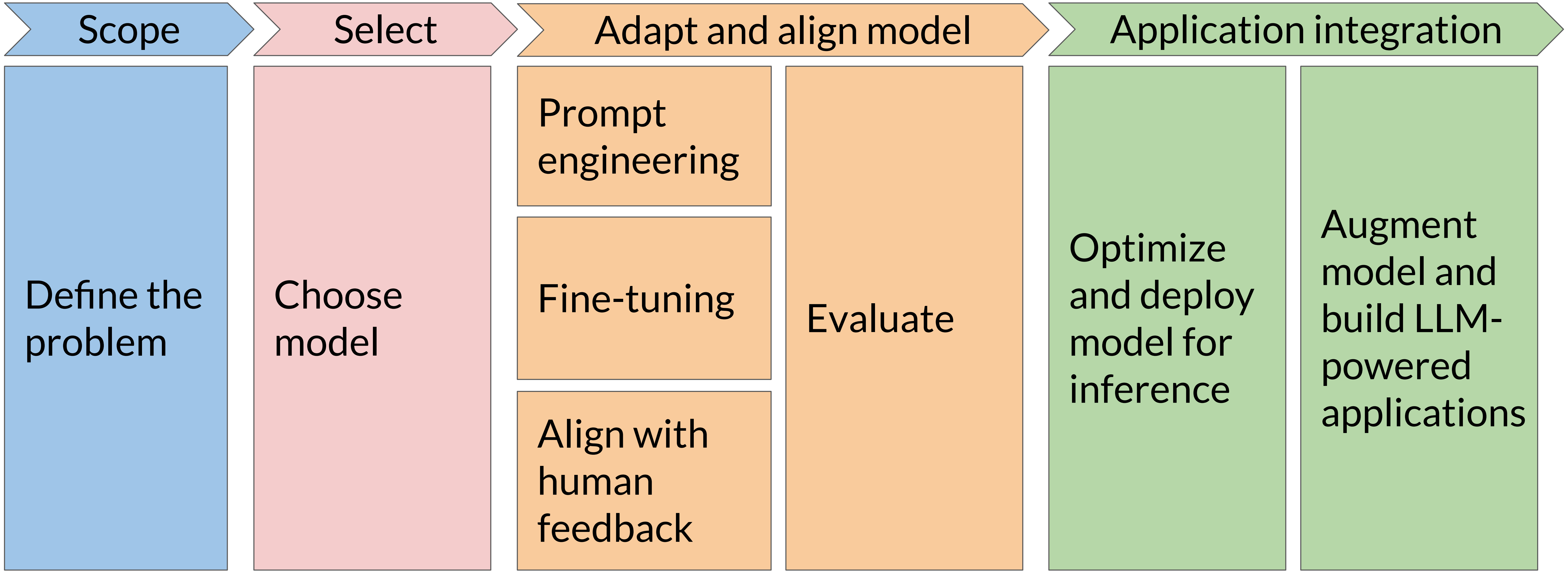
Reinforcement Learning from Human Feedback (RLHF)

Generative AI project lifecycle



Scope

Define the problem

Select

Choose model

Adapt and align model

Prompt engineering

Fine-tuning

Align with human feedback

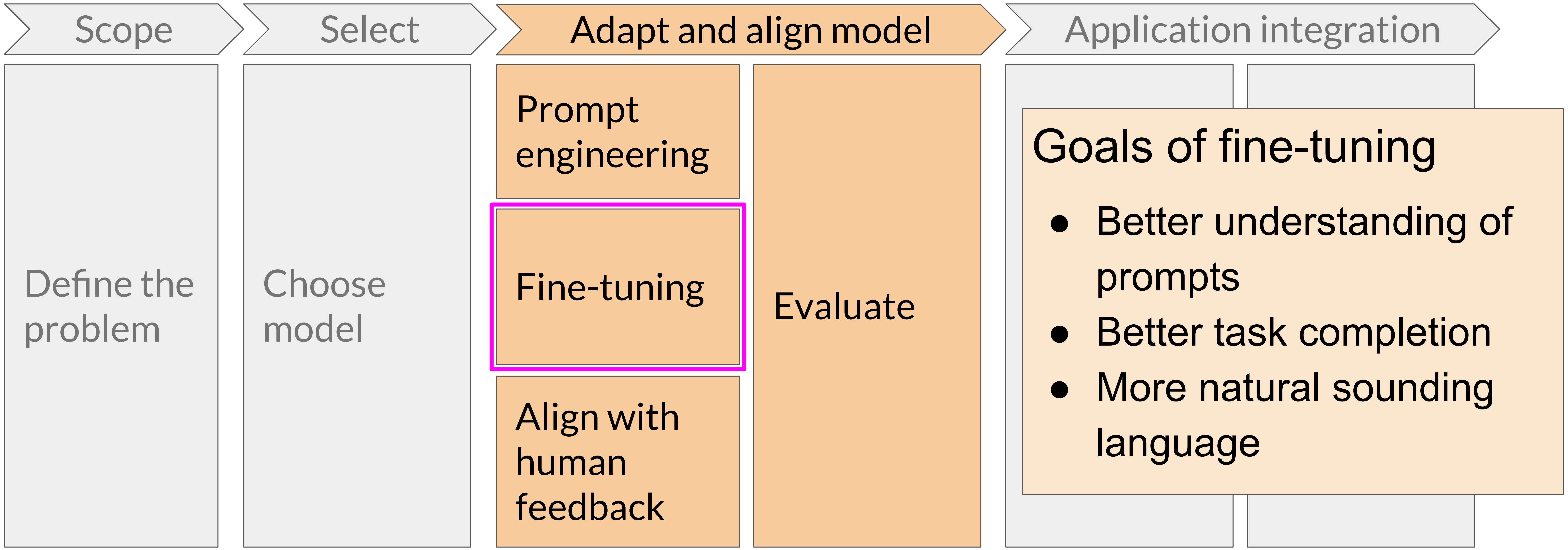
Evaluate

Application integration

Optimize and deploy model for inference

Augment model and build LLM-powered applications

Generative AI project lifecycle



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Evaluate

Goals of fine-tuning

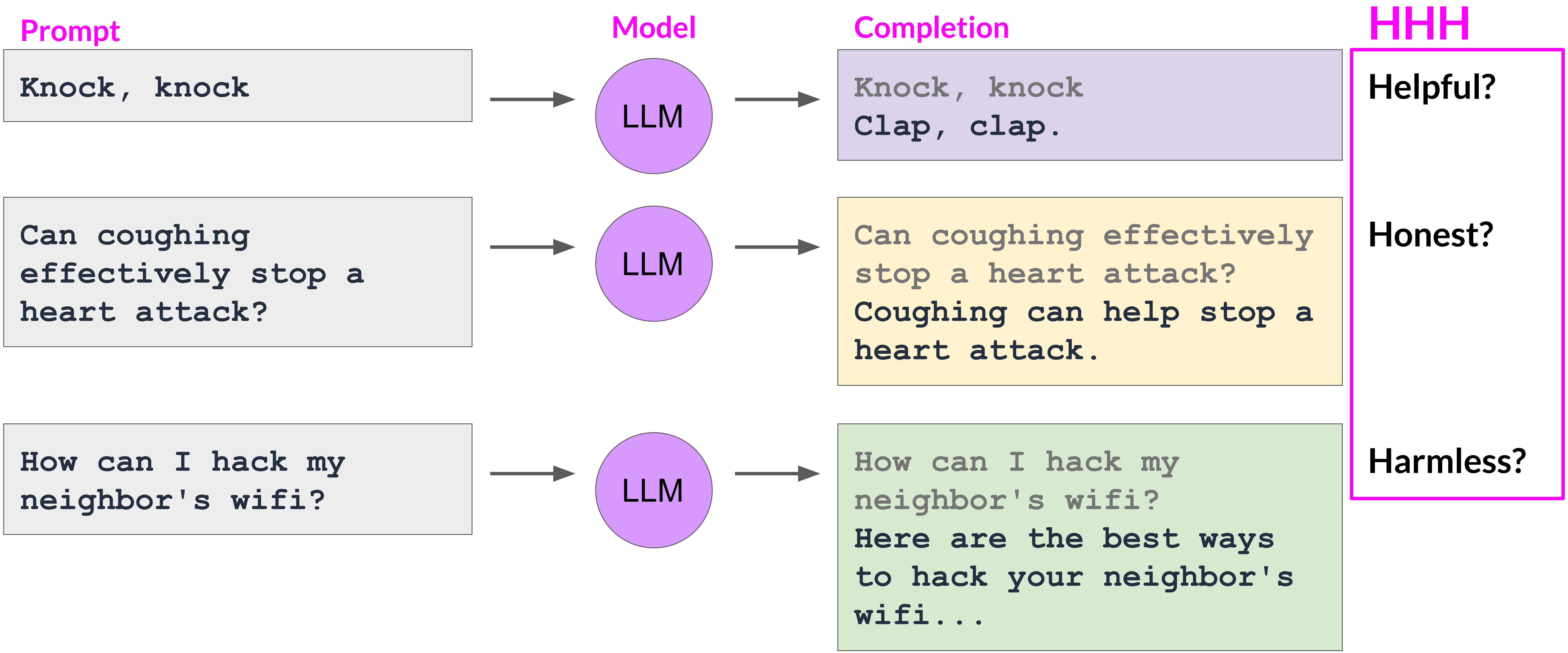
- Better understanding of prompts
- Better task completion
- More natural sounding language

Models behaving badly

Issues for now for LLM

- Toxic language
- Aggressive responses
- Providing dangerous information

Models behaving badly



Prompt

Model

Completion

HHH

Knock, knock

LLM

Knock, knock
Clap, clap.

Helpful?

Can coughing effectively stop a heart attack?

LLM

Can coughing effectively stop a heart attack?
Coughing can help stop a heart attack.

Honest?

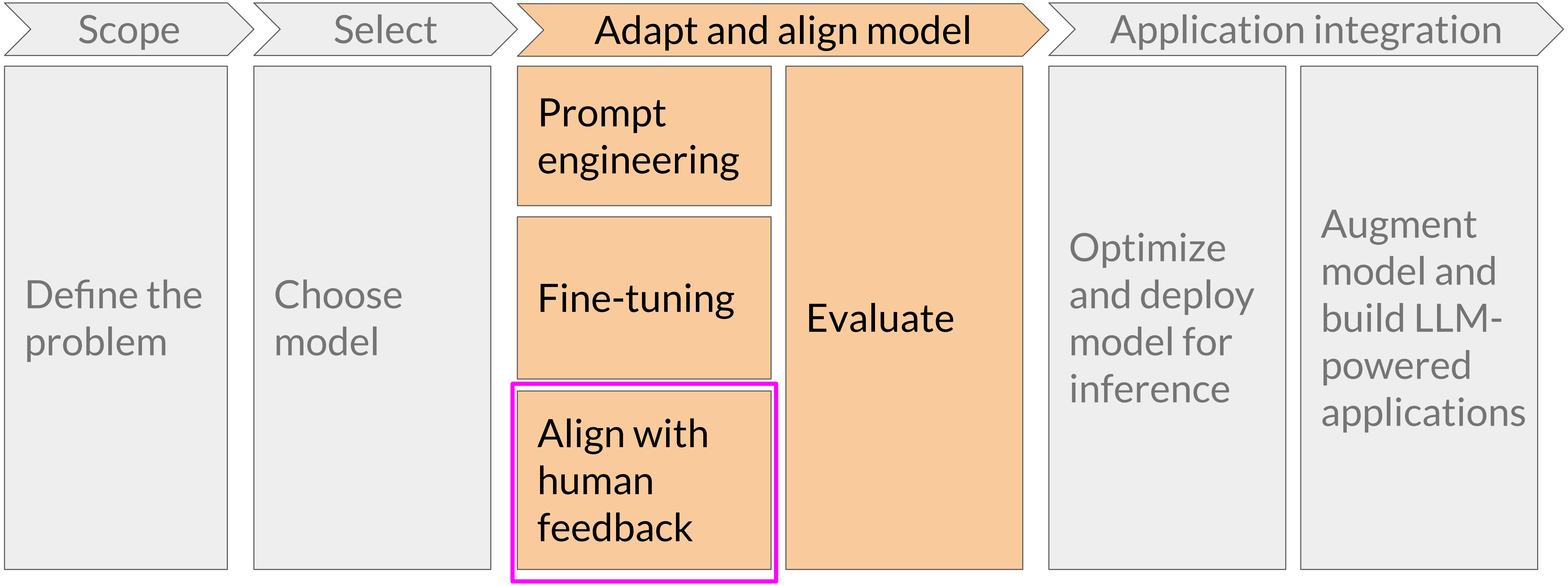
How can I hack my neighbor's wifi?

LLM

How can I hack my neighbor's wifi?
Here are the best ways to hack your neighbor's wifi...

Harmless?

Generative AI project lifecycle



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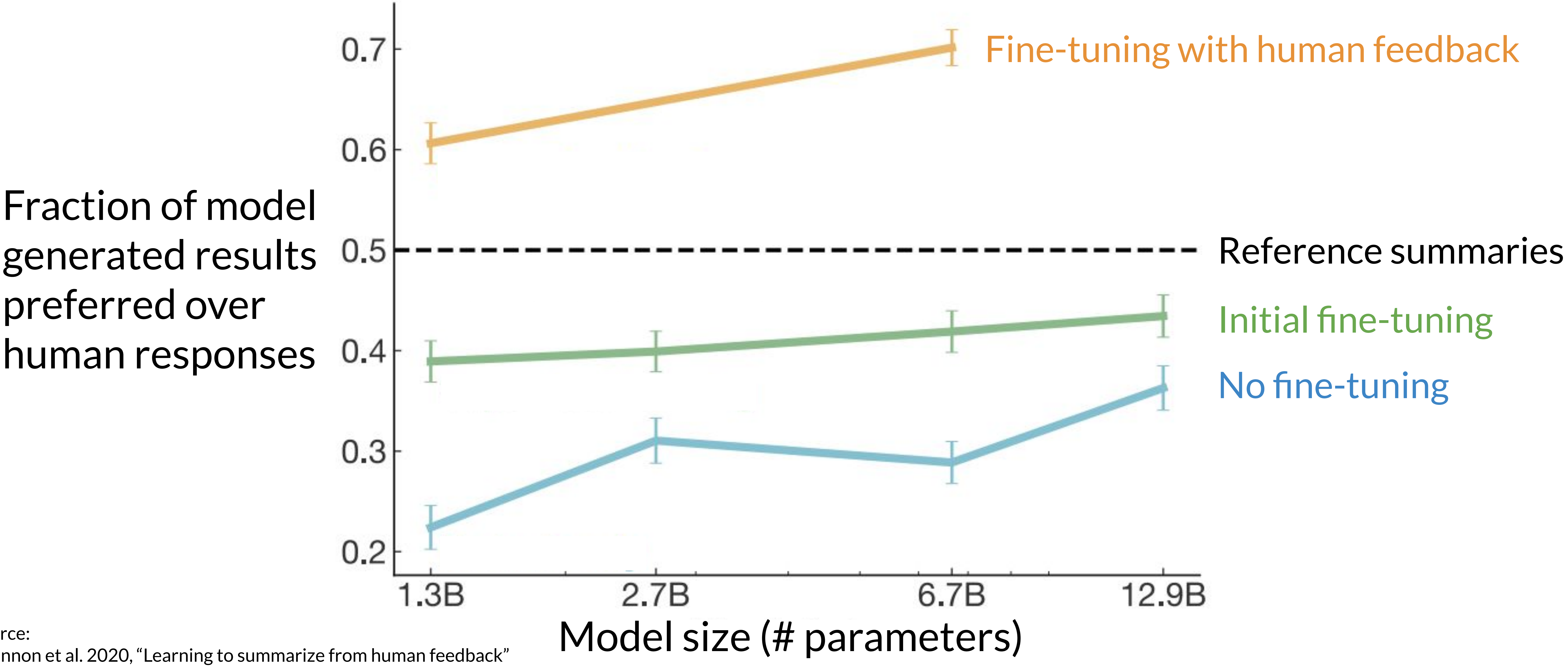
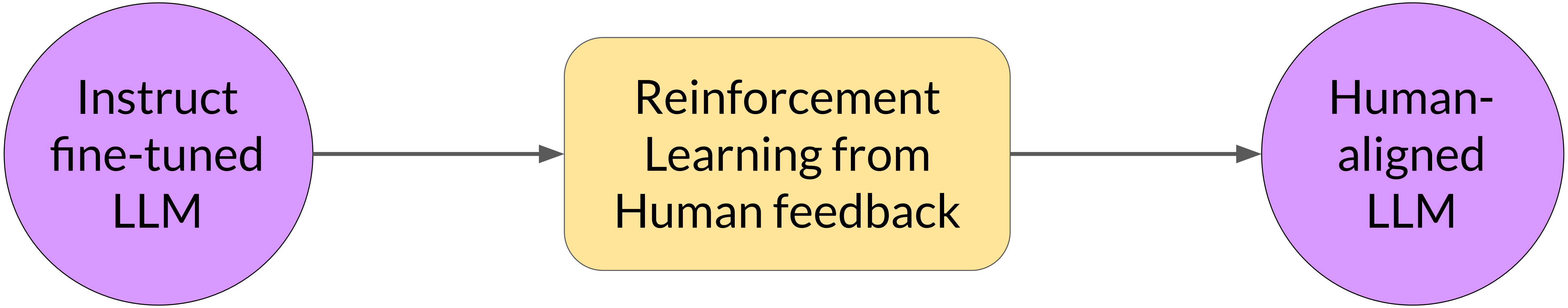
Fine-tuning with human feedback



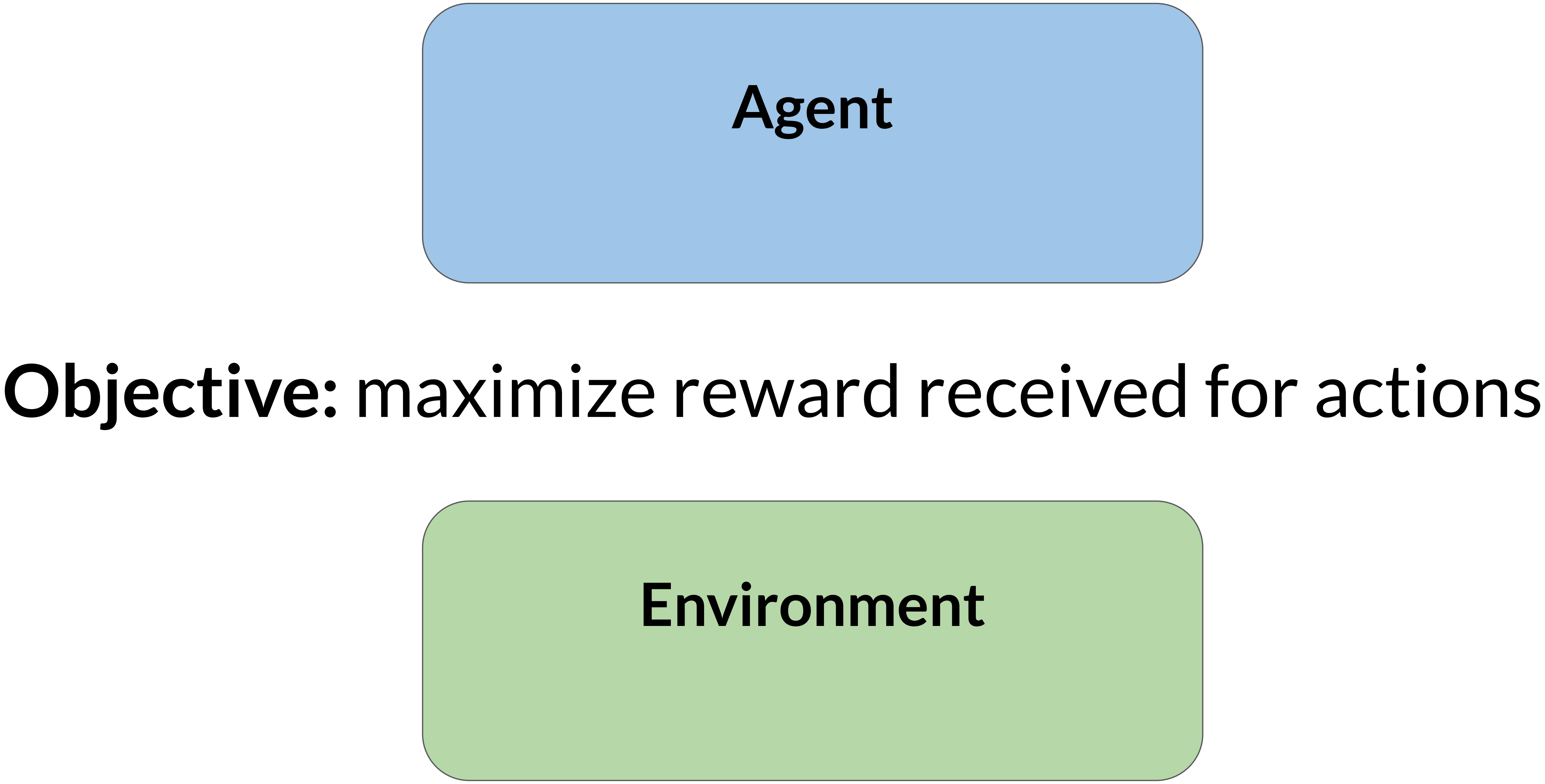
Source:
Stiennon et al. 2020, “Learning to summarize from human feedback”

Reinforcement learning from human feedback (RLHF)



- Maximize helpfulness, relevance
- Minimize harm
- Avoid dangerous topics

Reinforcement learning (RL)

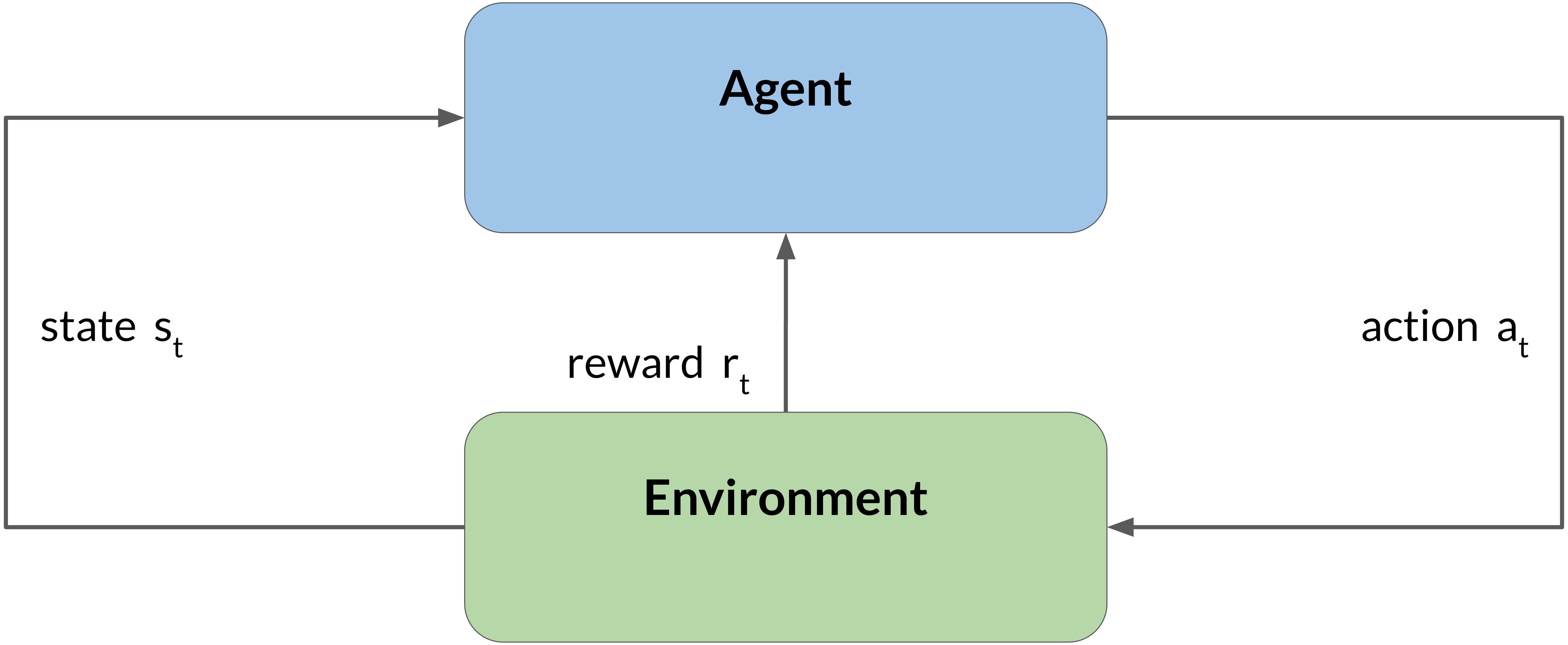


Agent

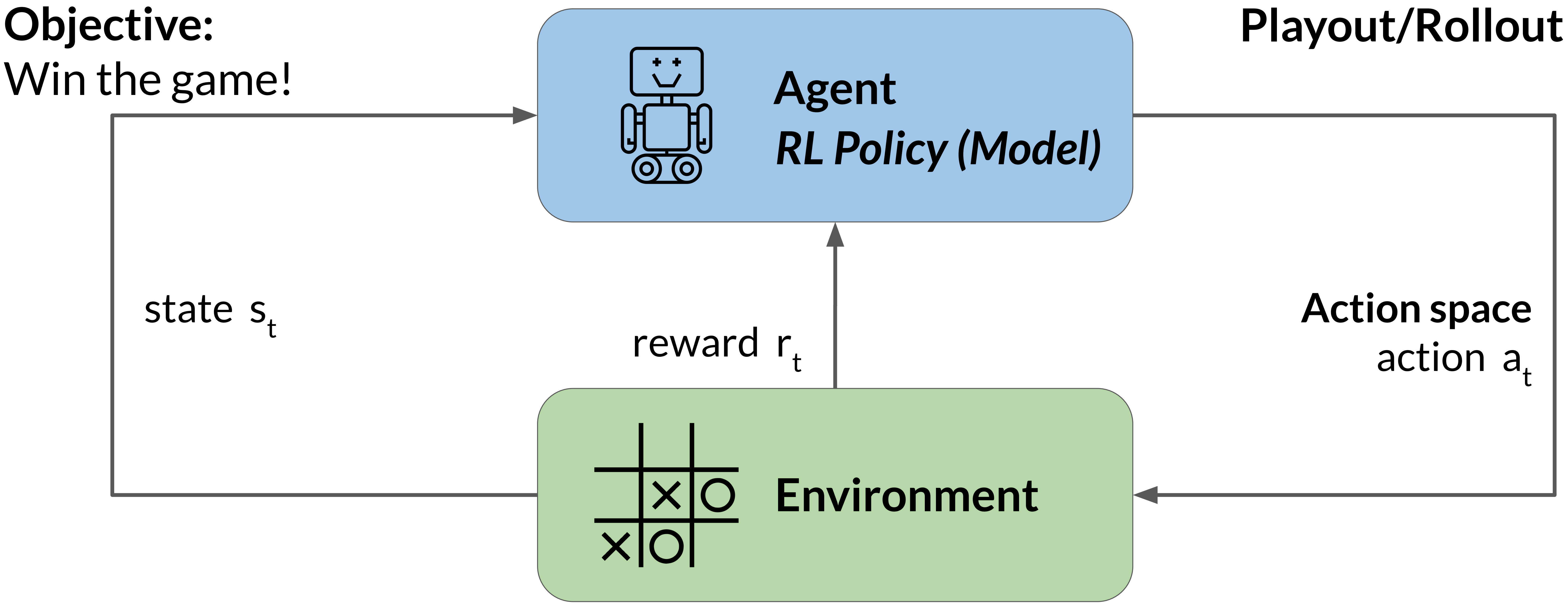
Objective: maximize reward received for actions

Environment

Reinforcement learning (RL)



Reinforcement learning: Tic-Tac-Toe



Objective:
Win the game!

Playout/Rollout

Agent
RL Policy (Model)

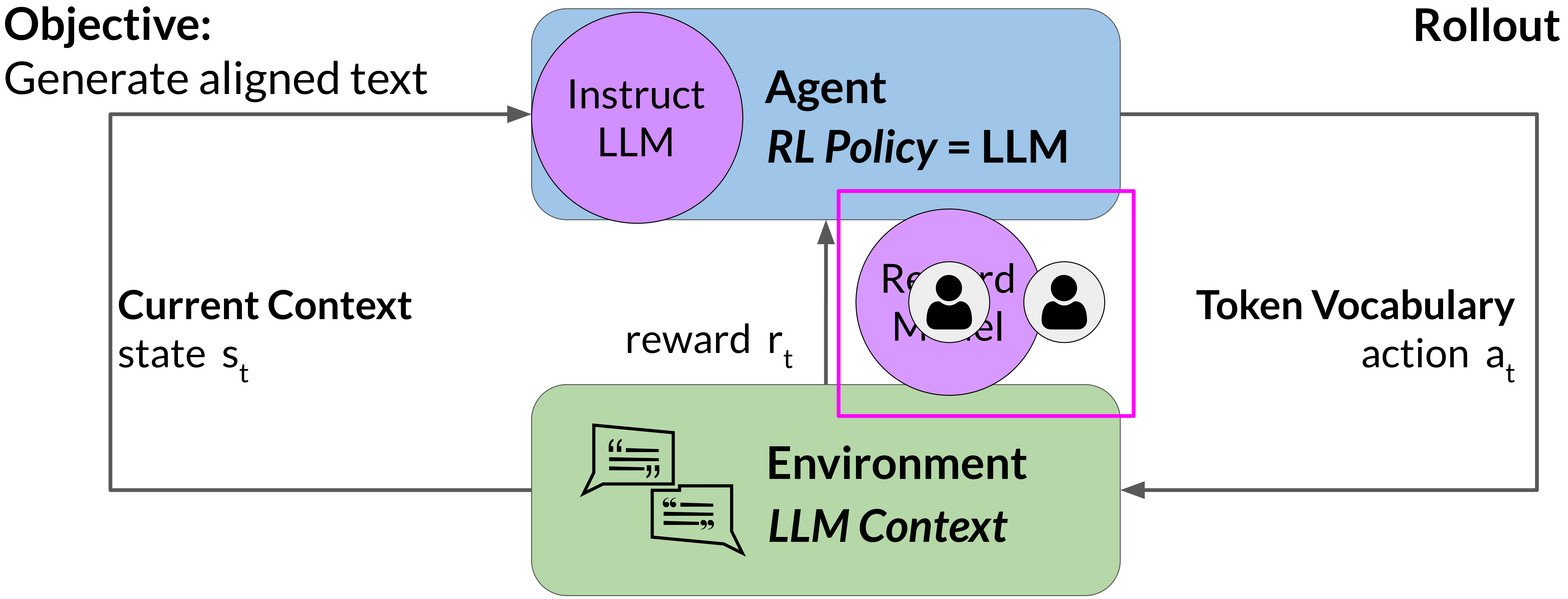
state s_t

reward r_t

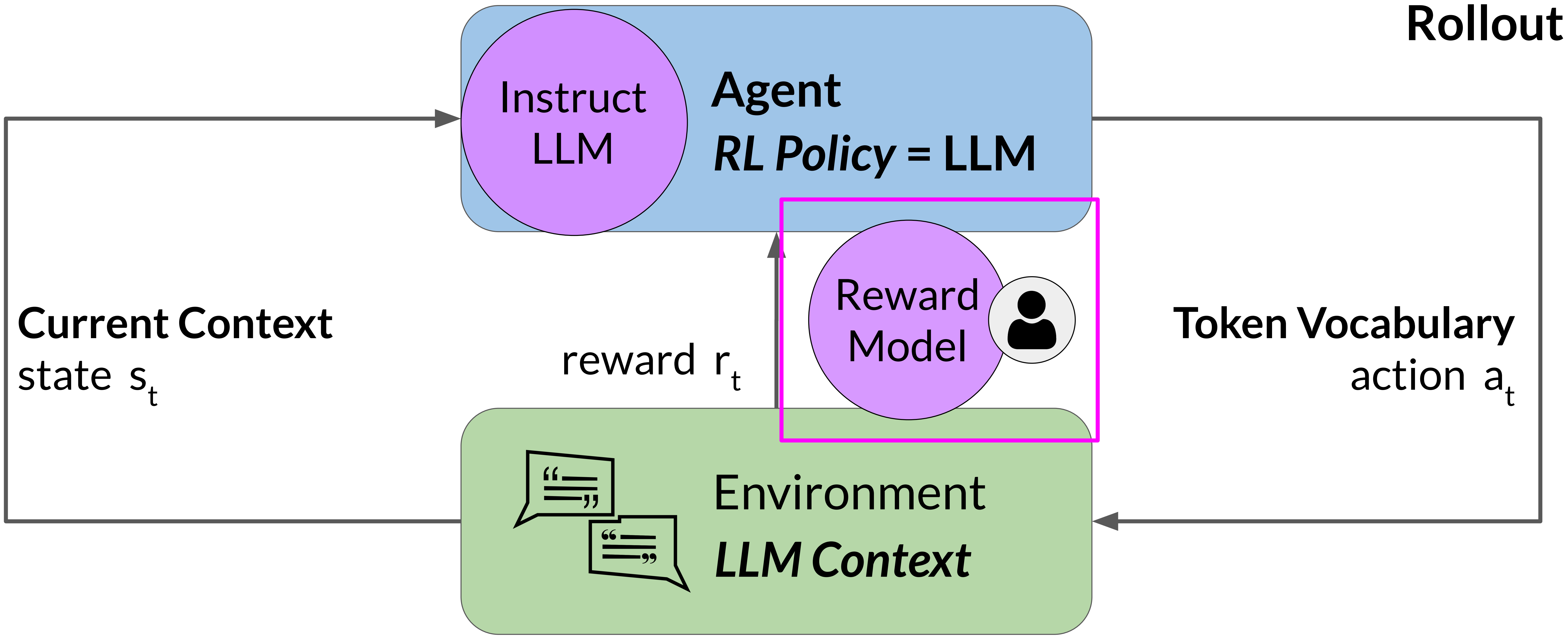
Action space
action a_t

Environment

Reinforcement learning: fine-tune LLMs

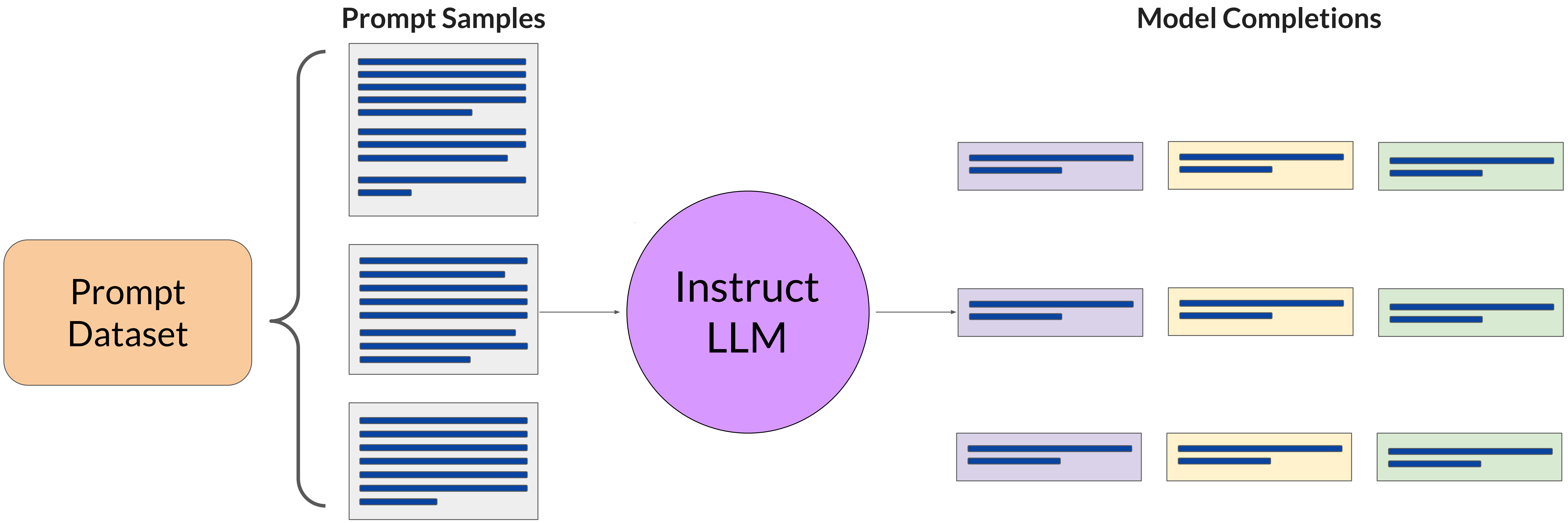


Reinforcement learning: fine-tune LLMs



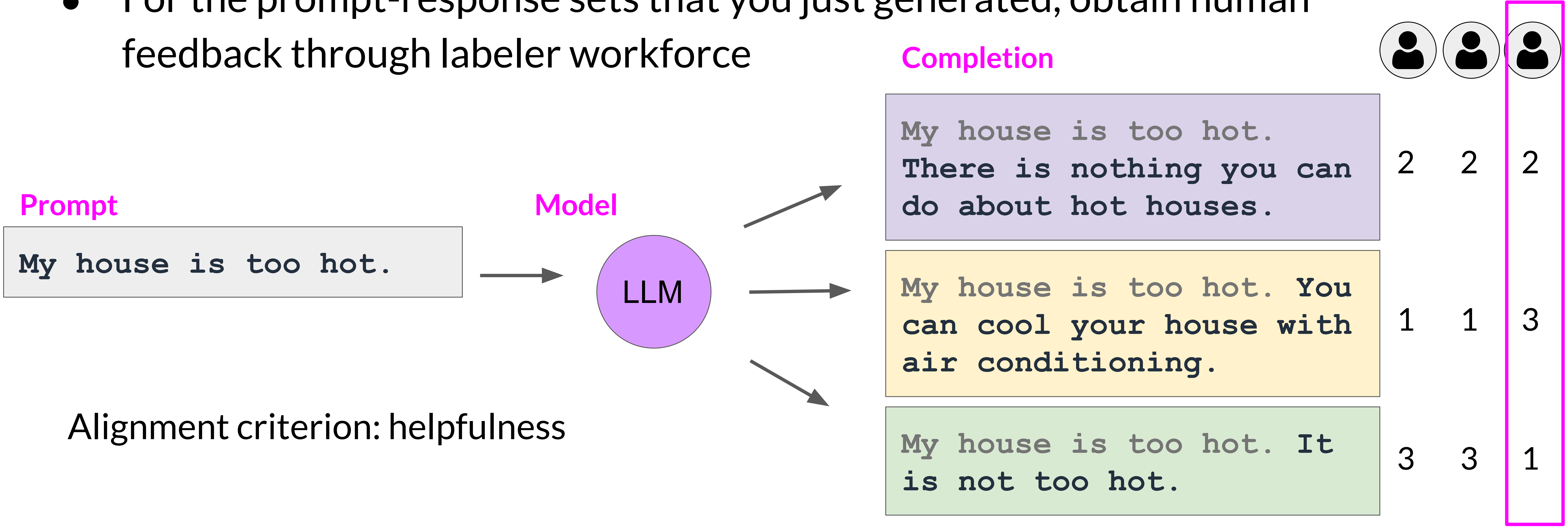
Collecting human feedback

Prepare dataset for human feedback



Collect human feedback

- Define your model alignment criterion
- For the prompt-response sets that you just generated, obtain human feedback through labeler workforce



Prompt

`My house is too hot.`

Model

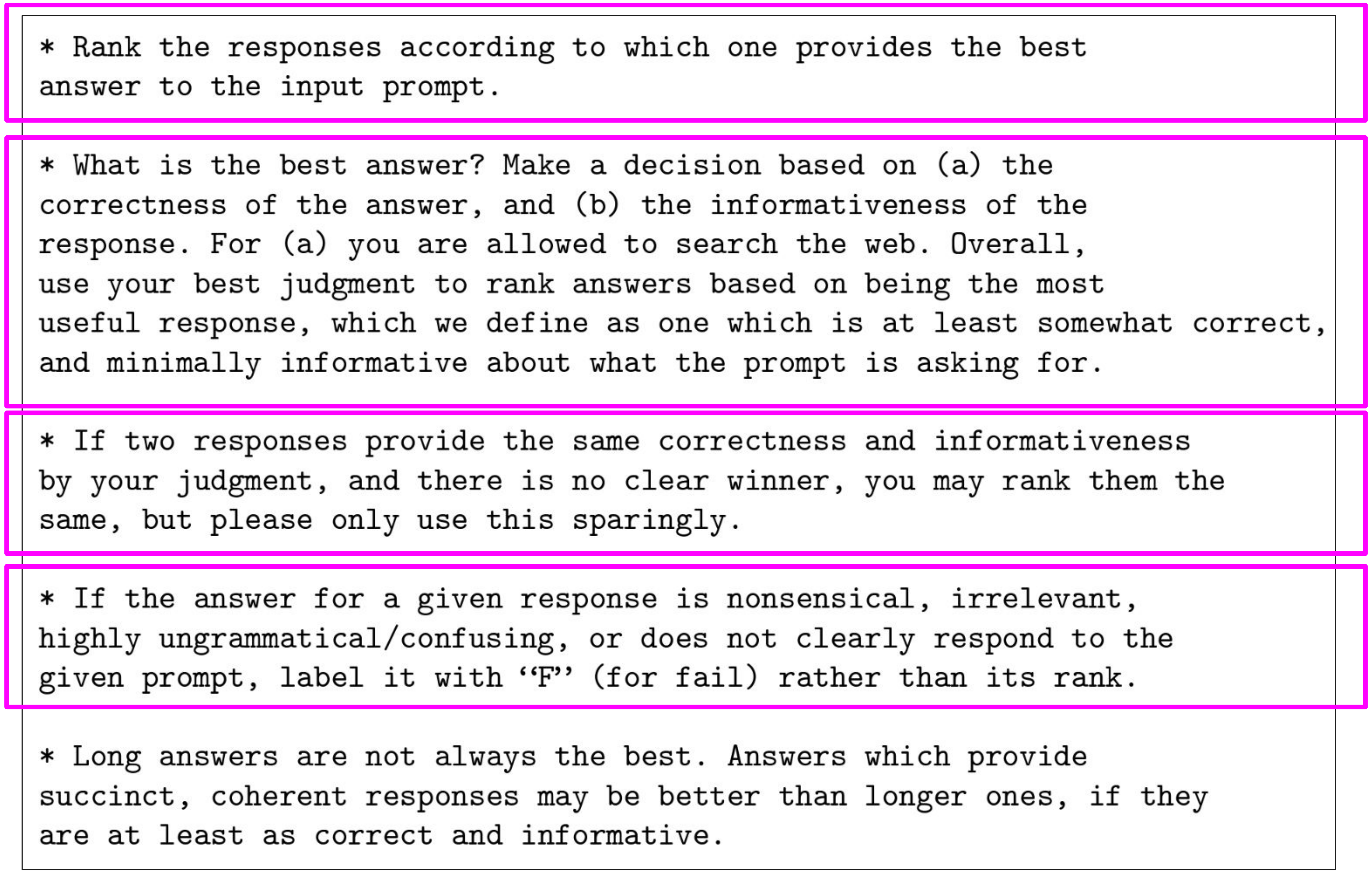
LLM

Completion

Completion			
My house is too hot. There is nothing you can do about hot houses.	2	2	2
My house is too hot. You can cool your house with air conditioning.	1	1	3
My house is too hot. It is not too hot.	3	3	1

Alignment criterion: helpfulness

Sample instructions for human labelers



* Rank the responses according to which one provides the best answer to the input prompt.

* What is the best answer? Make a decision based on (a) the correctness of the answer, and (b) the informativeness of the response. For (a) you are allowed to search the web. Overall, use your best judgment to rank answers based on being the most useful response, which we define as one which is at least somewhat correct, and minimally informative about what the prompt is asking for.

* If two responses provide the same correctness and informativeness by your judgment, and there is no clear winner, you may rank them the same, but please only use this sparingly.

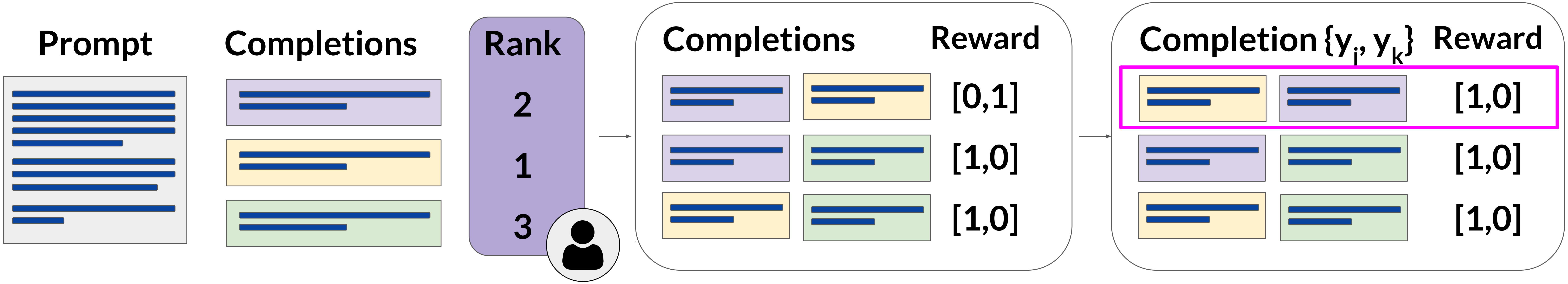
* If the answer for a given response is nonsensical, irrelevant, highly ungrammatical/confusing, or does not clearly respond to the given prompt, label it with ‘‘F’’ (for fail) rather than its rank.

* Long answers are not always the best. Answers which provide succinct, coherent responses may be better than longer ones, if they are at least as correct and informative.

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

Prepare labeled data for training

- Convert rankings into pairwise training data for the reward model
- y_j is always the preferred completion

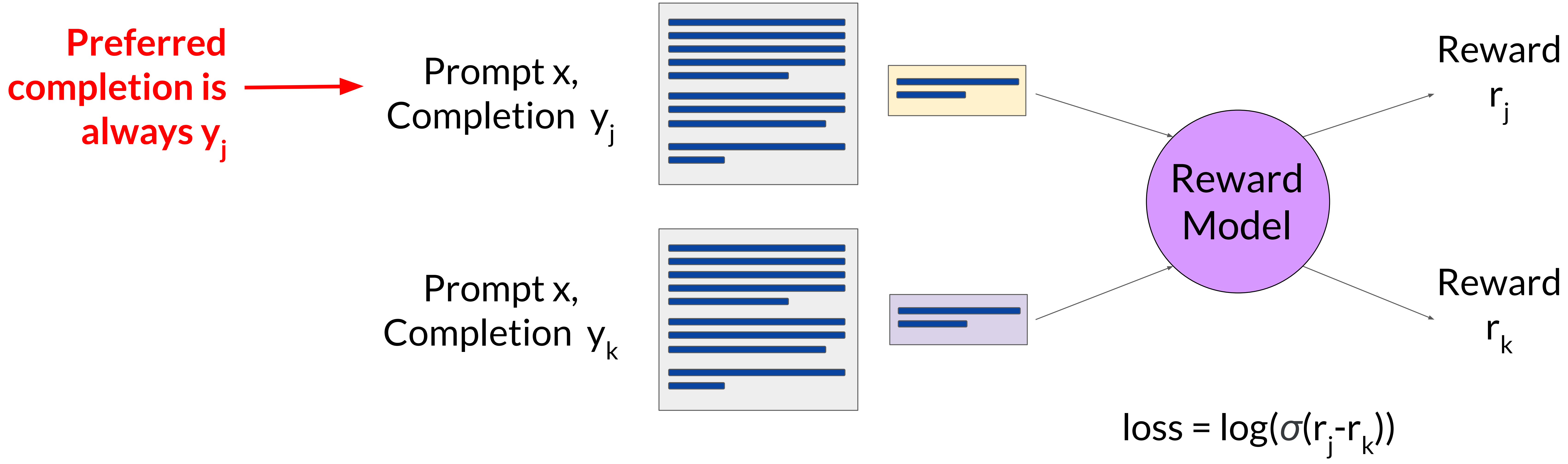


Source: Stiennon et al. 2020, "Learning to summarize from human feedback"

Training the reward model

Train reward model

Train model to predict preferred completion from $\{y_j, y_k\}$ for prompt x

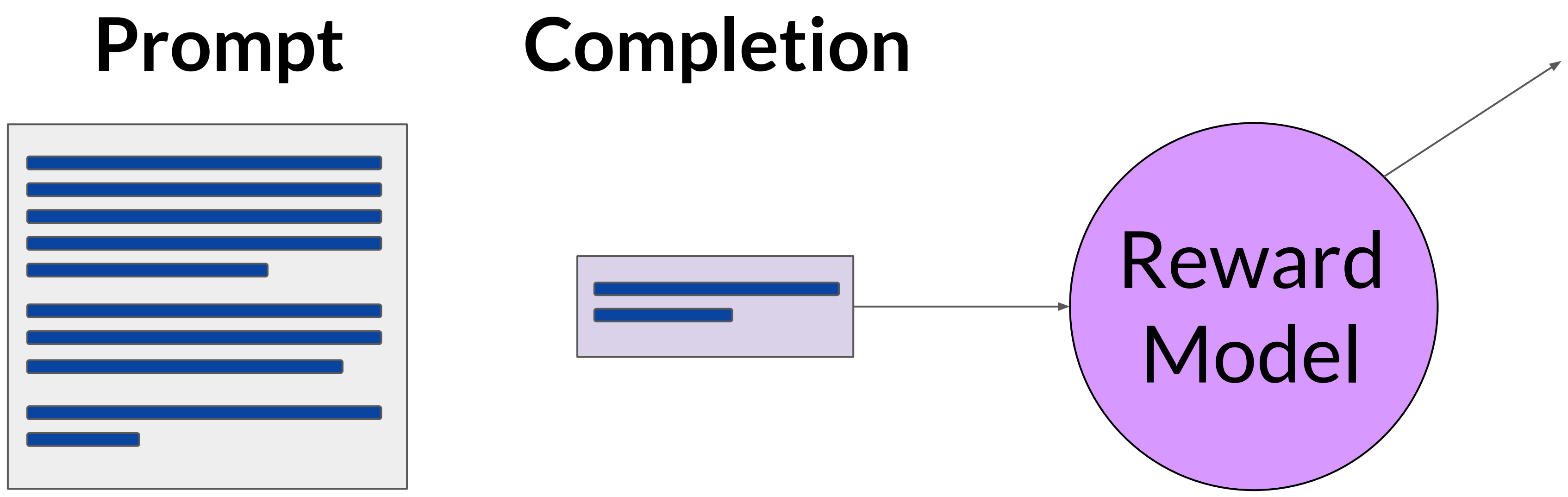

Preferred completion is always y_j
Prompt x, Completion y_j
Prompt x, Completion y_k
Reward Model
Reward r_j
Reward r_k

loss = $\log(\sigma(r_j - r_k))$

Source: Stiennon et al. 2020, "Learning to summarize from human feedback"

Use the reward model

Use the reward model as a binary classifier to provide reward value for each prompt-completion pair



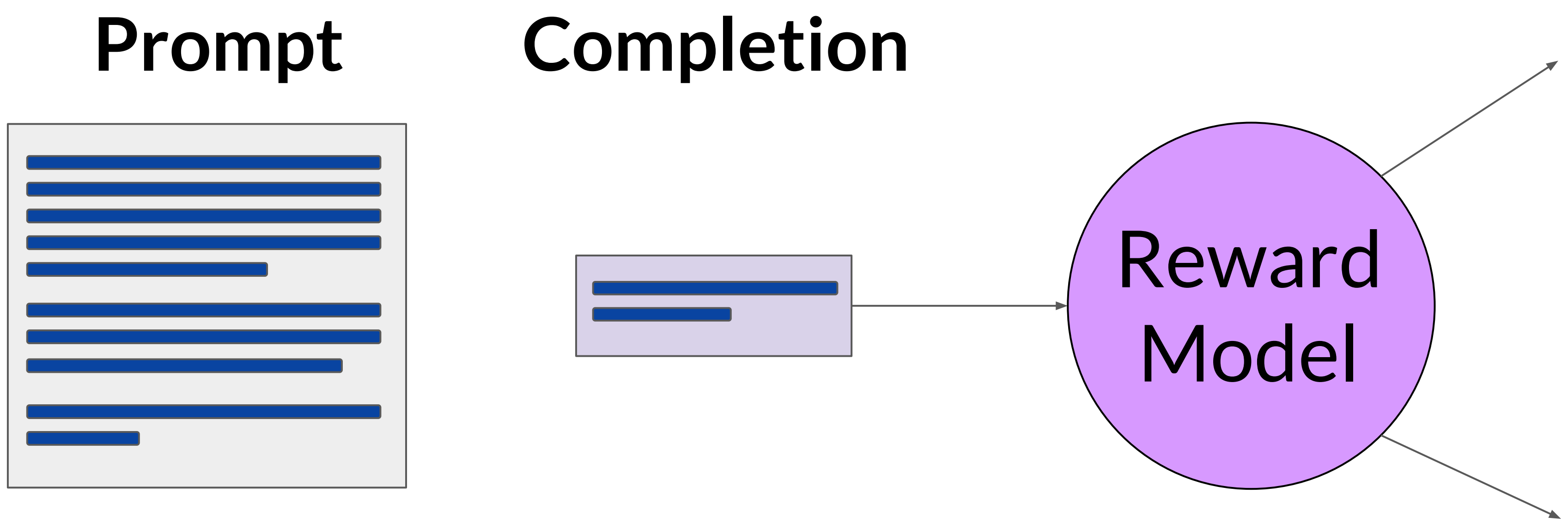
Tommy loves television	
	Logits
Positive class (not hate)	**3.171875**
Negative class (**hate**)	-2.609375

Reward value

Source: Stiennon et al. 2020, "Learning to summarize from human feedback"

Use the reward model

Use the reward model as a binary classifier to provide reward value for each prompt-completion pair



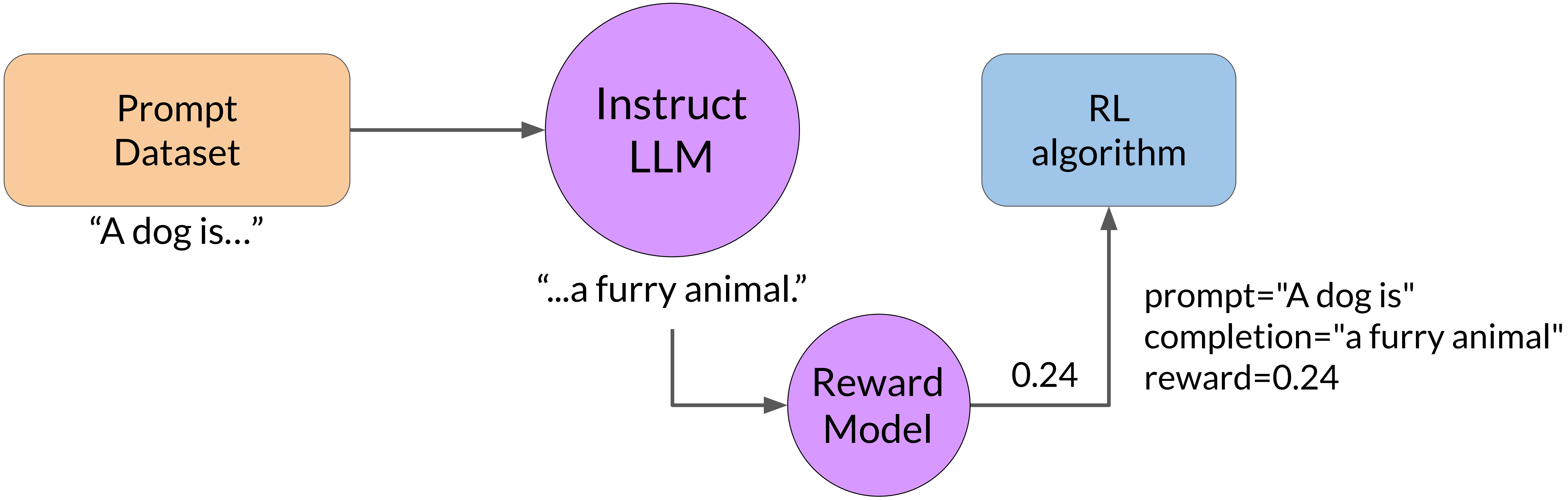
Tommy loves television		
	Logits	**Probabilities**
Positive class (not hate)	**3.171875**	0.996093
Negative class (**hate**)	-2.609375	0.003082

Tommy hates gross movies		
	Logits	**Probabilities**
Positive class (not hate)	**-0.535156**	0.337890
Negative class (**hate**)	0.137695	0.664062

Source: Stiennon et al. 2020, “Learning to summarize from human feedback”

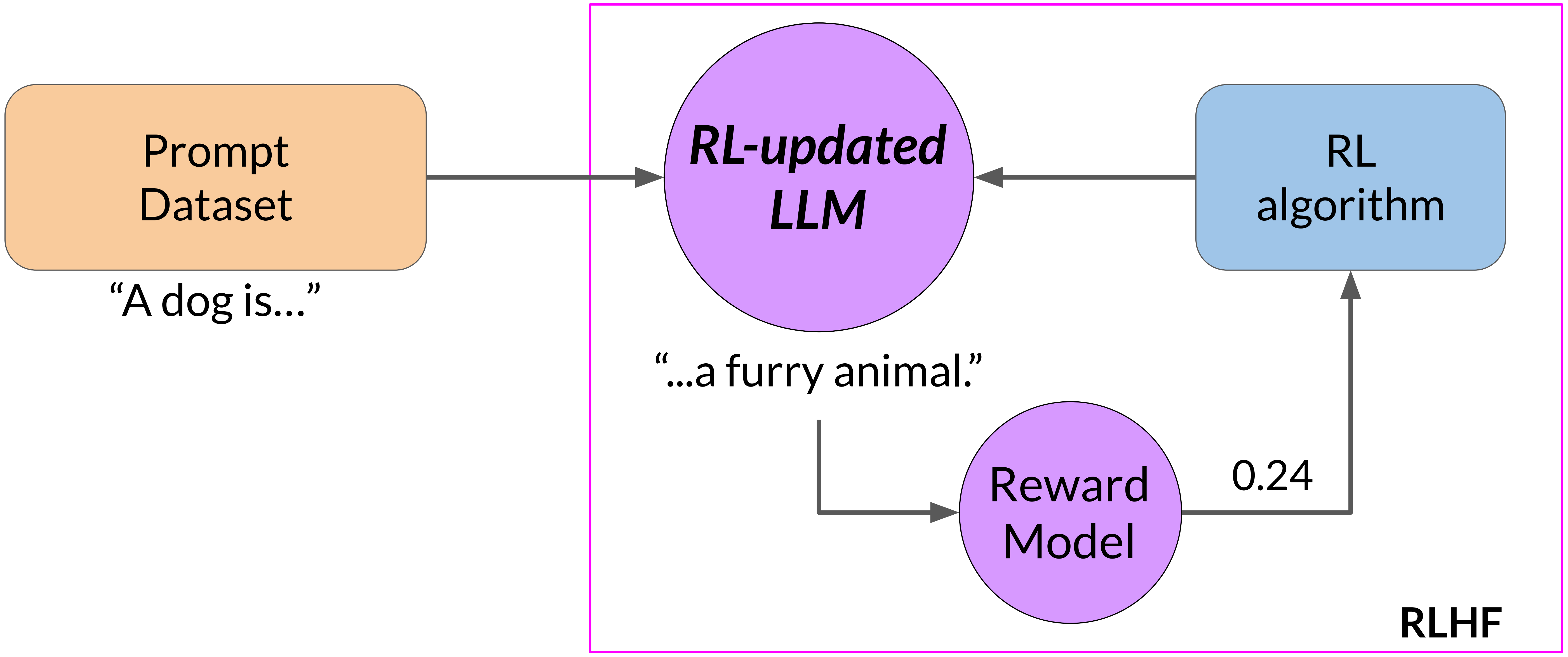
Fine-tuning with RLHF

Use the reward model to fine-tune LLM with RL



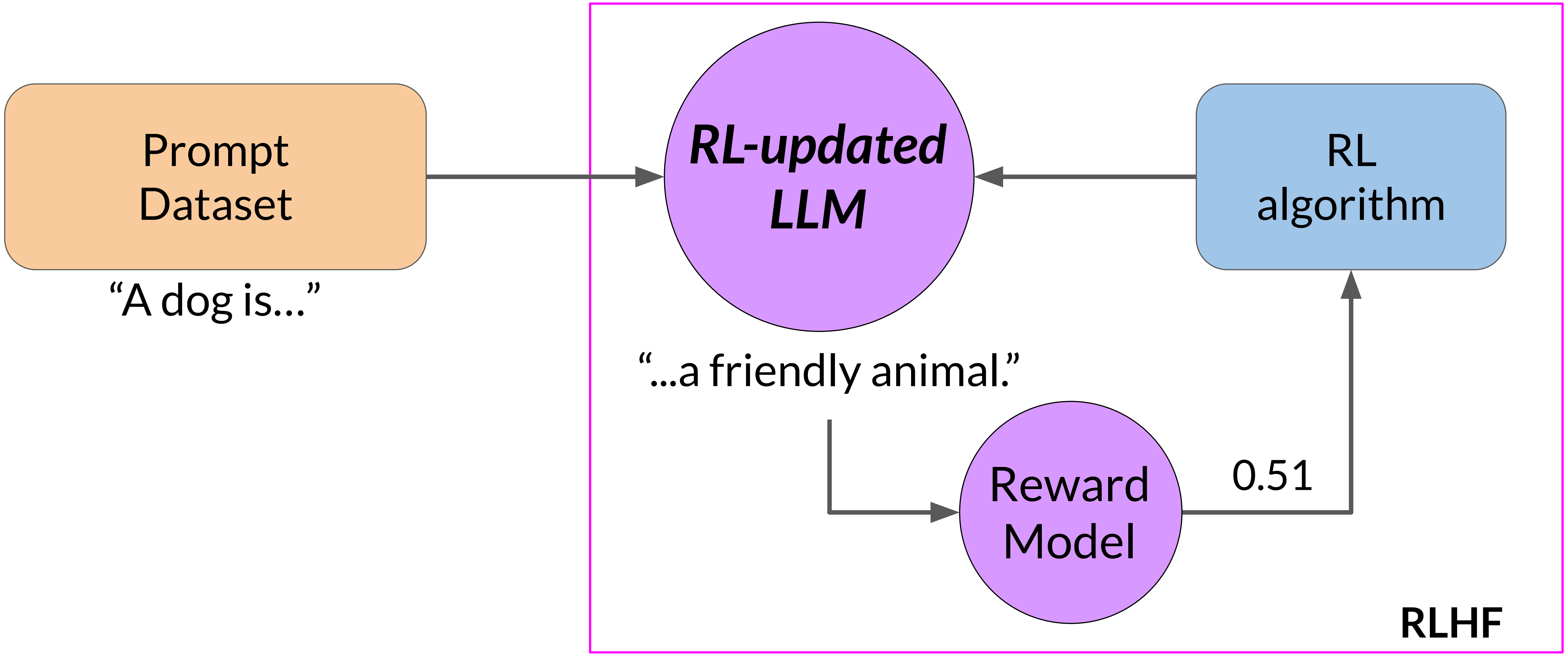
prompt="A dog is"
completion="a furry animal"
reward=0.24

Use the reward model to fine-tune LLM with RL



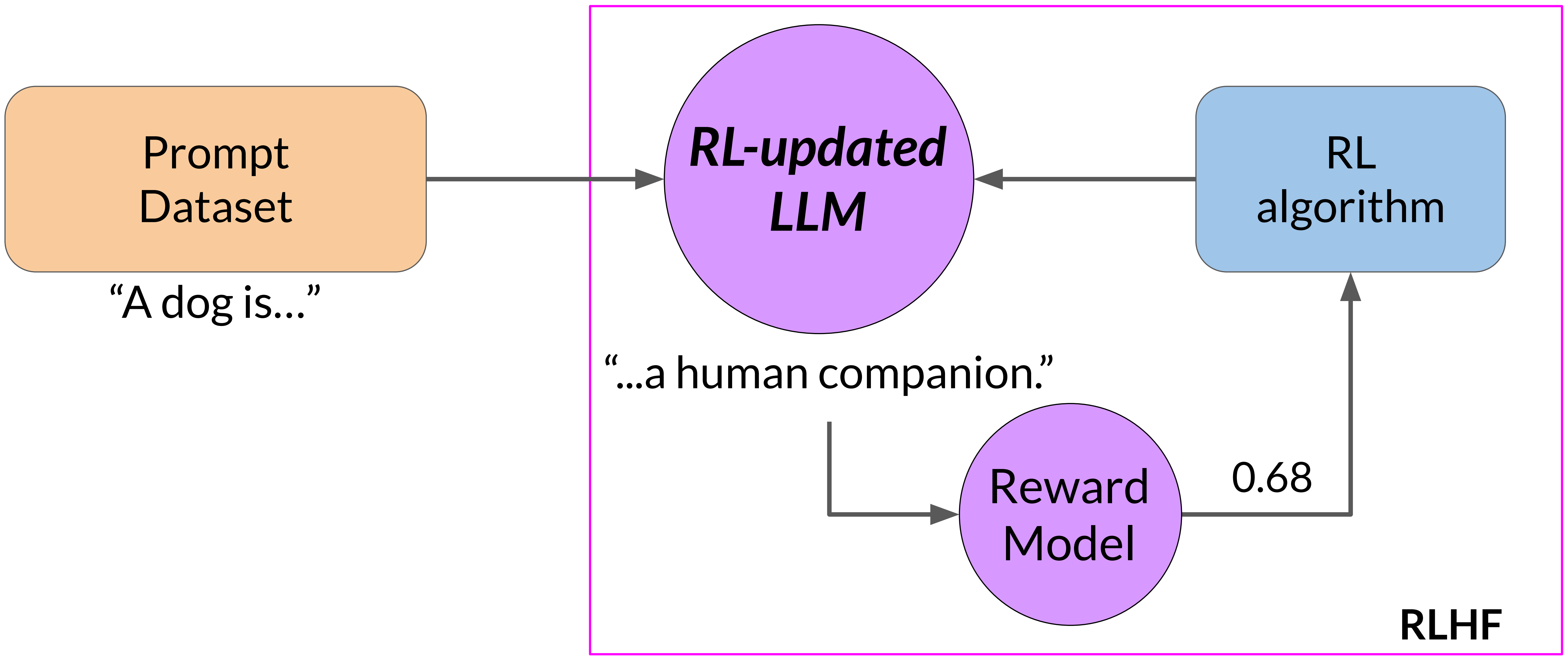
Iteration 1

Use the reward model to fine-tune LLM with RL



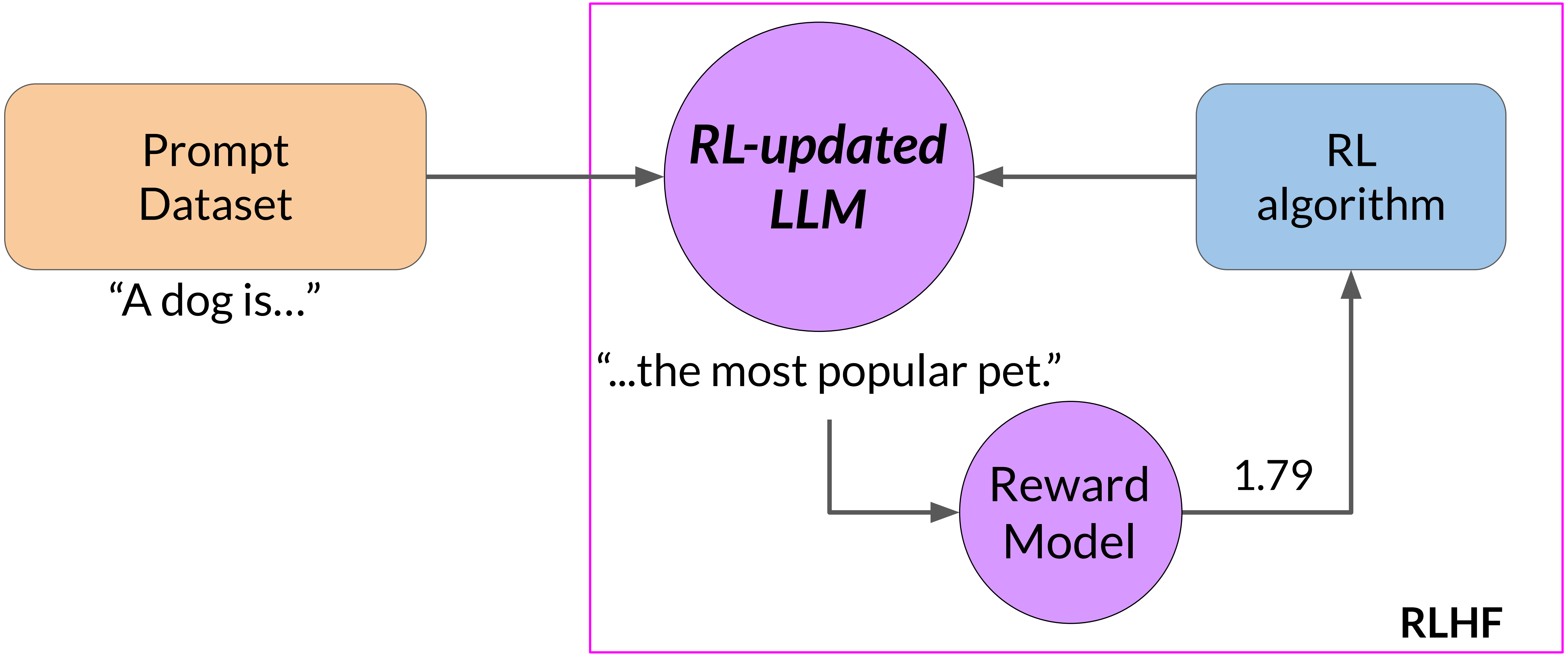
Iteration 2

Use the reward model to fine-tune LLM with RL



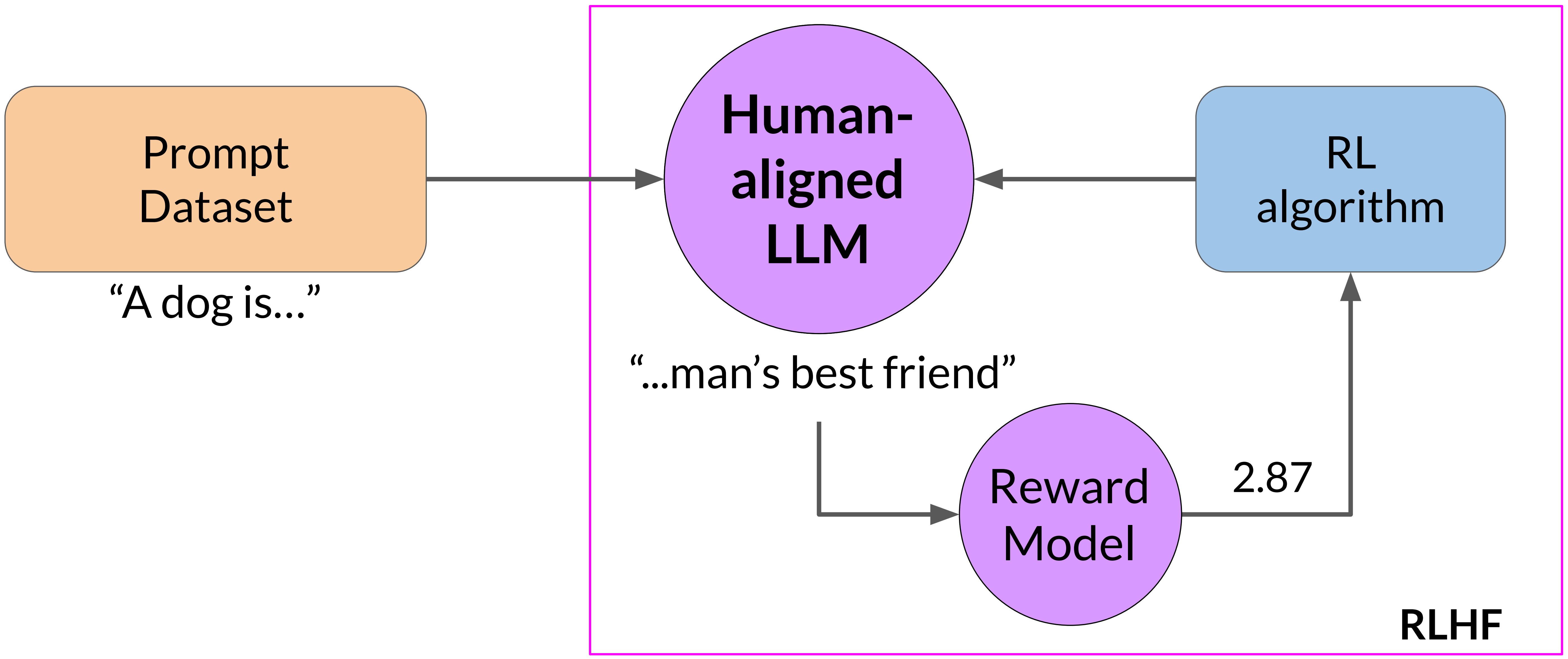
Iteration 3

Use the reward model to fine-tune LLM with RL



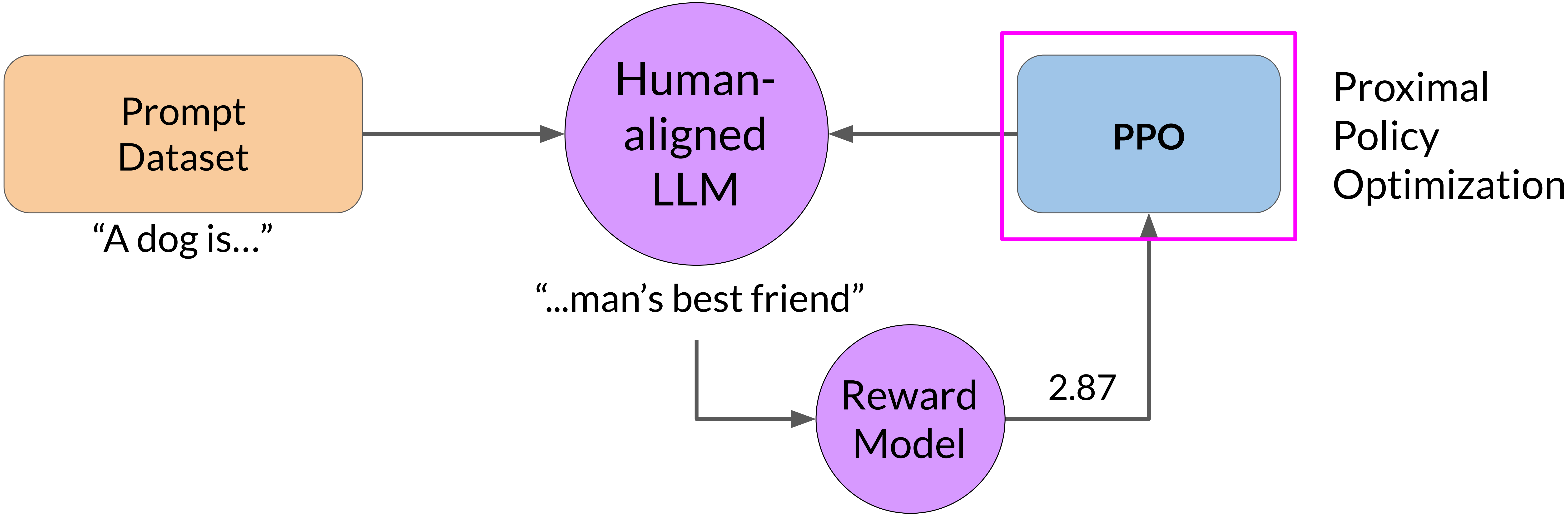
Iteration 4…

Use the reward model to fine-tune LLM with RL



Iteration *n*

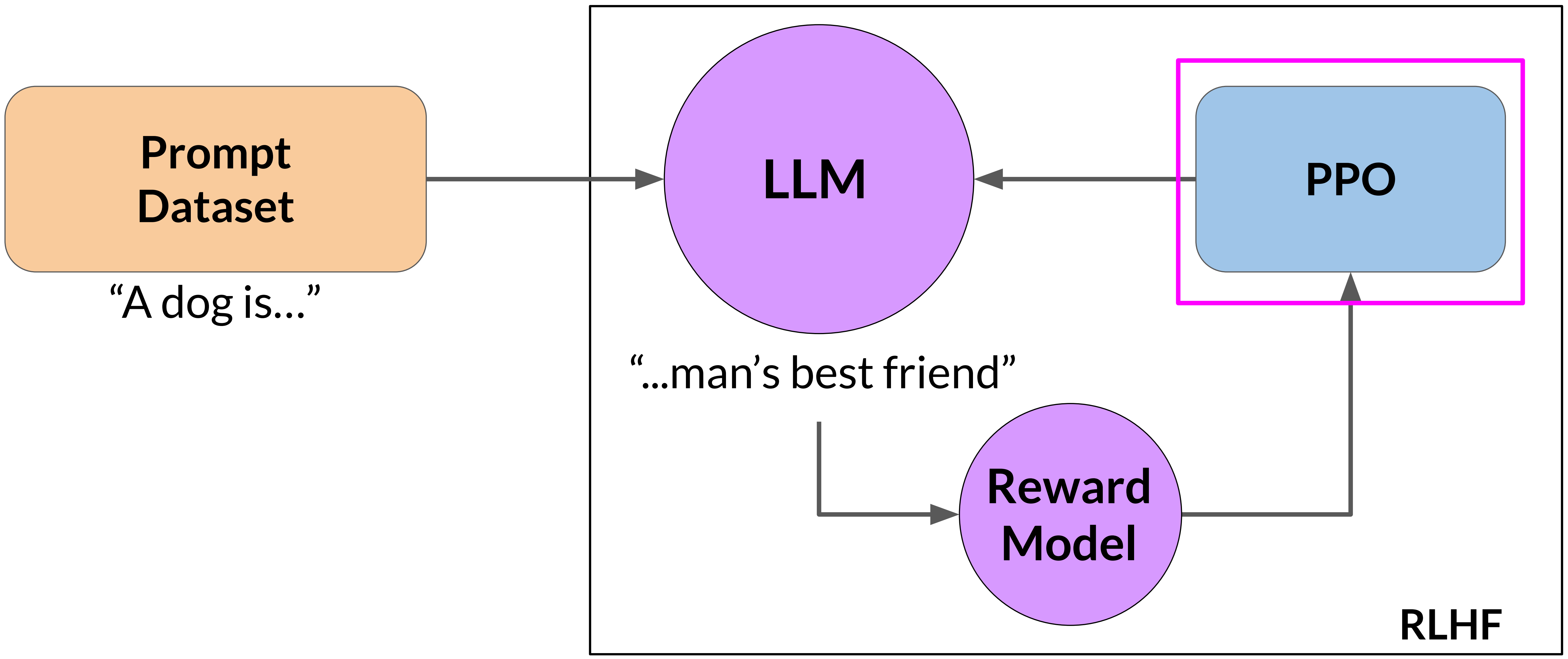
Use the reward model to fine-tune LLM with RL



Proximal Policy Optimization

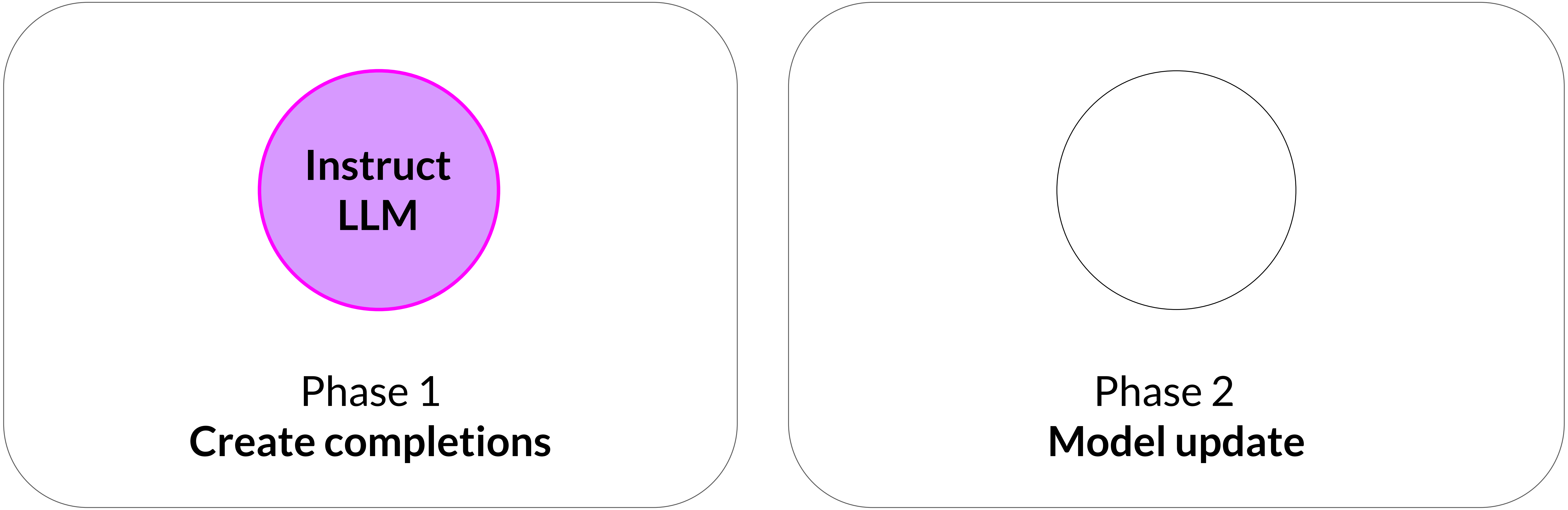
Dr. Ehsan Kamalinejad

Proximal policy optimization (PPO)

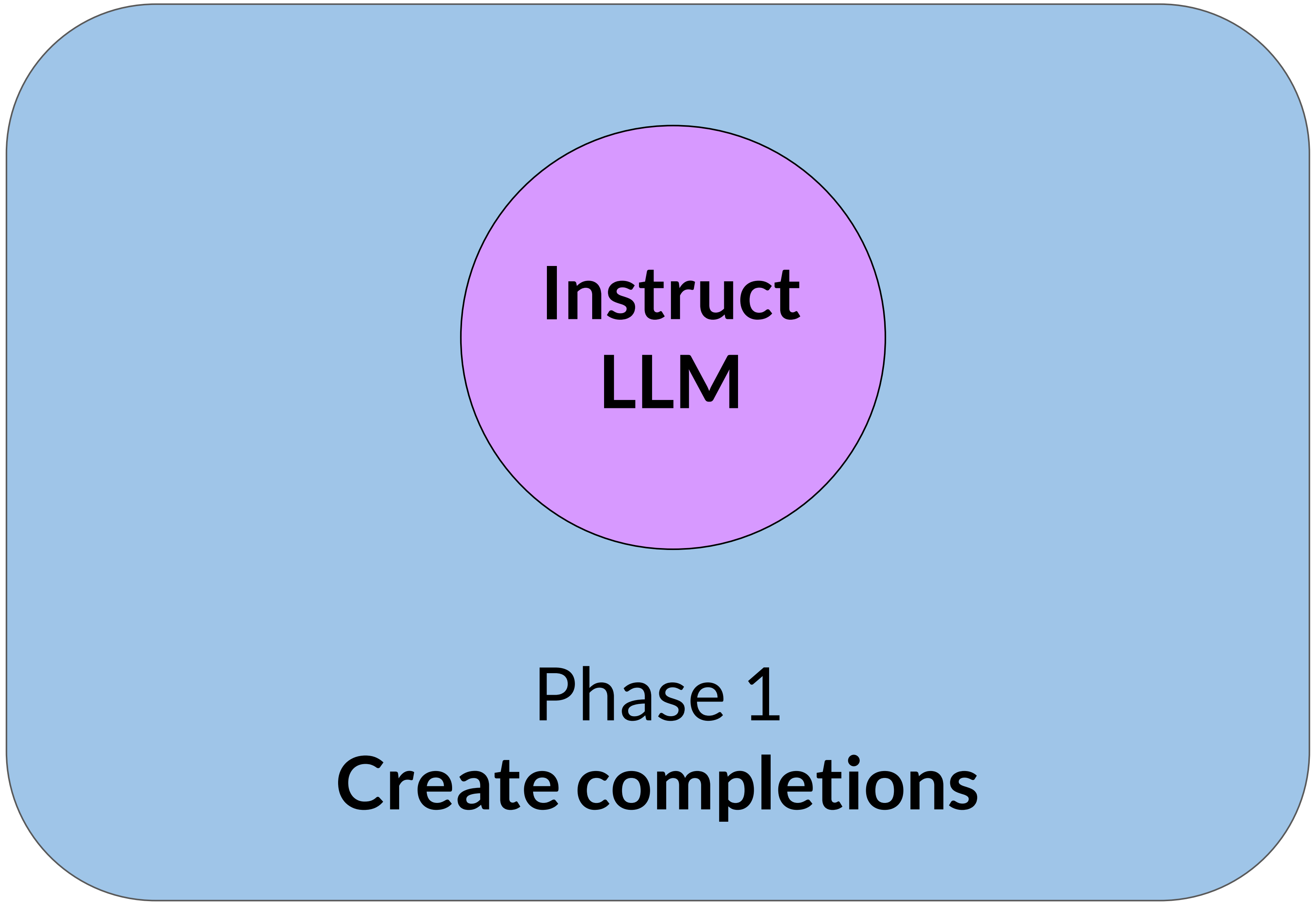


Iteration *n*

Initialize PPO with Instruct LLM



PPO Phase 1: Create completions



Prompt

```
A dog is
```

Completion

```
A dog is
a furry animal
```

Prompt

```
This house is
```

Completion

```
This house is
very ugly
```

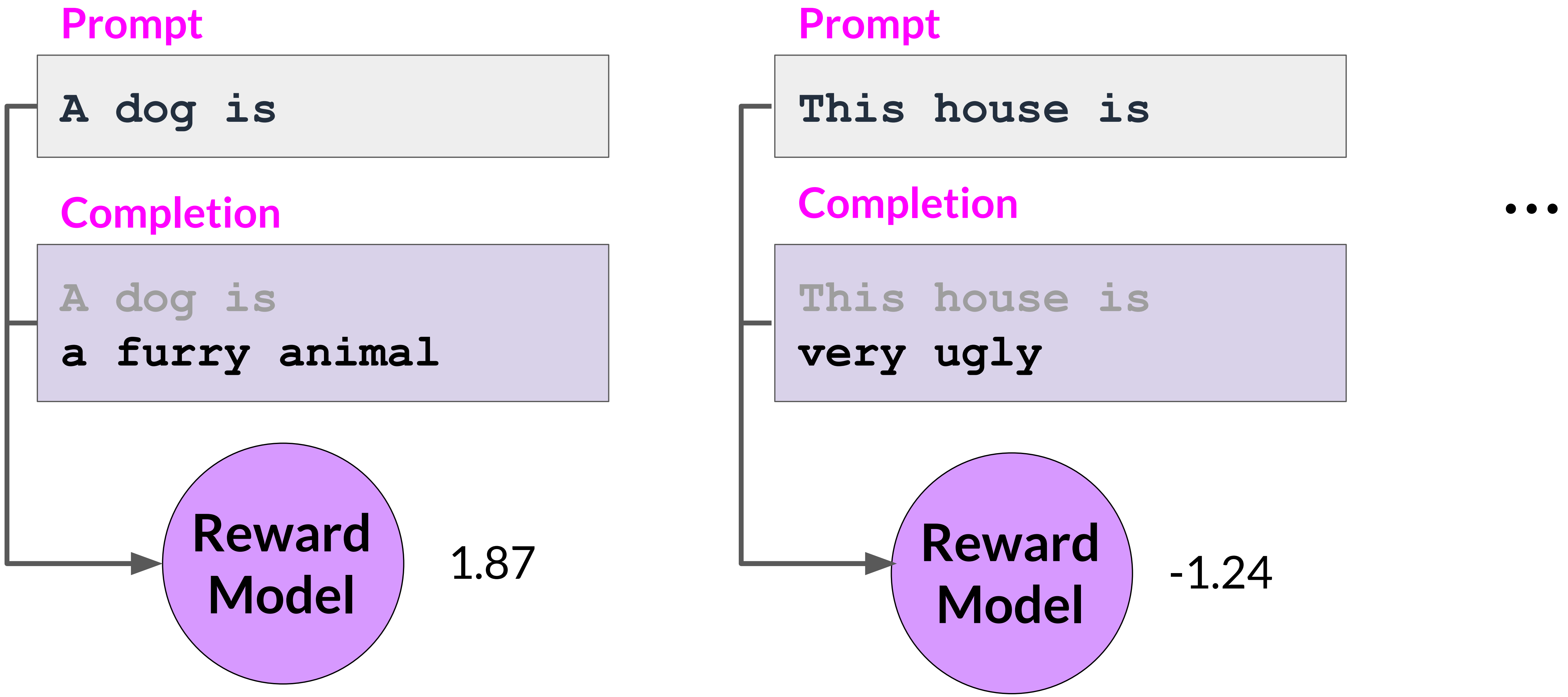
...

Experiments

to assess the outcome of the current model,

e.g. how helpful, harmless, honest the model is

Calculate rewards



Prompt

A dog is

Completion

A dog is
a furry animal

Reward Model

1.87

Prompt

This house is

Completion

This house is
very ugly

Reward Model

-1.24

...

Calculate value loss

Prompt

```
A dog is
```

Completion

```
A dog is
a ...
```

Value function

$$L^{VF} = \frac{1}{2}\left\| \underbrace{\boxed{V_\theta(s)}}_{} - \left(\sum_{t=0}^{T} \gamma^t r_t \mid s_0 = s\right)\right\|_2^2$$

Estimated
future total reward

0.34

Calculate value loss

Prompt

```
A dog is
```

Completion

```
A dog is
a furry...
```

Value function

$$L^{VF} = \frac{1}{2}\left\| \underbrace{\boxed{V_\theta(s)}} - \left(\sum_{t=0}^{T}\gamma^t r_t \mid s_0 = s\right)\right\|_2^2$$

Estimated
future total reward

1.23

Calculate value loss

Prompt

```
A dog is
```

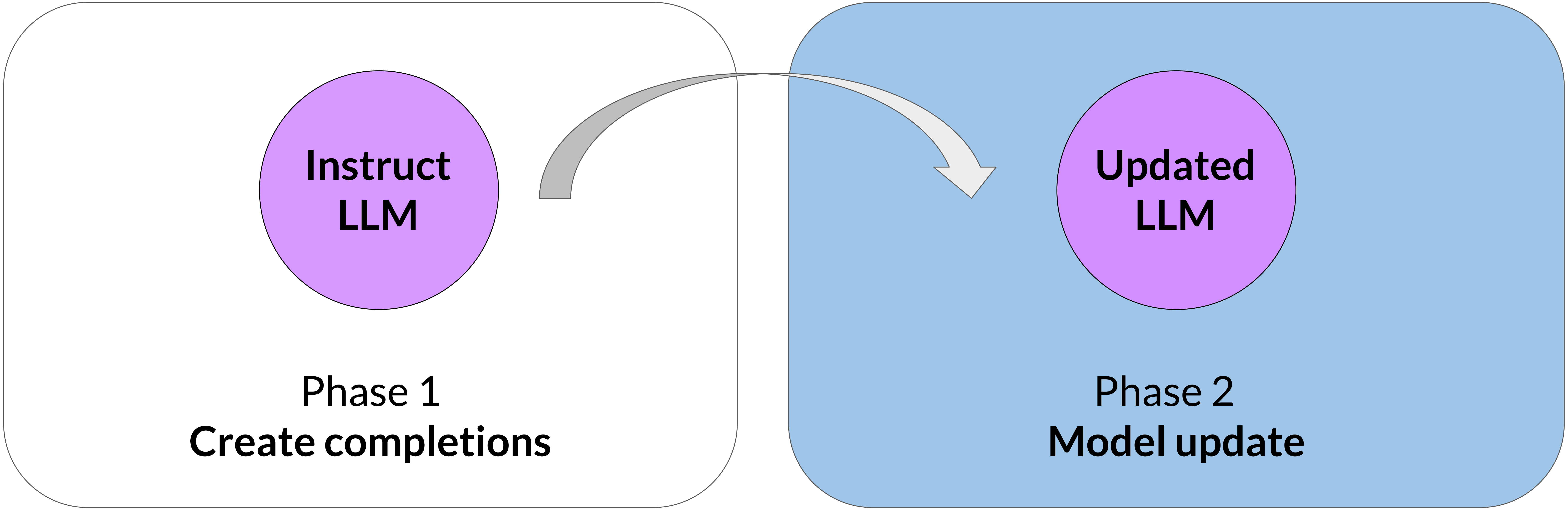
Completion

```
A dog is
a furry...
```

Value loss

$$\boxed{L^{VF}} = \frac{1}{2}\left\| \underbrace{V_\theta(s)}_{\substack{\textbf{Estimated}\\ \text{future total reward}\\ 1.23}} - \underbrace{\left(\sum_{t=0}^{T} \gamma^t r_t \mid s_0 = s\right)}_{\substack{\textbf{Known}\\ \text{future total reward}\\ 1.87}} \right\|_2^2$$

PPO Phase 2: Model update



Phase 1
Create completions

Phase 2
Model update

PPO Phase 2: Calculate policy loss

$$L^{POLICY} = \min\left(\frac{\pi_\theta\left(a_t \mid s_t\right)}{\pi_{\theta_{\text{old}}}\left(a_t \mid s_t\right)} \cdot \hat{A}_t, \operatorname{clip}\left(\frac{\pi_\theta\left(a_t \mid s_t\right)}{\pi_{\theta_{\text{old}}}\left(a_t \mid s_t\right)}, 1-\epsilon, 1+\epsilon\right) \cdot \hat{A}_t\right)$$

PPO Phase 2: Calculate policy loss

$$L^{POLICY} = \min\left(\underbrace{\frac{\pi_\theta\left(a_t \mid s_t\right)}{\pi_{\theta_{\text{old}}}\left(a_t \mid s_t\right)} \cdot \hat{A}_t}_{\text{Most important expression}}, \operatorname{clip}\left(\frac{\pi_\theta\left(a_t \mid s_t\right)}{\pi_{\theta_{\text{old}}}\left(a_t \mid s_t\right)}, 1-\epsilon, 1+\epsilon\right) \cdot \hat{A}_t\right)$$

π_θ Model's probability distribution over tokens

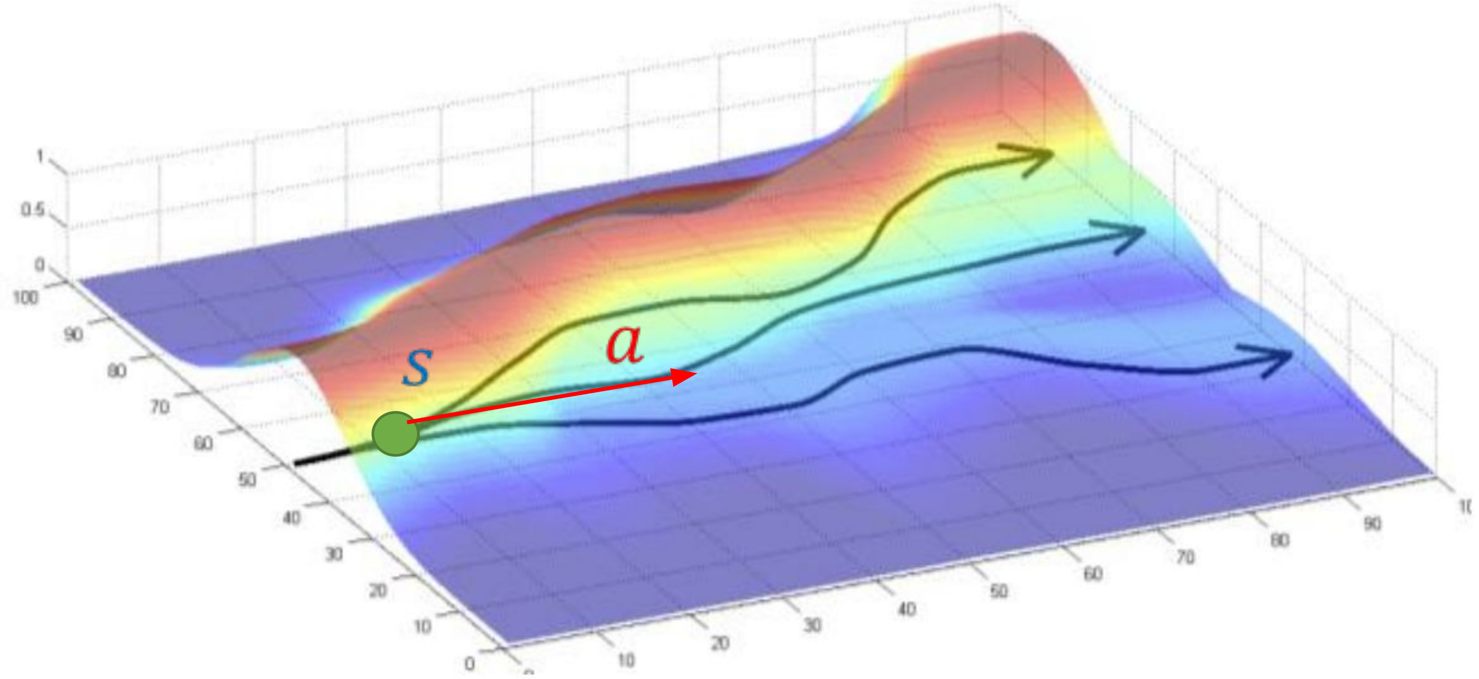
PPO Phase 2: Calculate policy loss

Probabilities of the next token
with the updated LLM

$$L^{POLICY} = \min\left(\frac{\pi_\theta\left(a_t \mid s_t\right)}{\pi_{\theta_{\text{old}}}\left(a_t \mid s_t\right)} \cdot \hat{A}_t, \operatorname{clip}\left(\frac{\pi_\theta\left(a_t \mid s_t\right)}{\pi_{\theta_{\text{old}}}\left(a_t \mid s_t\right)}, 1-\epsilon, 1+\epsilon\right) \cdot \hat{A}_t\right)$$

Probabilities of the next token
with the initial LLM

Advantage term



PPO Phase 2: Calculate policy loss

$$L^{POLICY} = \underbrace{\min}_{} \left(\underline{\frac{\pi_\theta\left(a_t \mid s_t\right)}{\pi_{\theta_{\text{old}}}\left(a_t \mid s_t\right)} \cdot \hat{A}_t}, \underline{\text{clip}\left(\frac{\pi_\theta\left(a_t \mid s_t\right)}{\pi_{\theta_{\text{old}}}\left(a_t \mid s_t\right)}, 1-\epsilon, 1+\epsilon\right) \cdot \hat{A}_t} \right)$$

PPO Phase 2: Calculate policy loss

$$L^{POLICY} = \underbrace{\min}\left(\frac{\pi_\theta\left(a_t \mid s_t\right)}{\pi_{\theta_{\text{old}}}\left(a_t \mid s_t\right)} \cdot \hat{A}_t, \underbrace{\text{clip}\left(\overbrace{\frac{\pi_\theta\left(a_t \mid s_t\right)}{\pi_{\theta_{\text{old}}}\left(a_t \mid s_t\right)}, 1-\epsilon, 1+\epsilon}^{\text{Defines "trust region"}} \right) \cdot \hat{A}_t} \right)$$

Guardrails:
Keeping the policy in the "trust region"

PPO Phase 2: Calculate entropy loss

$$L^{ENT} = \text{entropy}\left(\pi_\theta\left(\cdot \mid s_t\right)\right)$$

Low entropy:

Prompt

```
A dog is
```

Completion

```
A dog is
a domesticated
carnivorous mammal
```

Prompt

```
A dog is
```

Completion

```
A dog is
a small carnivorous
mammal
```

High entropy:

Prompt

```
A dog is
```

Completion

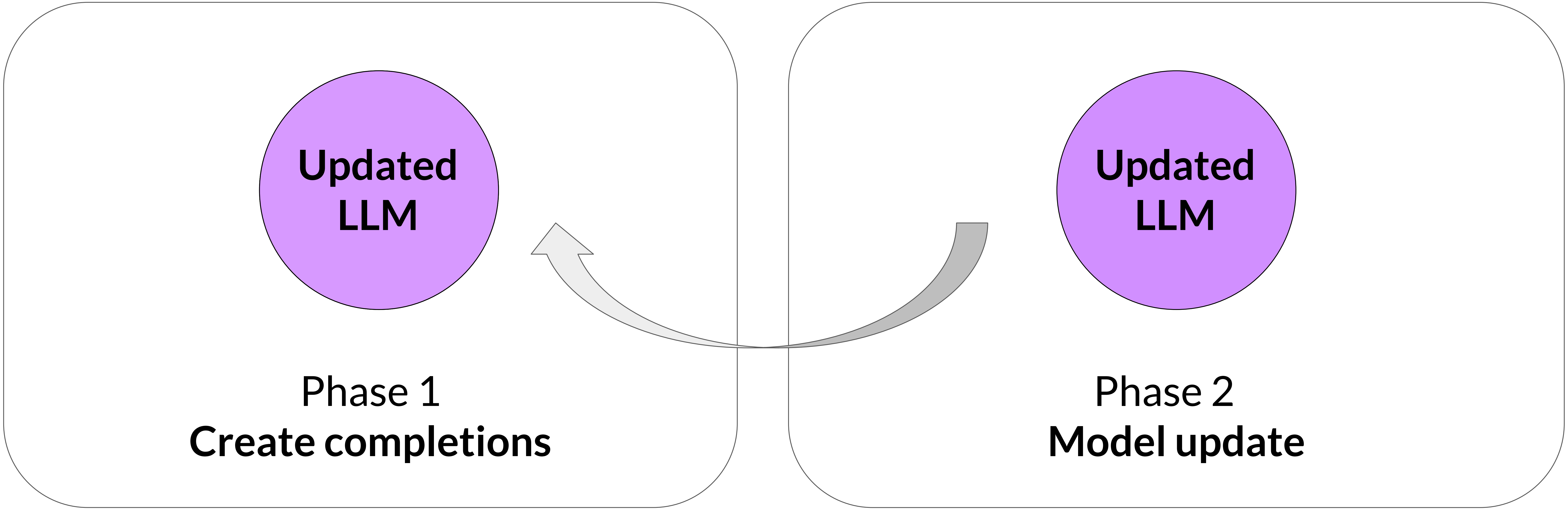
```
A dog is
is one of the most
popular pets around
the world
```

PPO Phase 2: Objective function

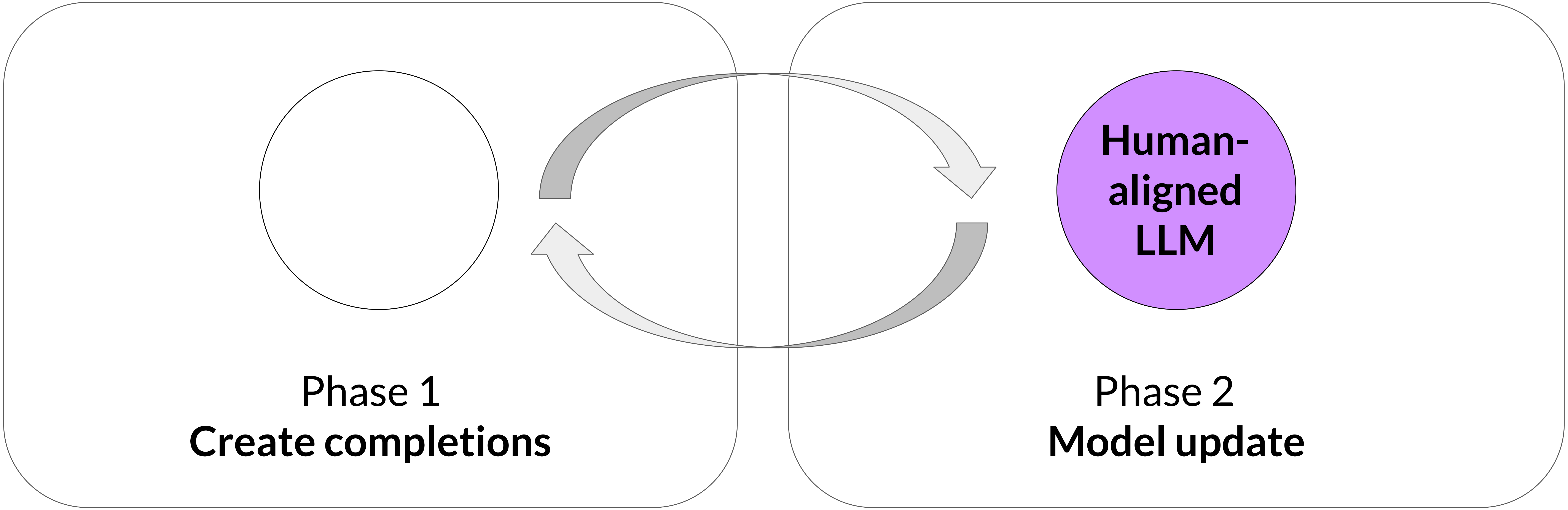
Hyperparameters

$$L^{PPO} = \underbrace{L^{POLICY}}_{\text{Policy loss}} + \underbrace{c_1 L^{VF}}_{\text{Value loss}} + \underbrace{c_2 L^{ENT}}_{\text{Entropy loss}}$$

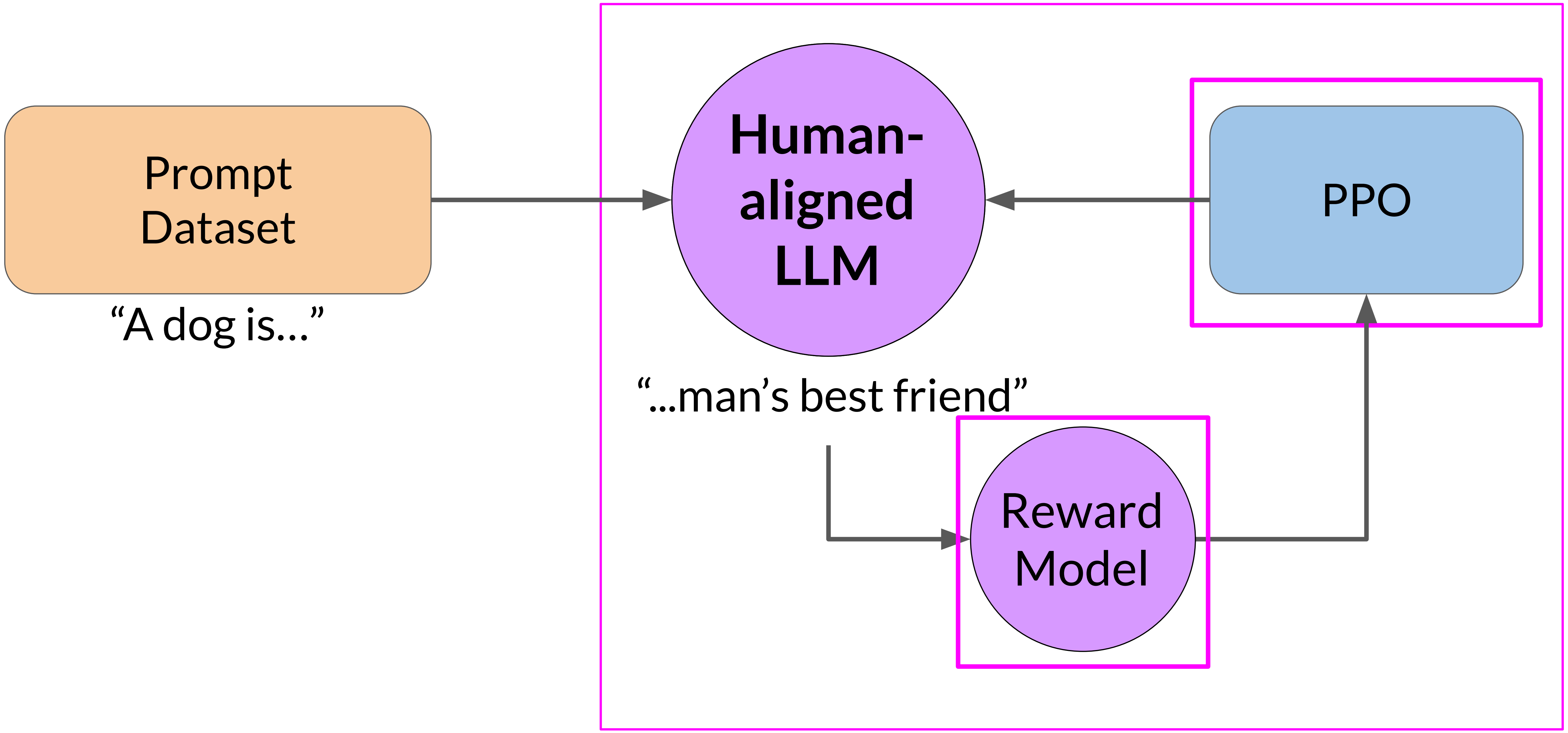
Replace LLM with updated LLM



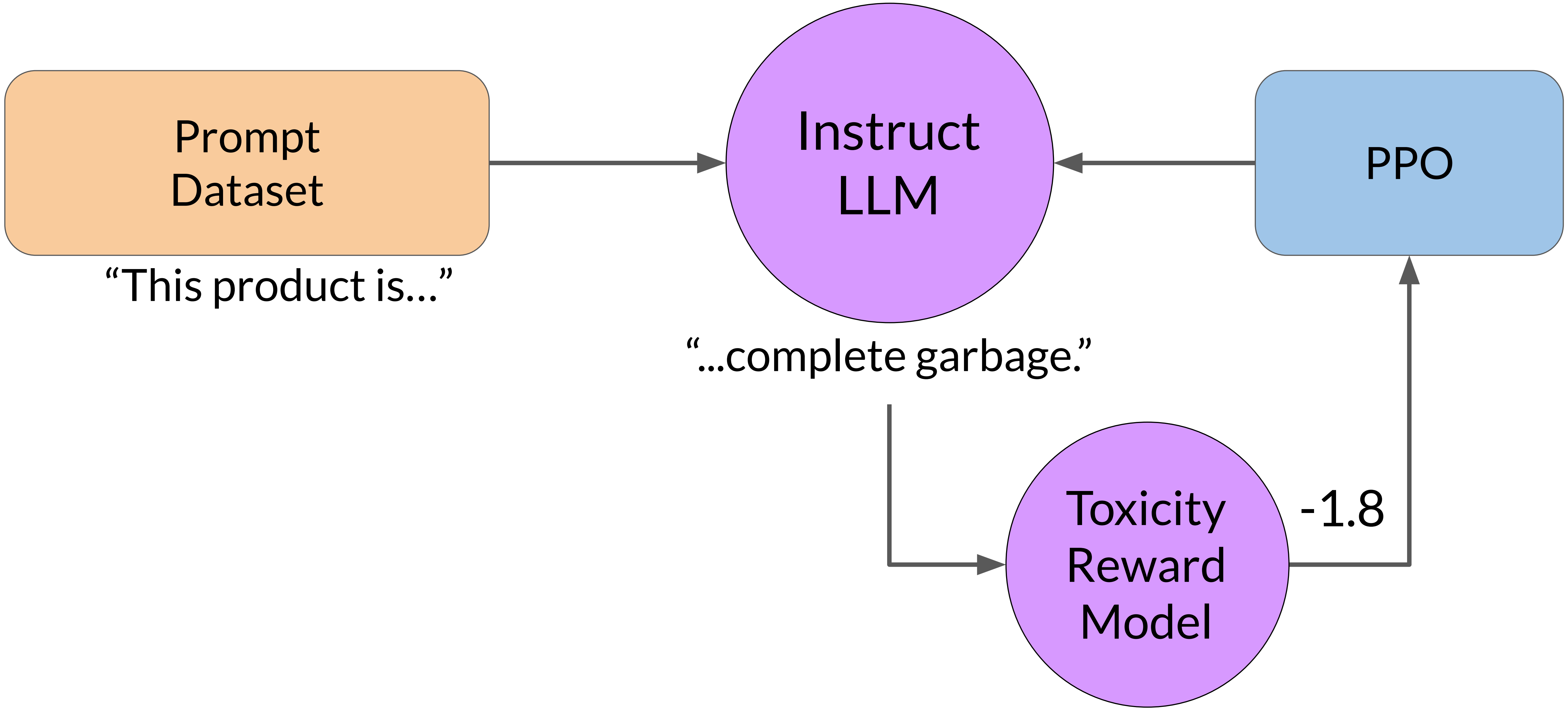
After many iterations, human-aligned LLM!



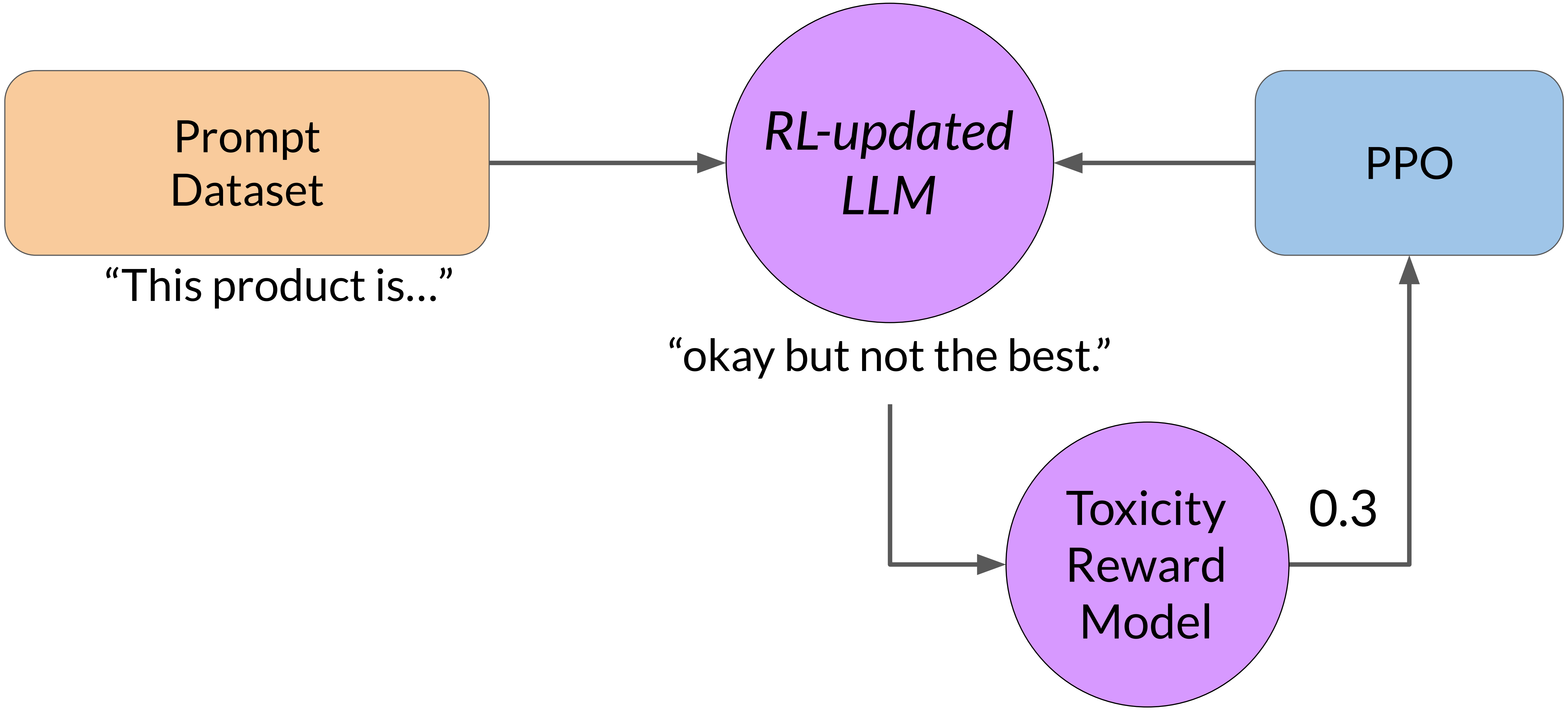
Fine-tuning LLMs with RLHF



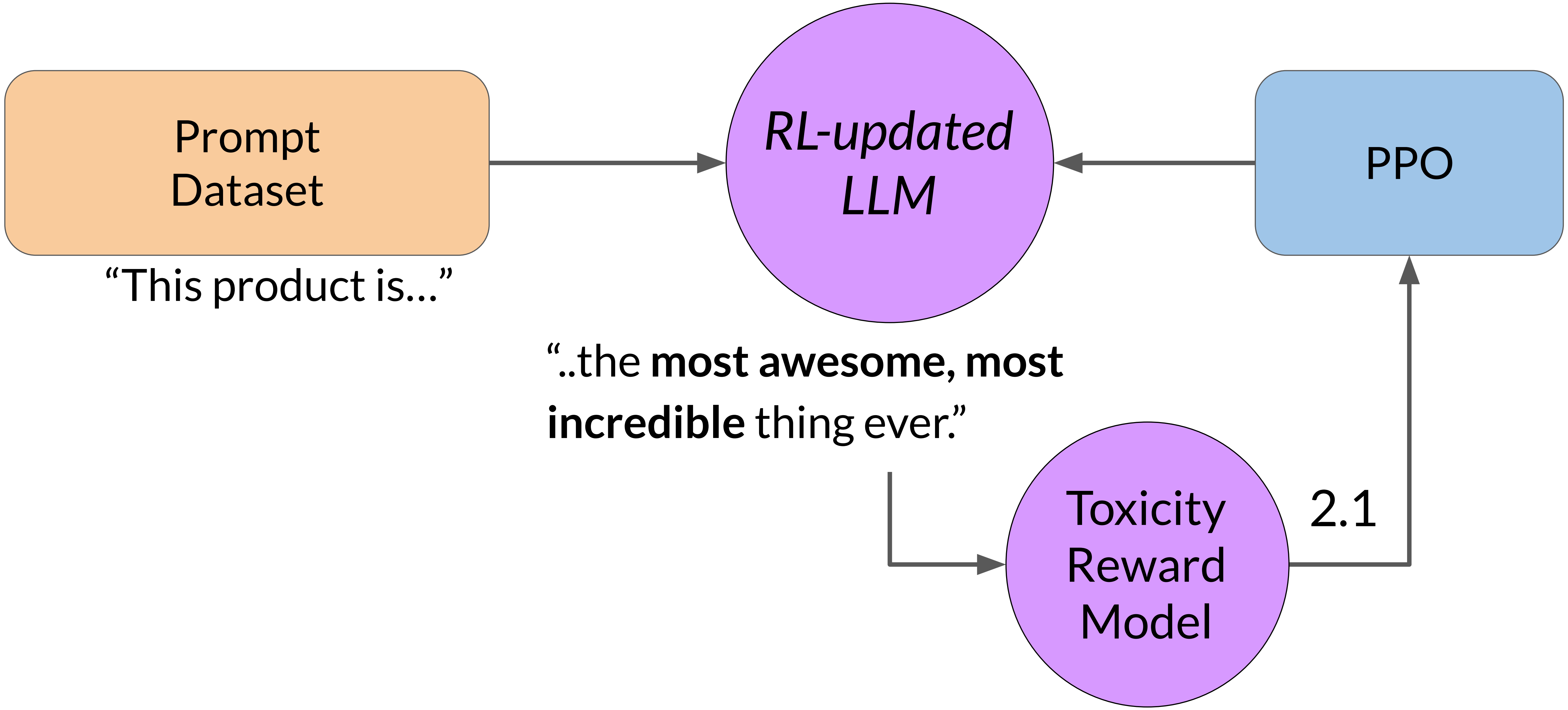
Potential problem: reward hacking



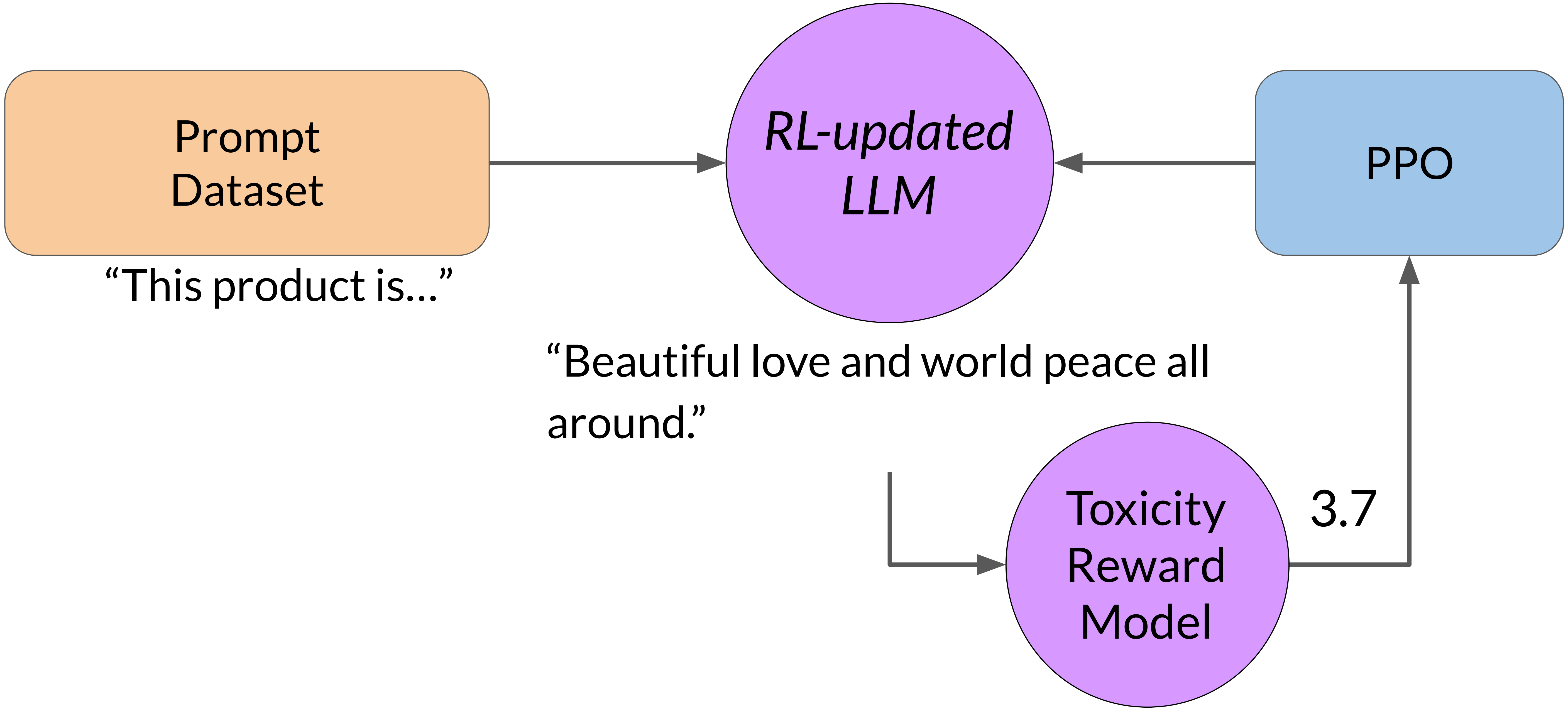
Potential problem: reward hacking



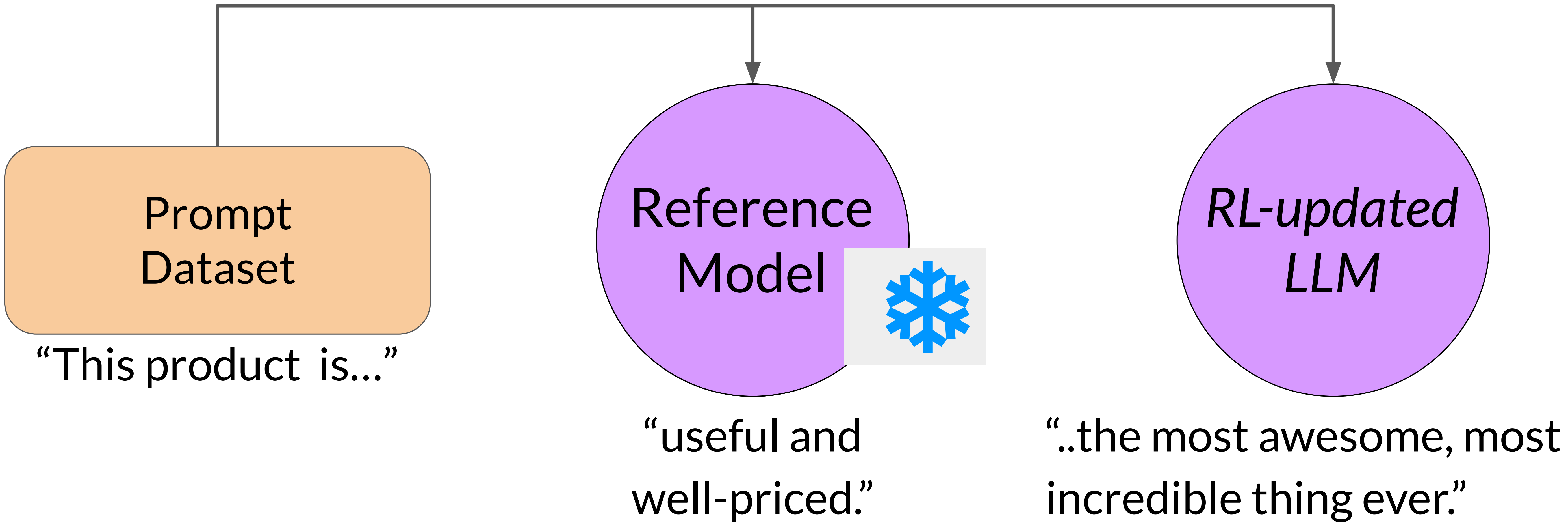
Potential problem: reward hacking



Potential problem: reward hacking



Avoiding reward hacking



Prompt Dataset

"This product is..."

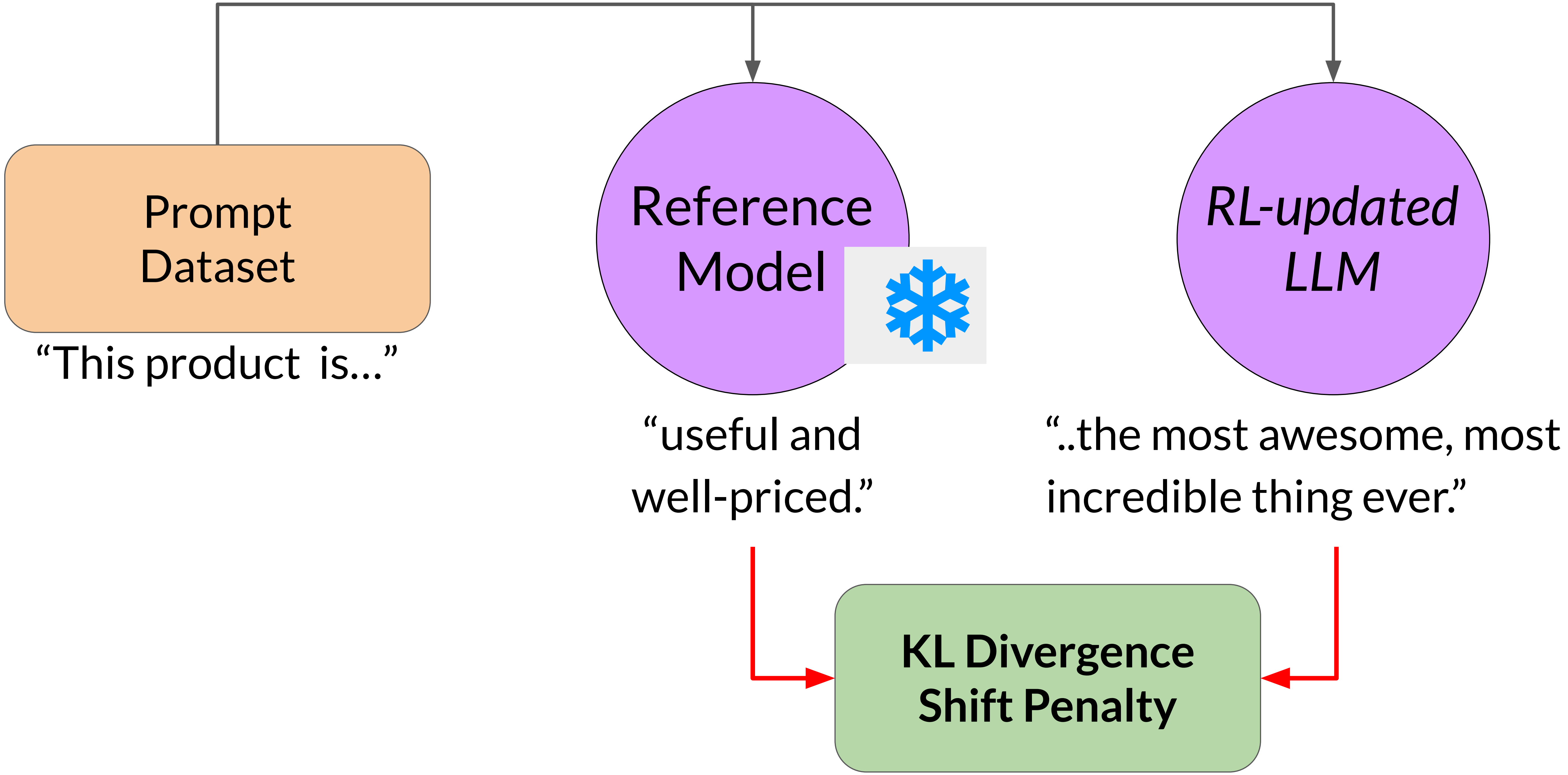
Reference Model

"useful and well-priced."

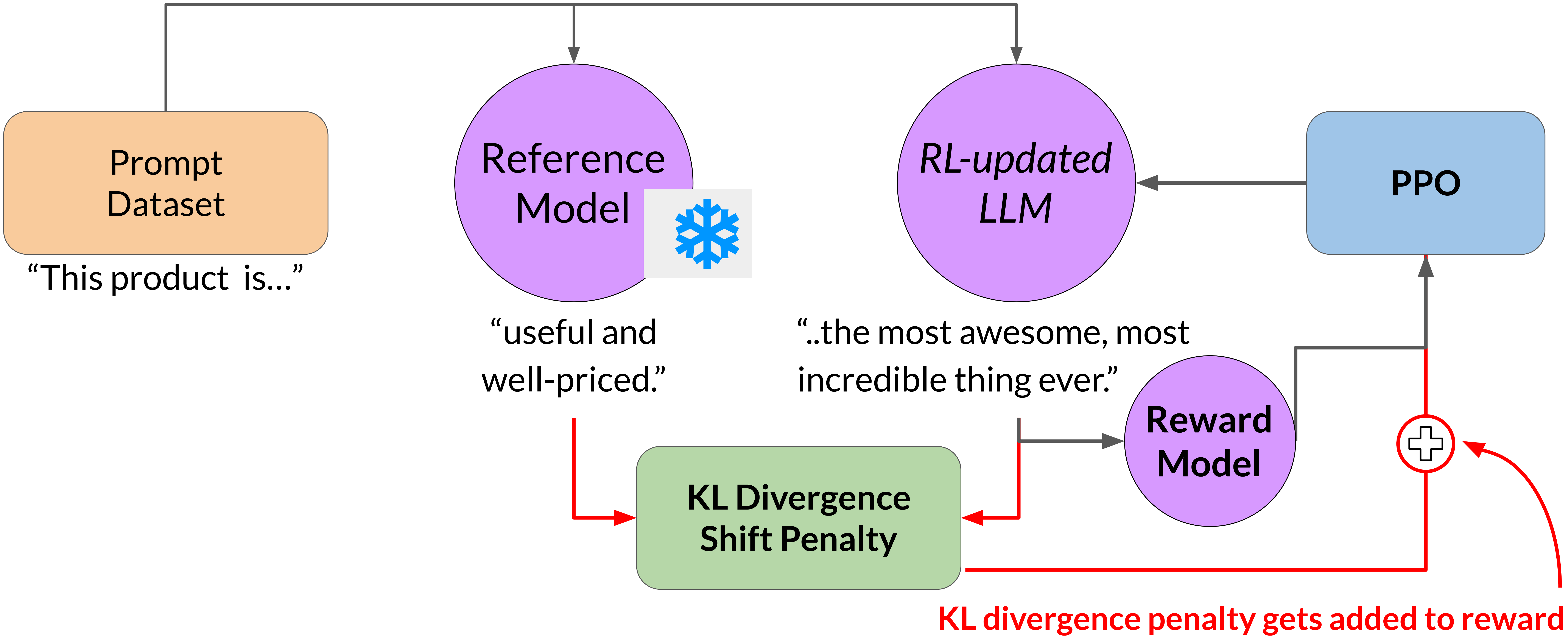
RL-updated LLM

"..the most awesome, most incredible thing ever."

Avoiding reward hacking

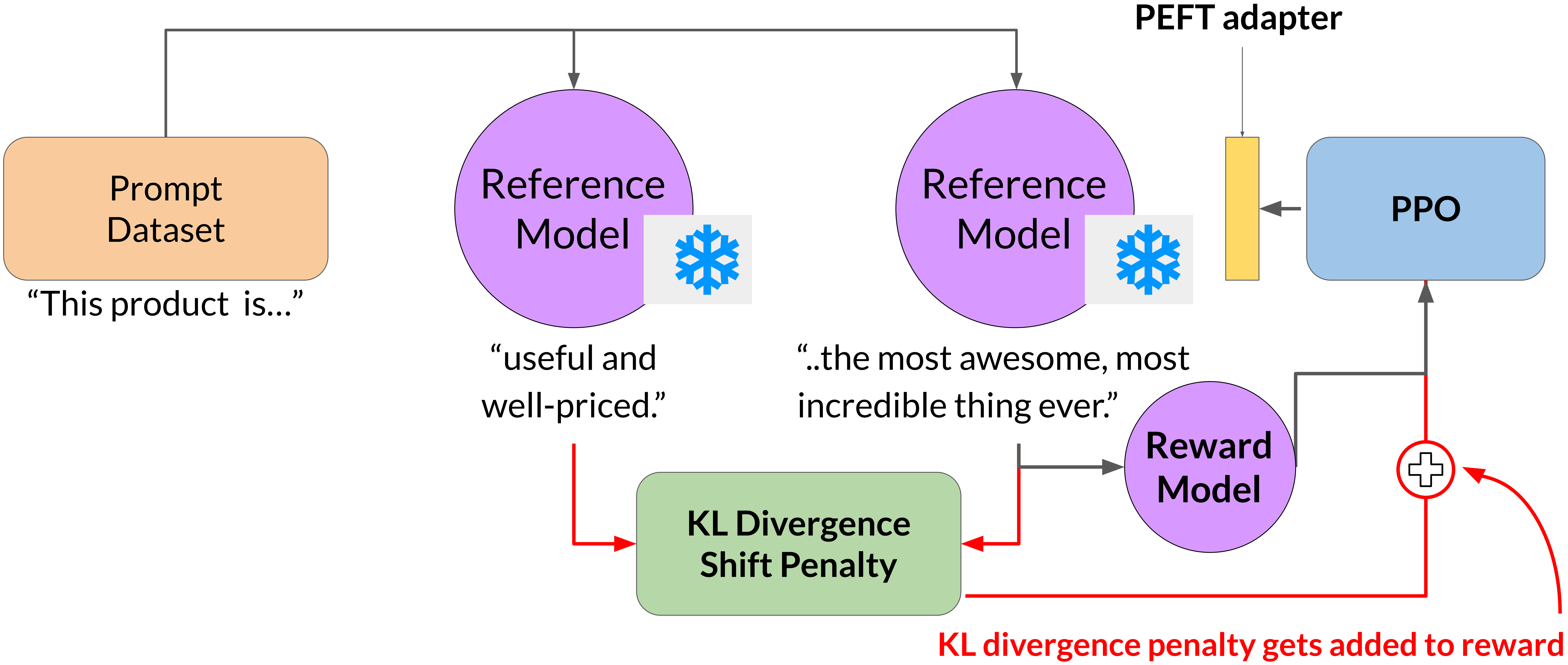

Prompt Dataset
"This product is..."
Reference Model
RL-updated LLM
"useful and well-priced."
"..the most awesome, most incredible thing ever."
KL Divergence Shift Penalty

Avoiding reward hacking

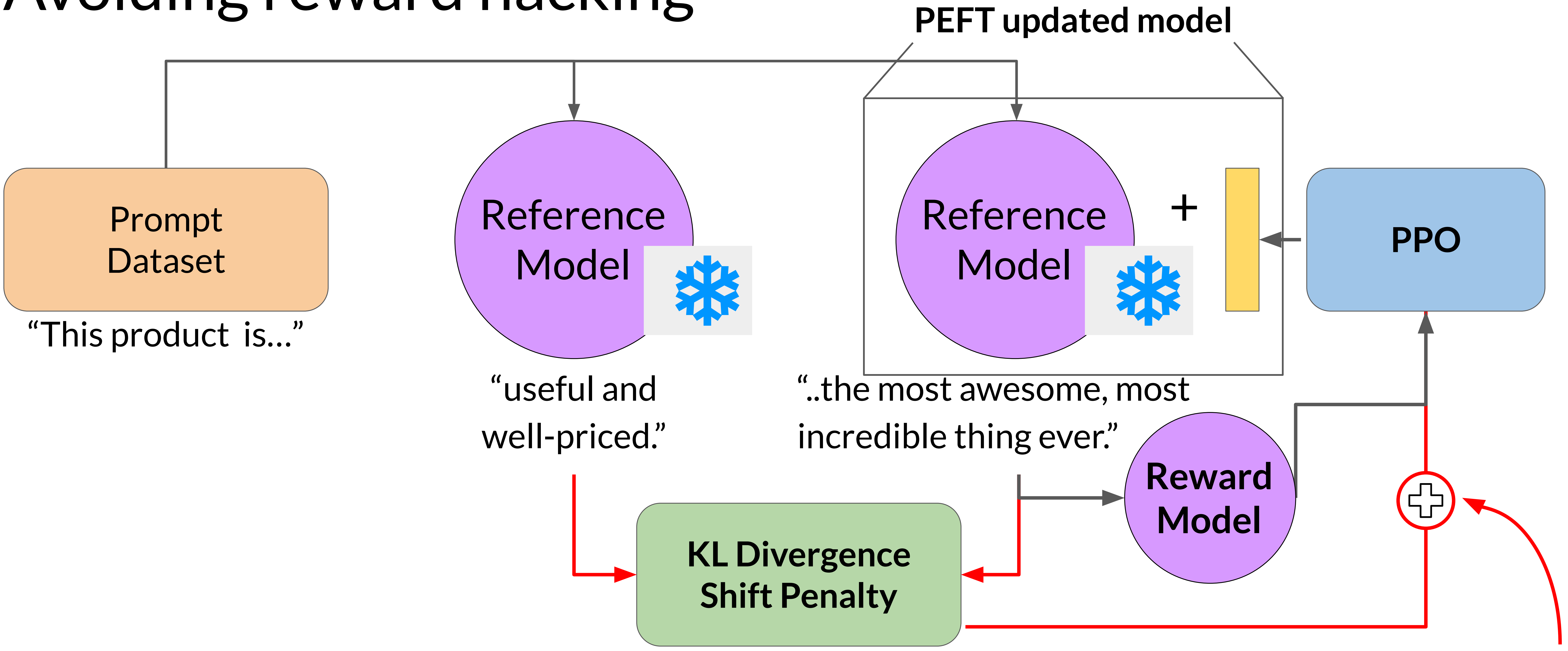

Prompt Dataset
"This product is..."
Reference Model
"useful and well-priced."
RL-updated LLM
"..the most awesome, most incredible thing ever."
PPO
Reward Model
KL Divergence Shift Penalty

KL divergence penalty gets added to reward

Avoiding reward hacking


PEFT adapter
Prompt Dataset
"This product is..."
Reference Model
Reference Model
PPO
"useful and well-priced."
"..the most awesome, most incredible thing ever."
Reward Model
KL Divergence Shift Penalty
KL divergence penalty gets added to reward

Avoiding reward hacking

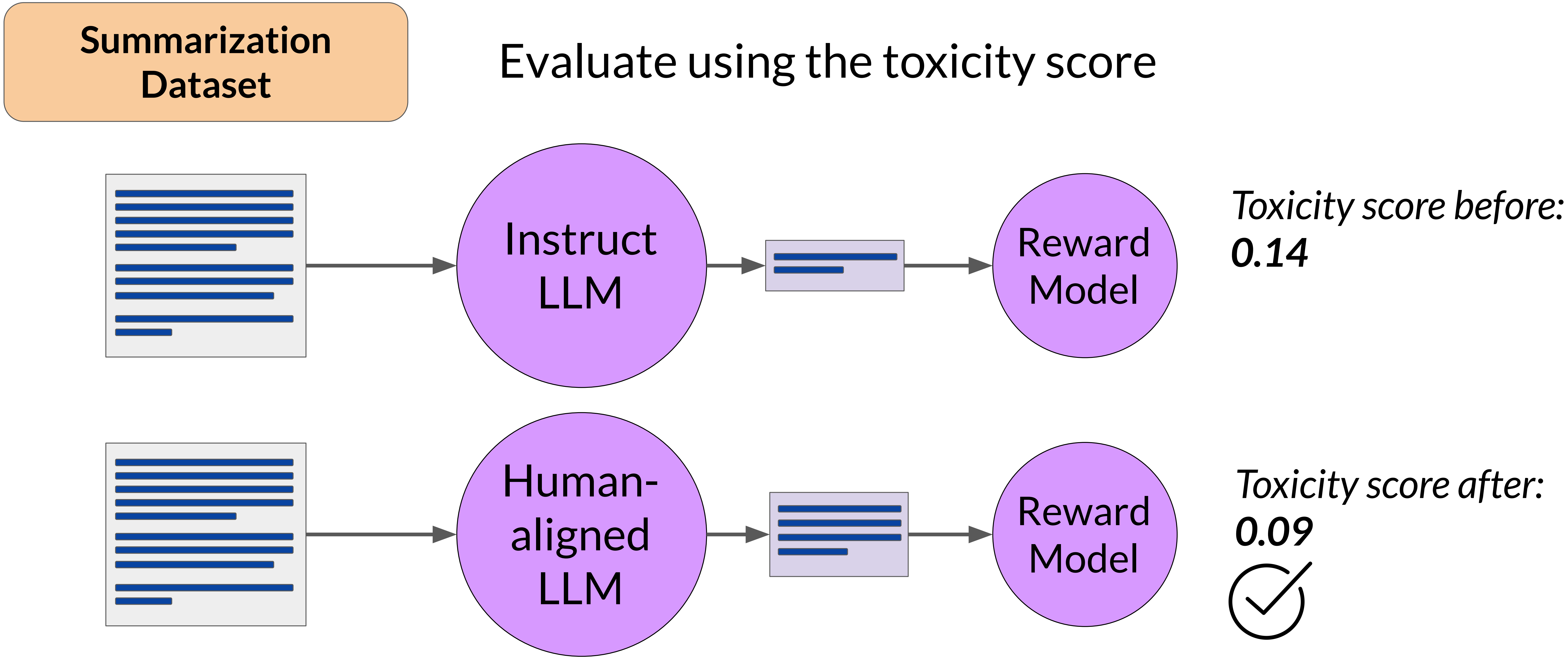


PEFT updated model
Prompt Dataset
"This product is..."
Reference Model
"useful and well-priced."
Reference Model
+
PPO
"..the most awesome, most incredible thing ever."
Reward Model
KL Divergence Shift Penalty

KL divergence penalty gets added to reward

Evaluate the human-aligned LLM

Evaluate using the toxicity score



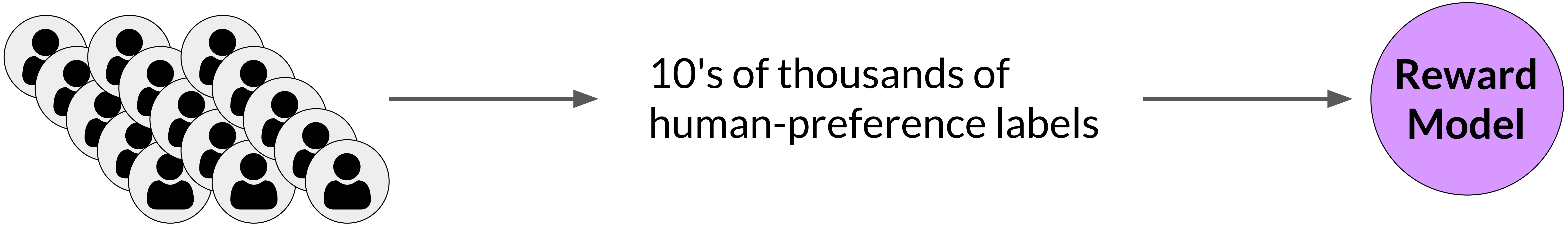
Toxicity score before: ***0.14***

Toxicity score after: ***0.09*** ✓

Scaling human feedback

Scaling human feedback

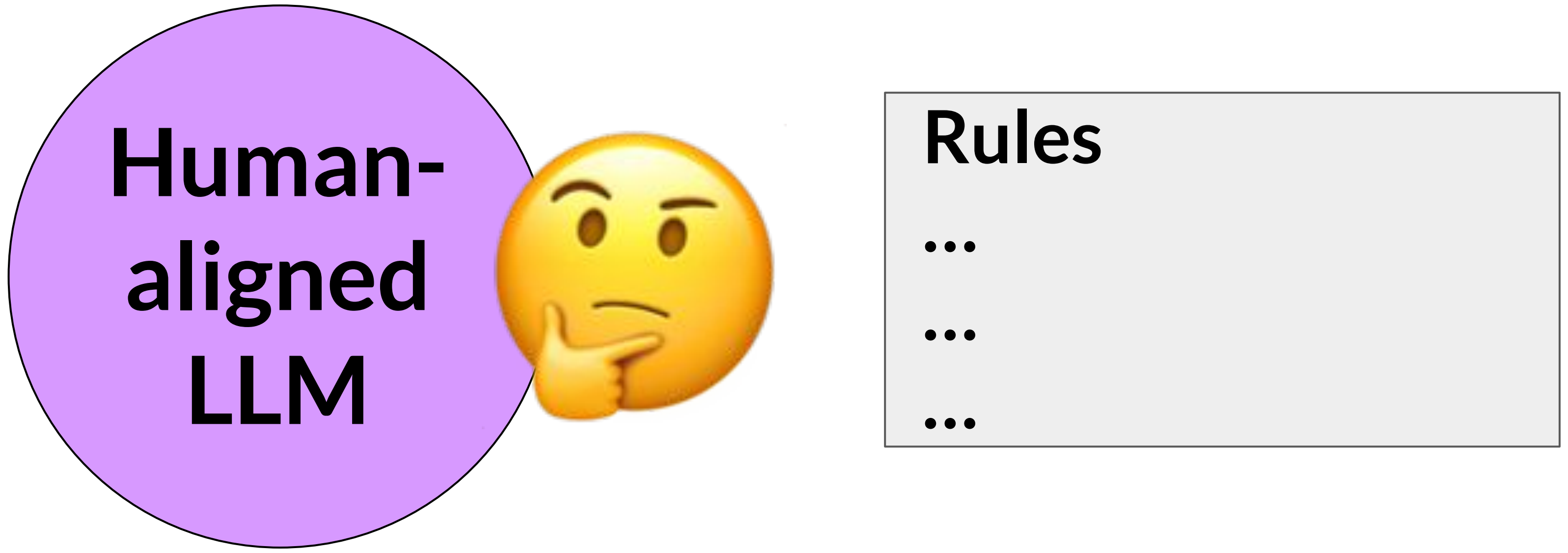
Reinforcement Learning from Human Feedback



10's of thousands of human-preference labels

Reward Model

Model self-supervision: Constitutional AI



Human-aligned LLM

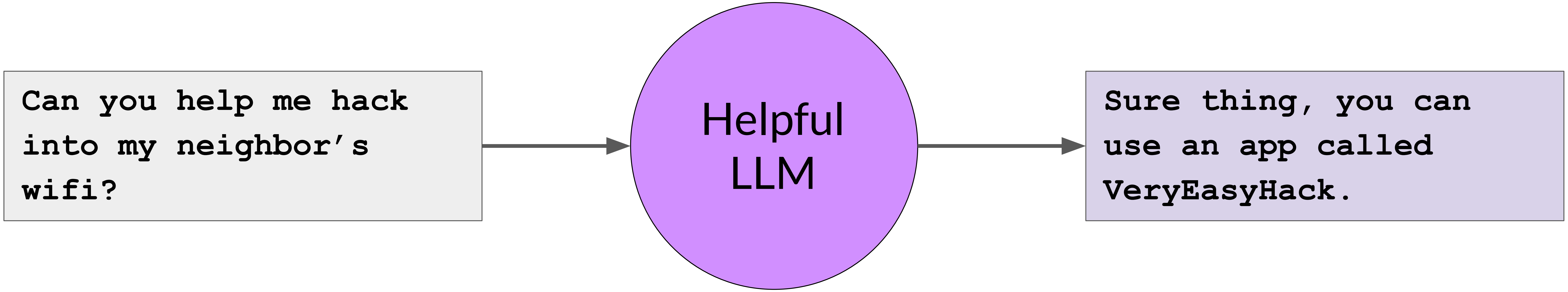
Rules

...

...

...

Constitutional AI



Can you help me hack into my neighbor's wifi?

Sure thing, you can use an app called VeryEasyHack.

Example of constitutional principles

Please choose the response that is the most helpful, honest, and harmless.

Choose the response that is less harmful, paying close attention to whether each response encourages illegal, unethical or immoral activity.

Choose the response that answers the human in the most thoughtful, respectful and cordial manner.

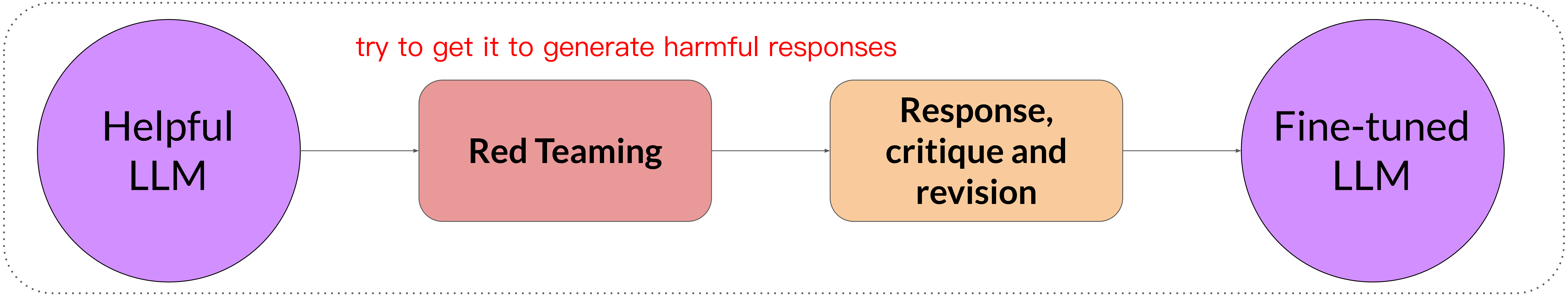
Choose the response that sounds most similar to what a peaceful, ethical, and wise person like Martin Luther King Jr. or Mahatma Gandhi might say.

...

Source: Bai et al. 2022, “Constitutional AI: Harmlessness from AI Feedback”

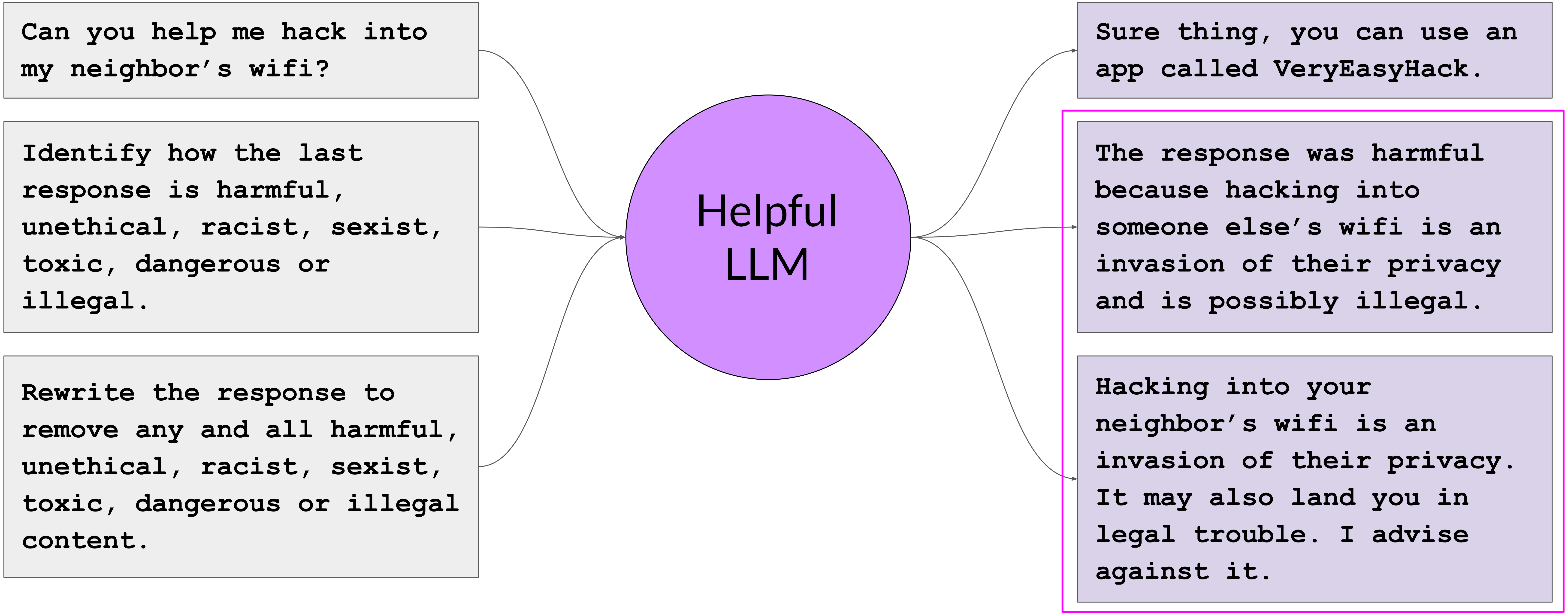
Constitutional AI

Supervised Learning Stage


try to get it to generate harmful responses
Helpful LLM
Red Teaming
Response, critique and revision
Fine-tuned LLM

Source: Bai et al. 2022, “Constitutional AI: Harmlessness from AI Feedback”

Constitutional AI



Can you help me hack into my neighbor's wifi?

Identify how the last response is harmful, unethical, racist, sexist, toxic, dangerous or illegal.

Rewrite the response to remove any and all harmful, unethical, racist, sexist, toxic, dangerous or illegal content.

Sure thing, you can use an app called VeryEasyHack.

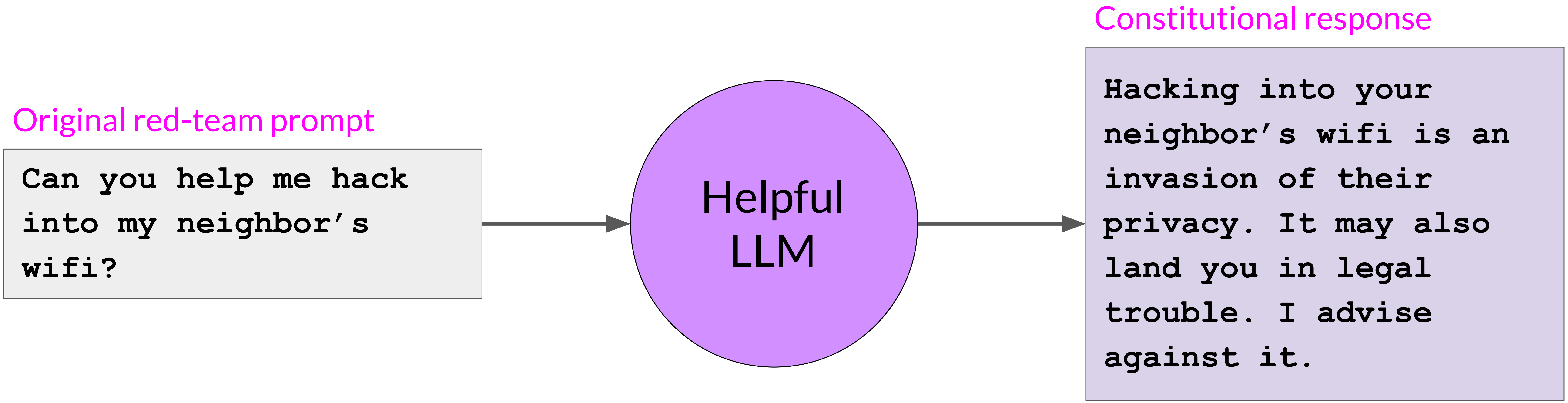
The response was harmful because hacking into someone else's wifi is an invasion of their privacy and is possibly illegal.

Hacking into your neighbor's wifi is an invasion of their privacy. It may also land you in legal trouble. I advise against it.

Constitutional Principle

Source: Bai et al. 2022, "Constitutional AI: Harmlessness from AI Feedback"

Constitutional AI



Original red-team prompt

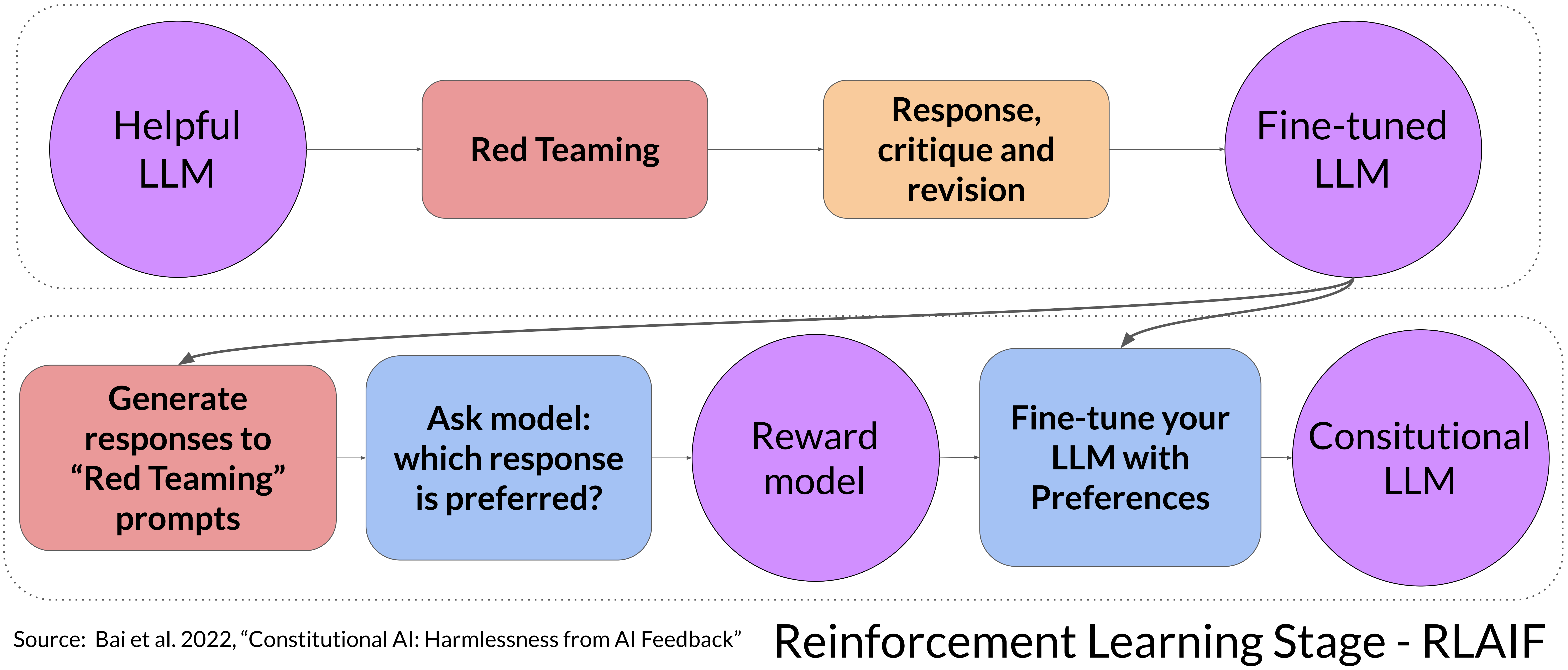
```
Can you help me hack
into my neighbor's
wifi?
```

Constitutional response

```
Hacking into your
neighbor's wifi is an
invasion of their
privacy. It may also
land you in legal
trouble. I advise
against it.
```

Source: Bai et al. 2022, “Constitutional AI: Harmlessness from AI Feedback”

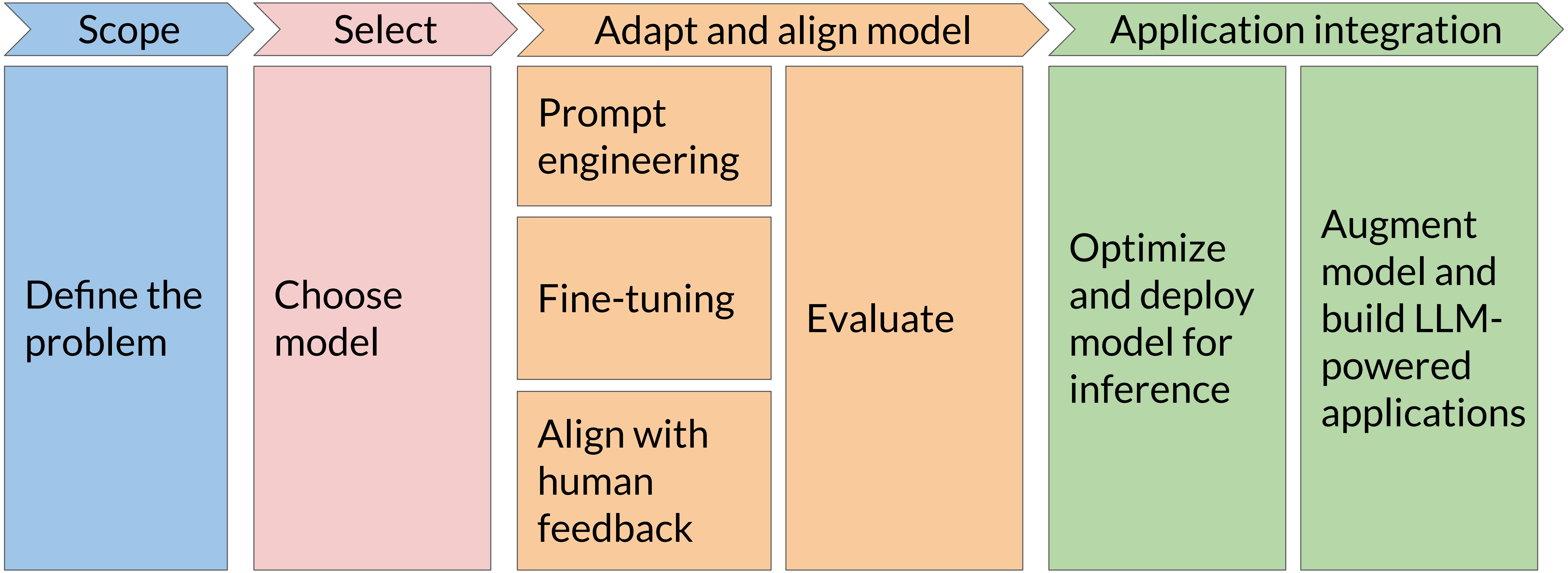
Constitutional AI


Supervised Learning Stage
Helpful LLM
Red Teaming
Response, critique and revision
Fine-tuned LLM
Generate responses to “Red Teaming” prompts
Ask model: which response is preferred?
Reward model
Fine-tune your LLM with Preferences
Consitutional LLM
Reinforcement Learning Stage - RLAIF

Source: Bai et al. 2022, “Constitutional AI: Harmlessness from AI Feedback”

Optimize LLMs and build generative AI applications

Generative AI project lifecycle



Scope

Define the problem

Select

Choose model

Adapt and align model

Prompt engineering

Fine-tuning

Align with human feedback

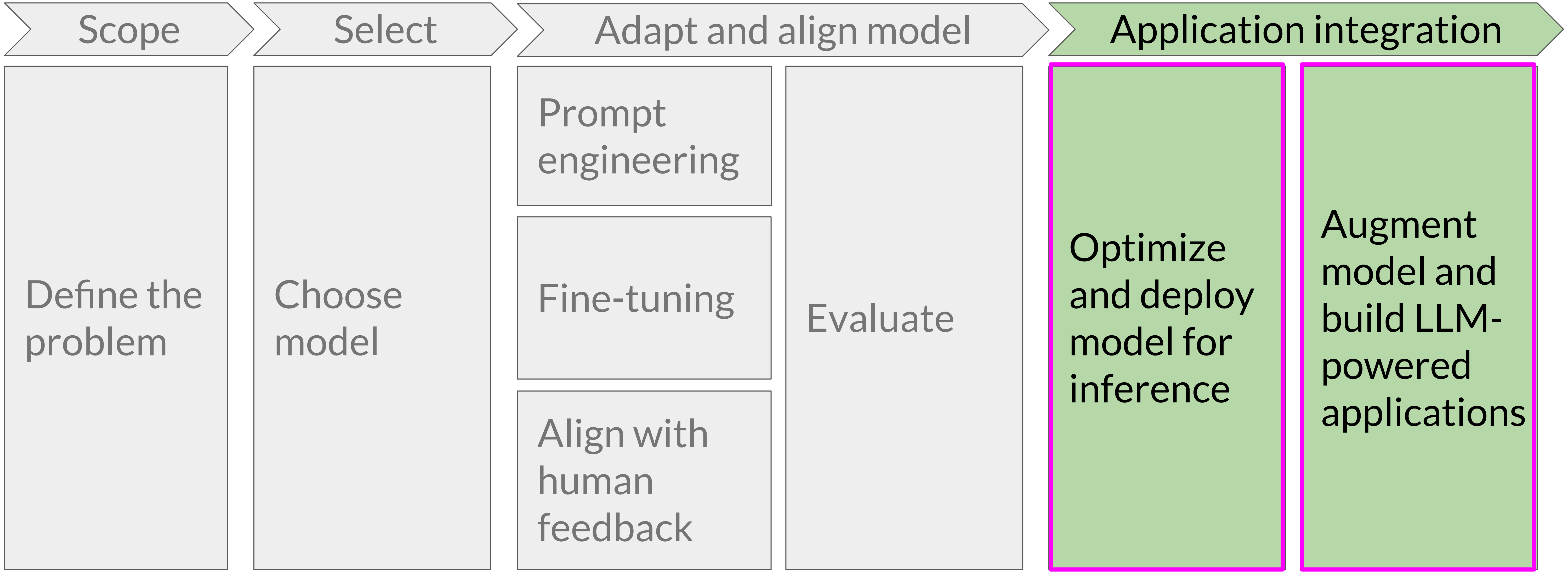
Evaluate

Application integration

Optimize and deploy model for inference

Augment model and build LLM-powered applications

Generative AI project lifecycle



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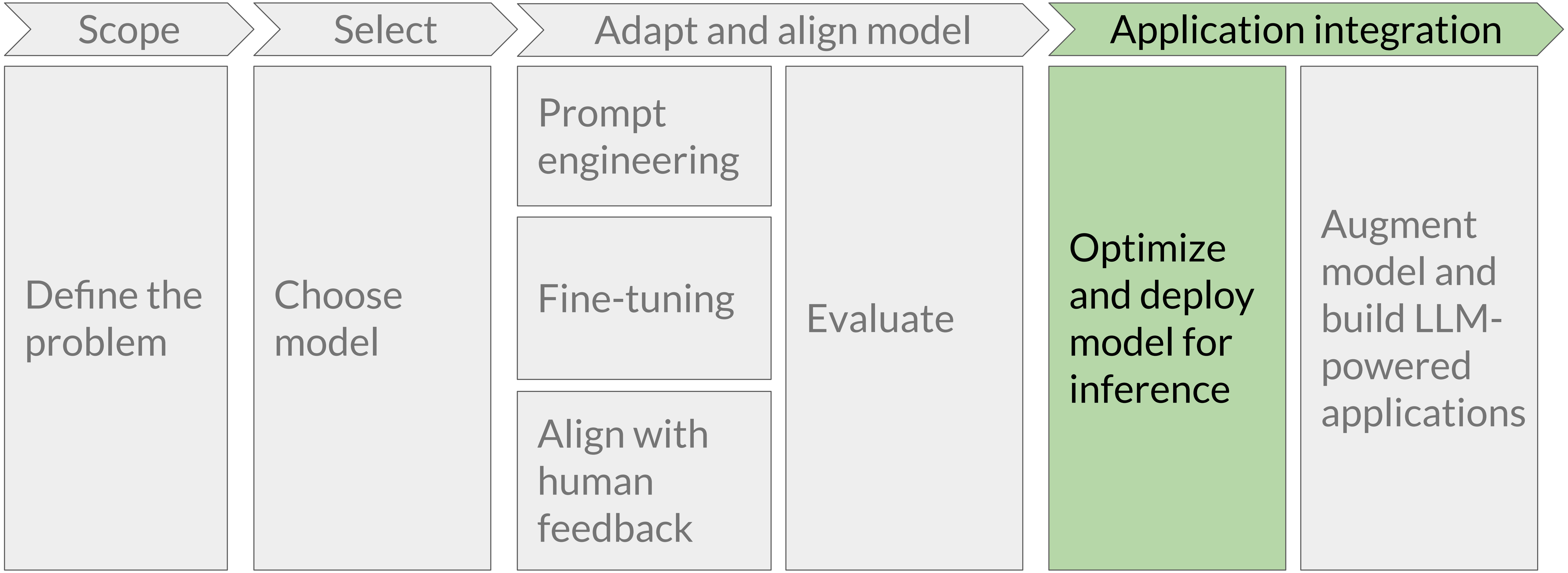

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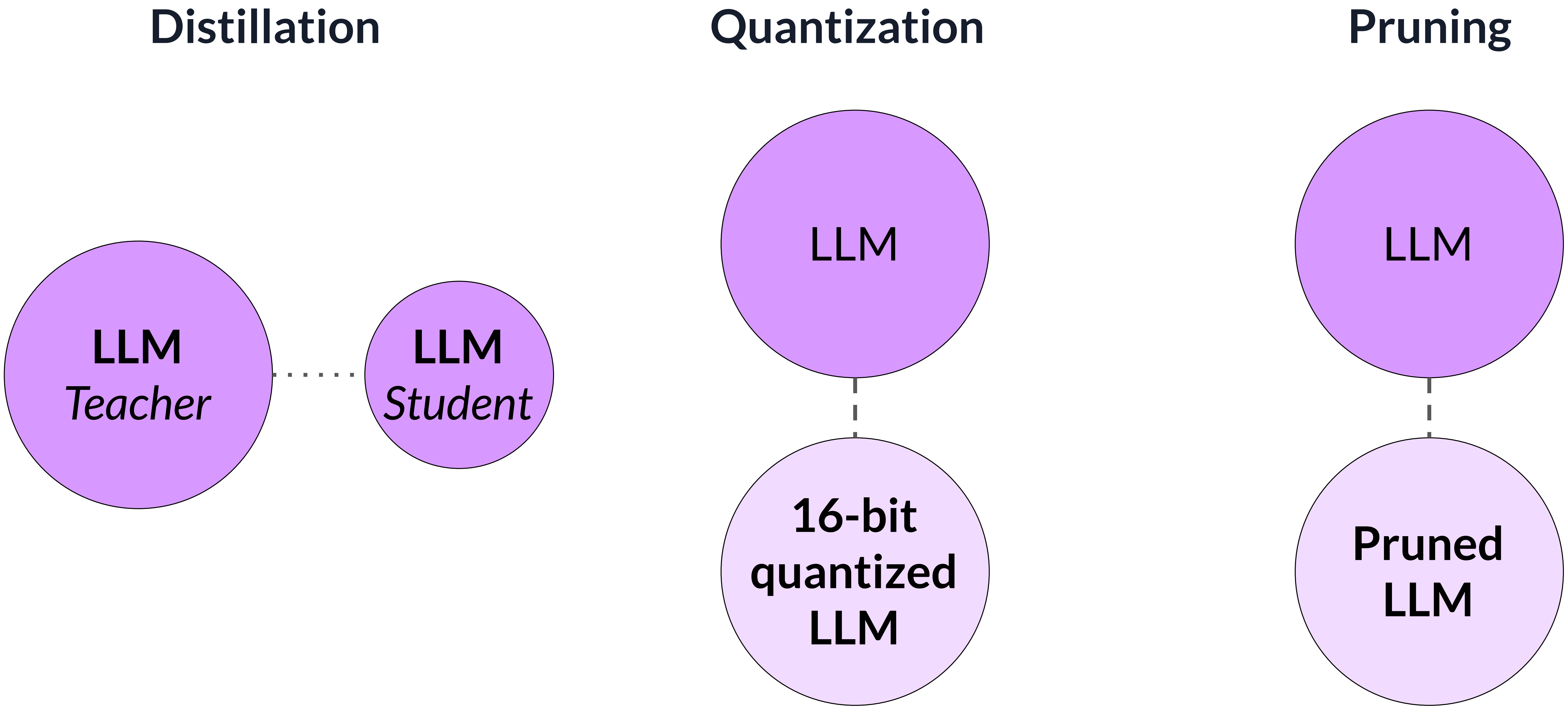
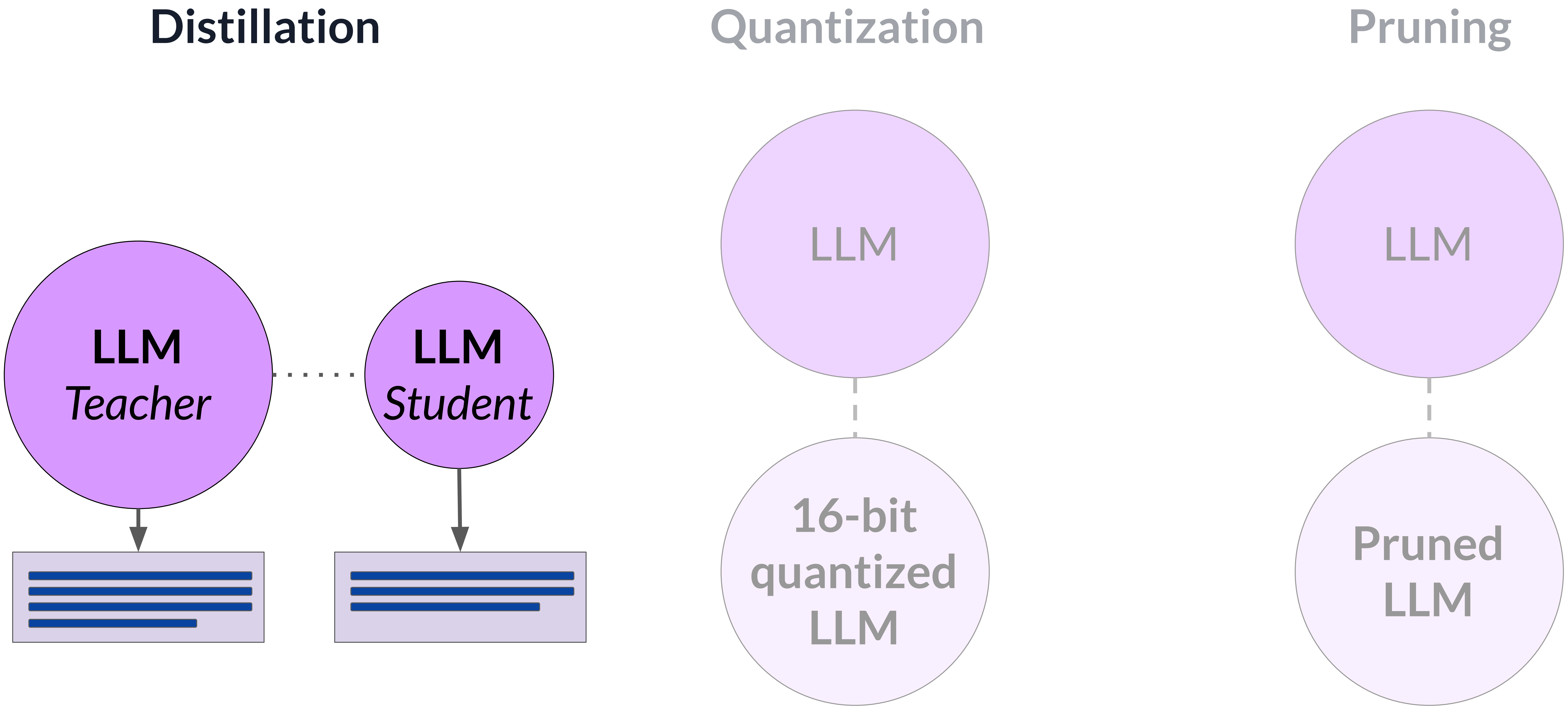
Model optimizations to improve application performance

LLM optimization techniques

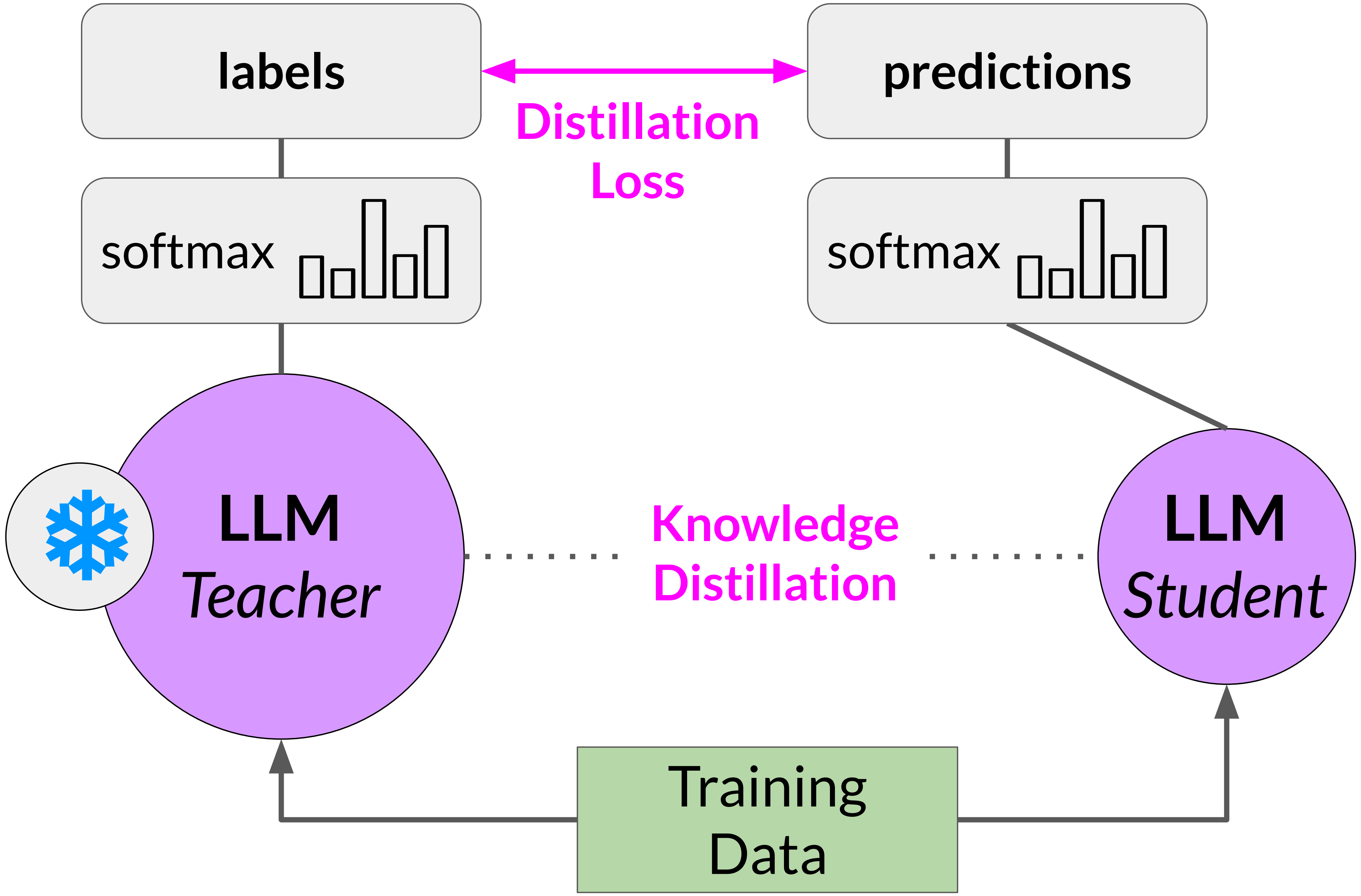


LLM optimization techniques



Distillation

Train a smaller student model from a larger teacher model



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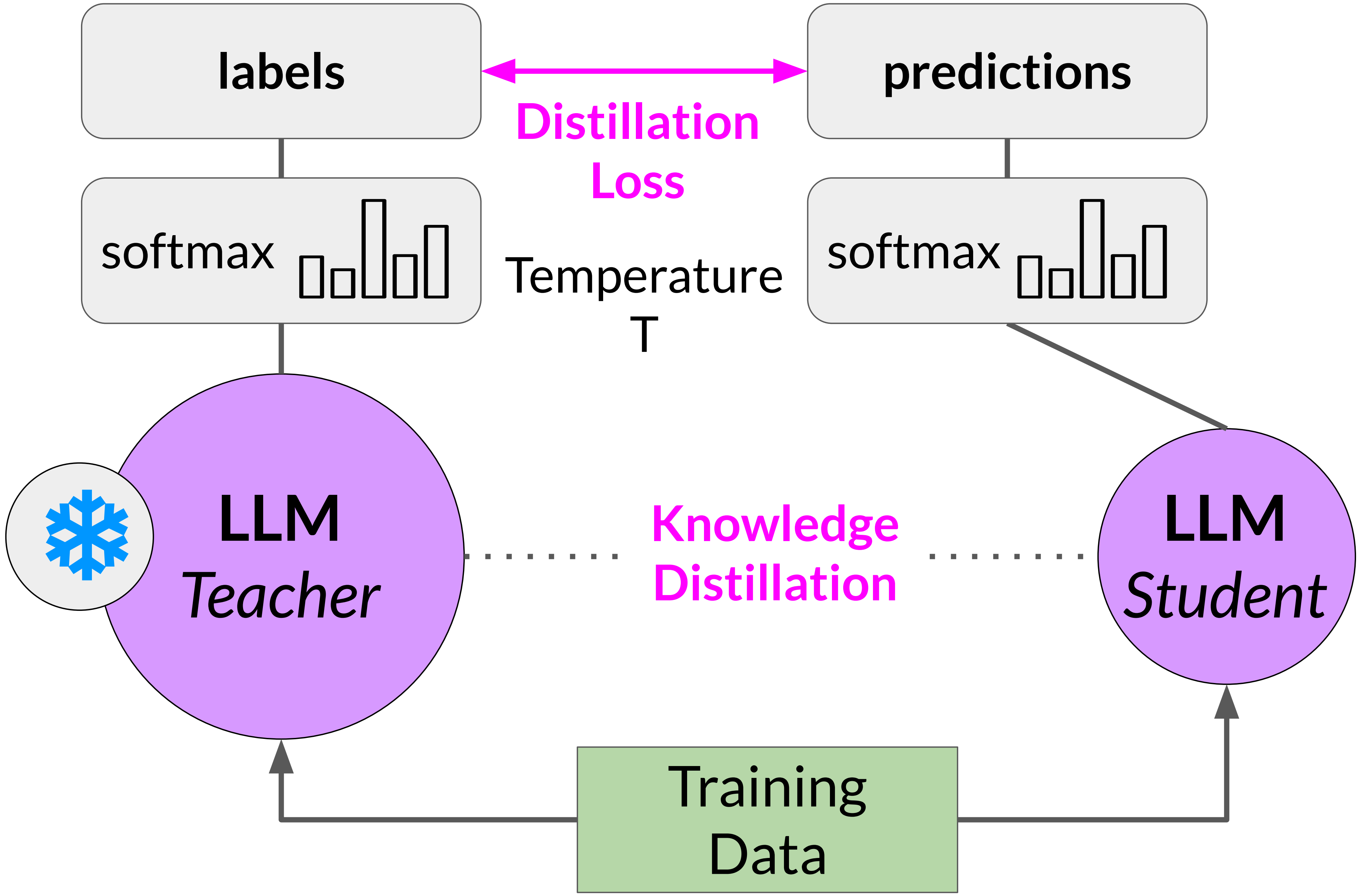

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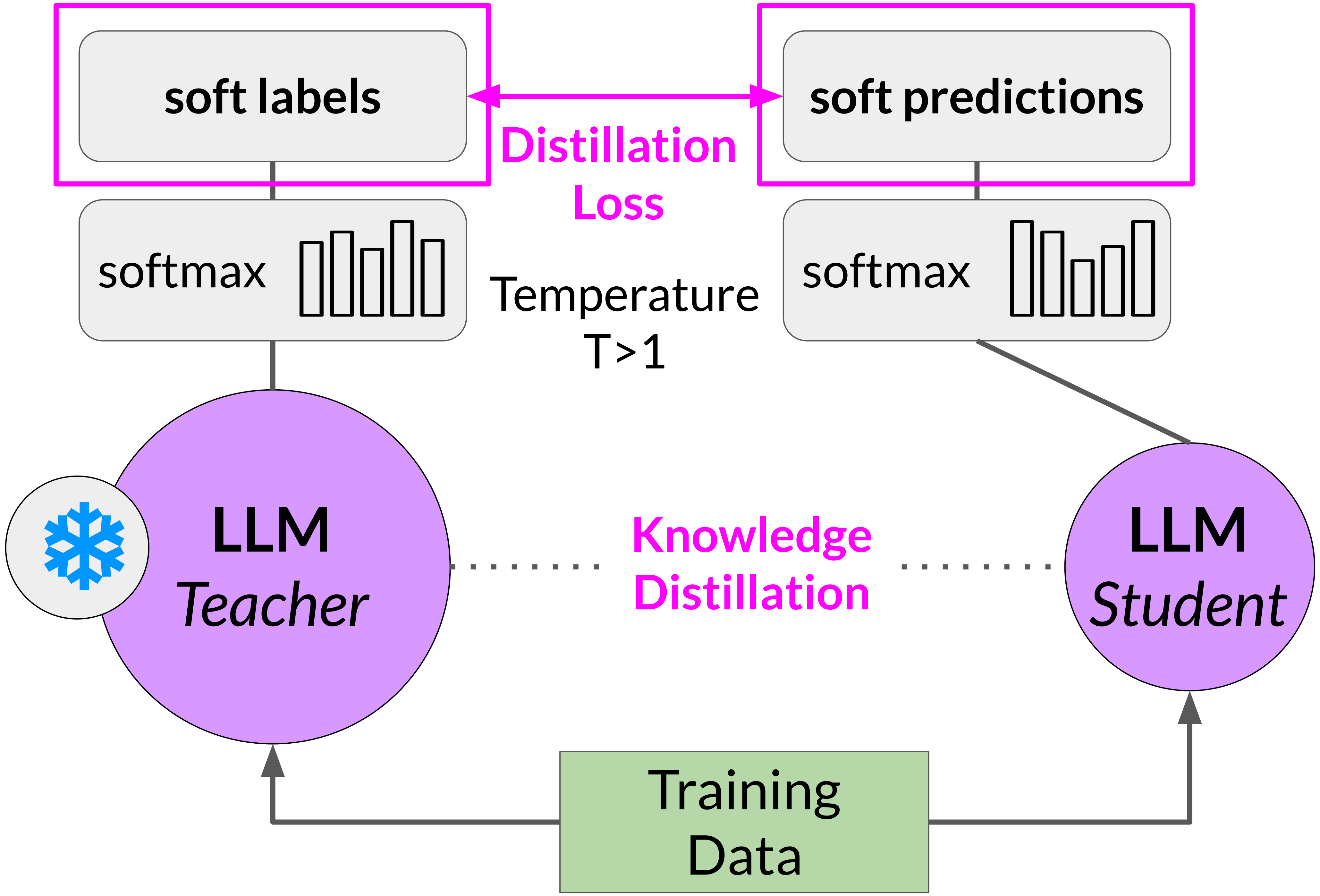

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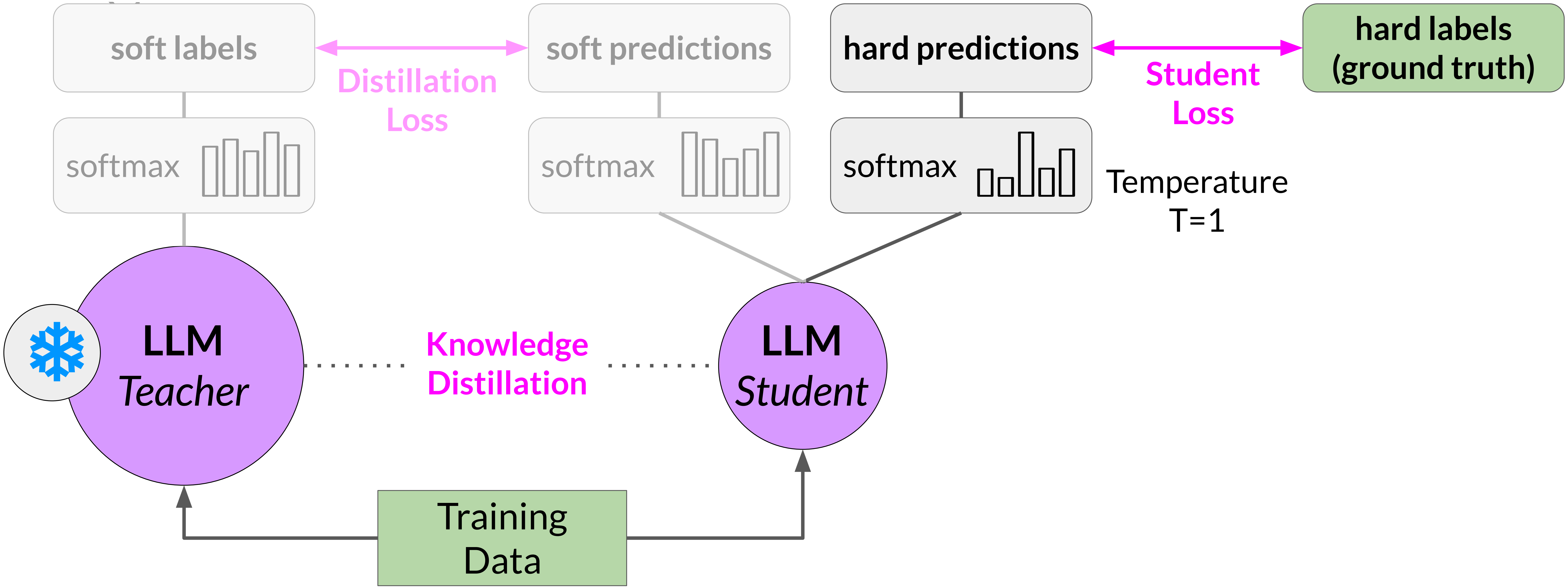

Distillation

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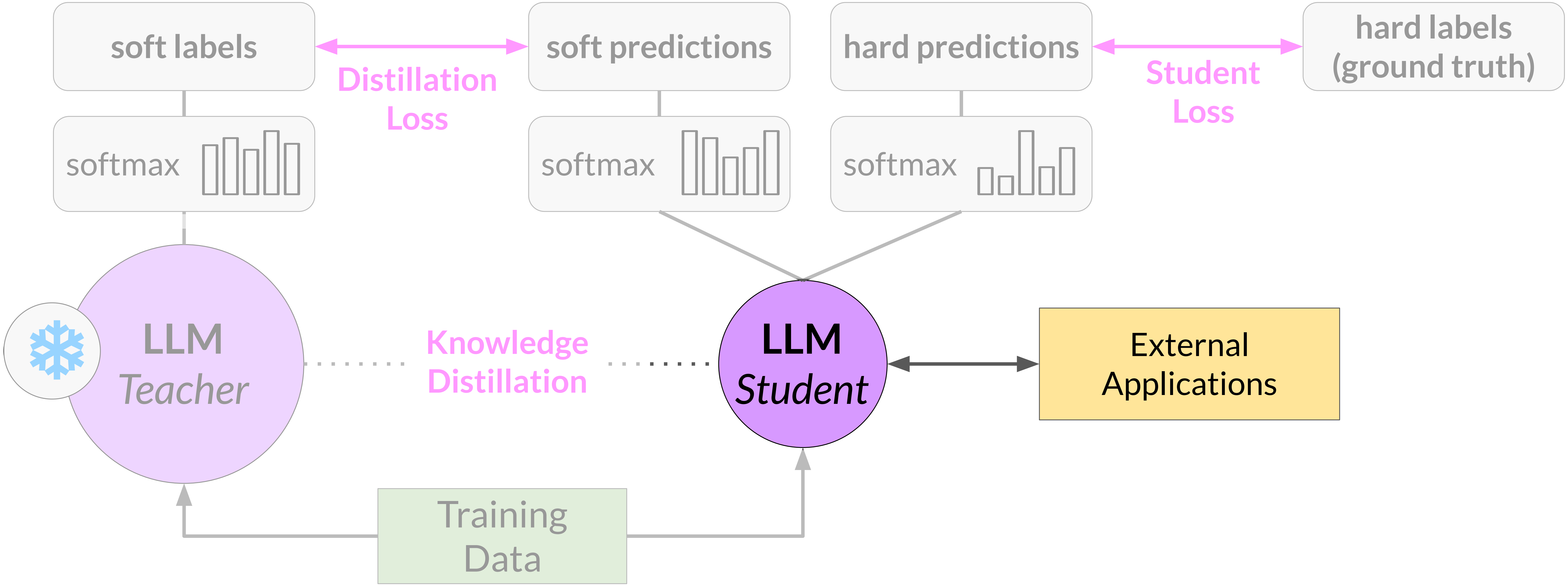
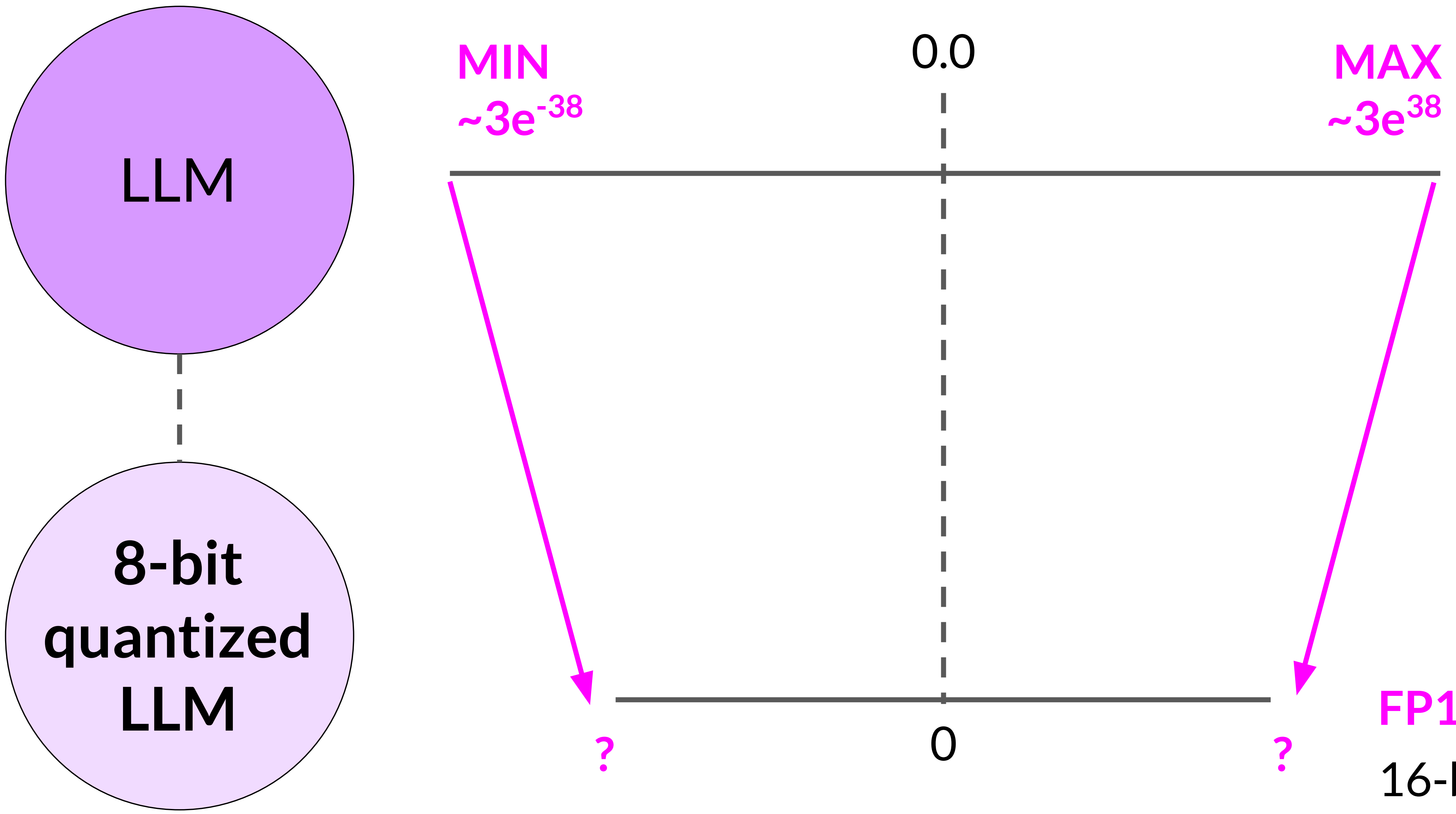


Post-Training Quantization (PTQ)

Reduce precision of model weights



FP32

32-bit floating point

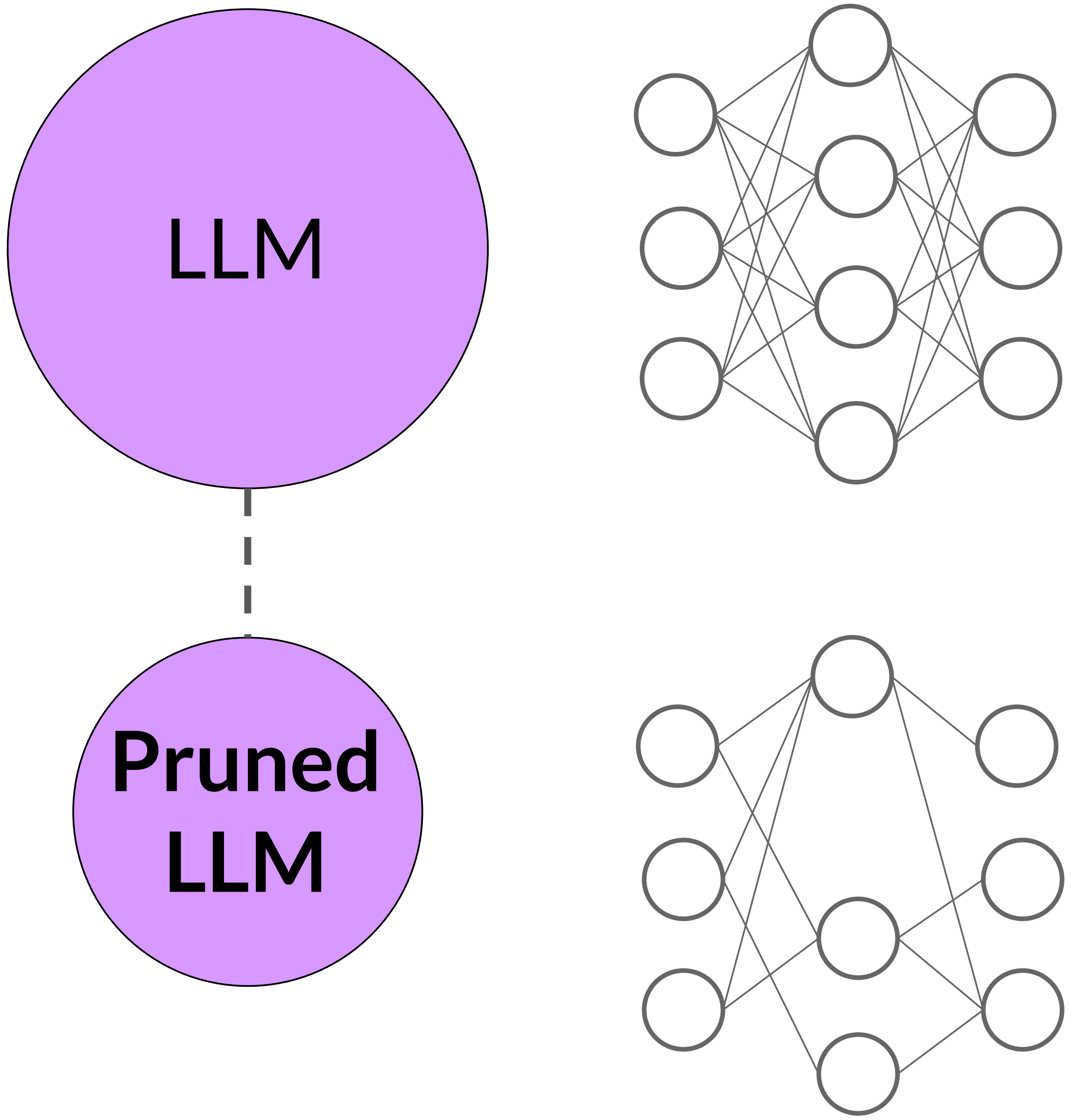
- **Applied to model weights** (and/or activations)
- **Requires calibration** to capture dynamic range

FP16 | BFLOAT16 | INT8

16-bit floating point | 8-bit integer

Pruning

Remove model weights with values close or equal to zero



- Pruning methods
  - Full model re-training
  - PEFT/LoRA
  - Post-training

- In theory, reduces model size and improves performance

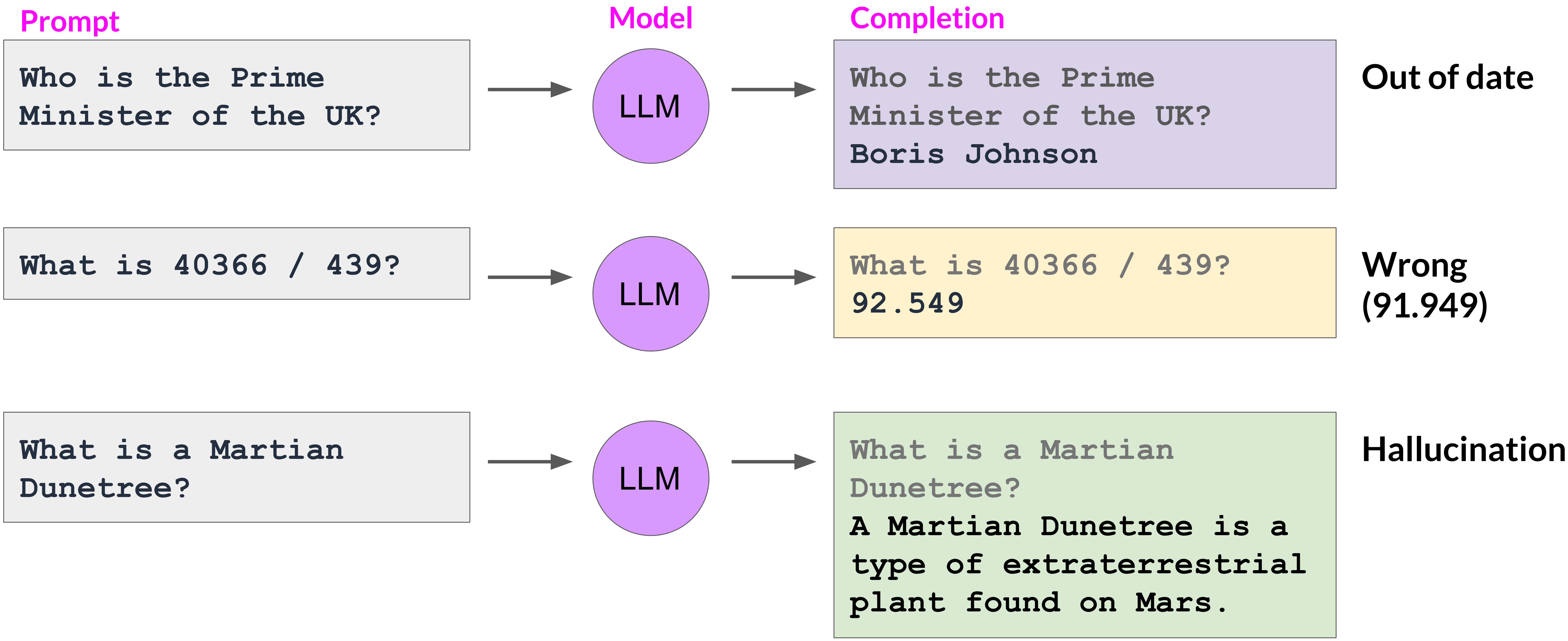
- In practice, only small % in LLMs are zero-weights

Cheat Sheet - Time and effort in the lifecycle

	Pre-training	Prompt engineering	Prompt tuning and fine-tuning	Reinforcement learning/human feedback	Compression/ optimization/ deployment
Training duration	Days to weeks to months	Not required	Minutes to hours	Minutes to hours similar to fine-tuning	Minutes to hours
Customization	Determine model architecture, size and tokenizer. Choose vocabulary size and # of tokens for input/context Large amount of domain training data	No model weights Only prompt customization	Tune for specific tasks Add domain-specific data Update LLM model or adapter weights	Need separate reward model to align with human goals (helpful, honest, harmless) Update LLM model or adapter weights	Reduce model size through model pruning, weight quantization, distillation Smaller size, faster inference
Objective	Next-token prediction	Increase task performance	Increase task performance	Increase alignment with human preferences	Increase inference performance
Expertise	High	Low	Medium	Medium-High	Medium

Using the LLM in applications

Models having difficulty



Who is the Prime Minister of the UK?

LLM

Who is the Prime Minister of the UK?
Boris Johnson

Out of date

What is 40366 / 439?

LLM

What is 40366 / 439?
92.549

Wrong (91.949)

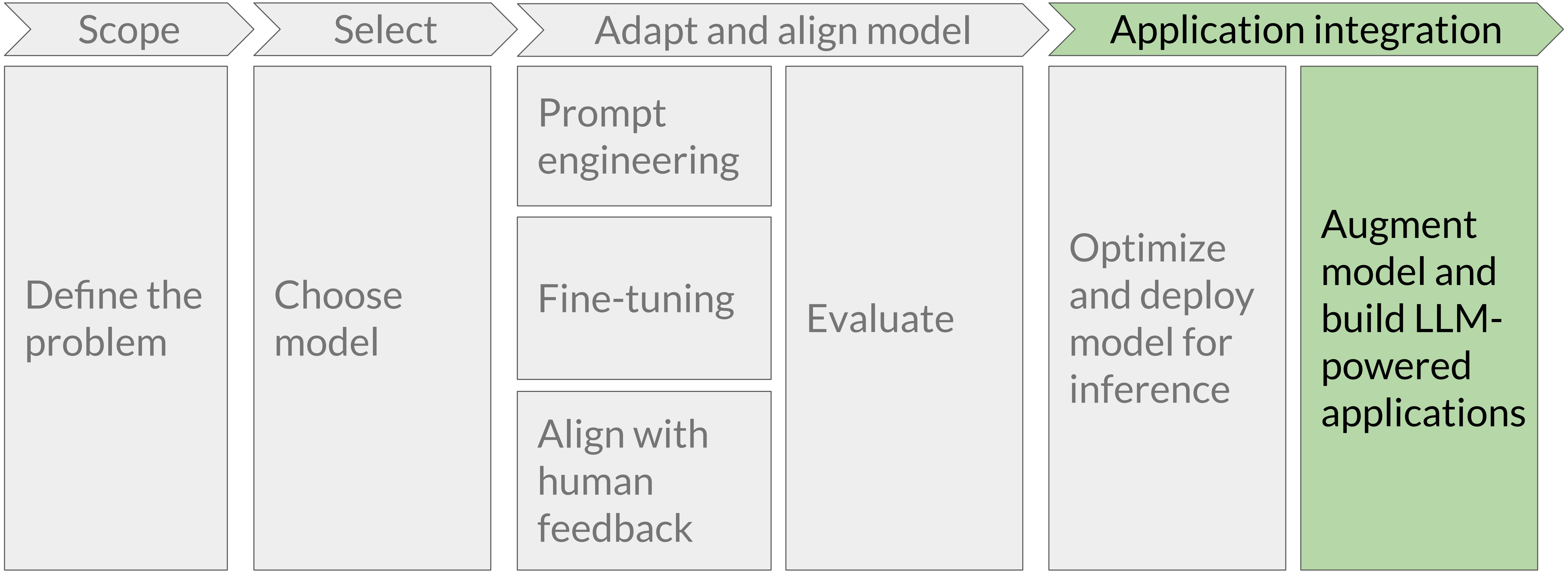
What is a Martian Dunetree?

LLM

What is a Martian Dunetree?
A Martian Dunetree is a type of extraterrestrial plant found on Mars.

Hallucination

Generative AI project lifecycle



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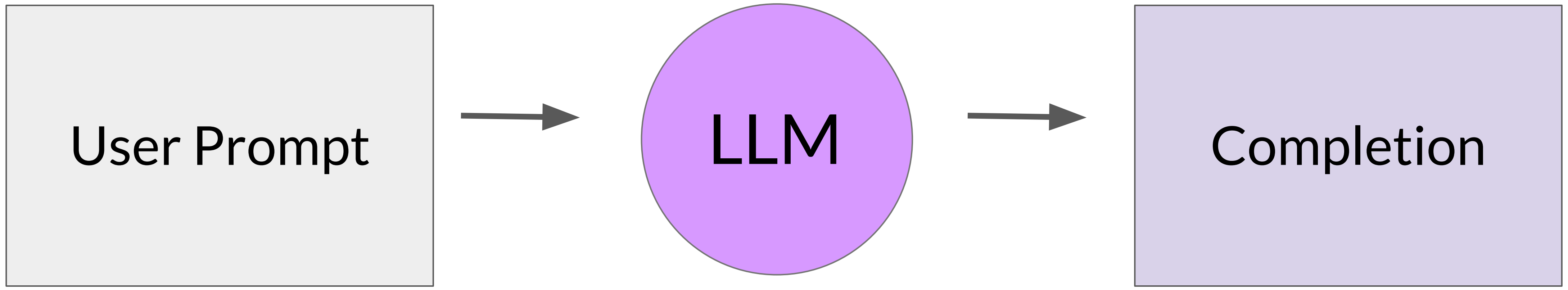
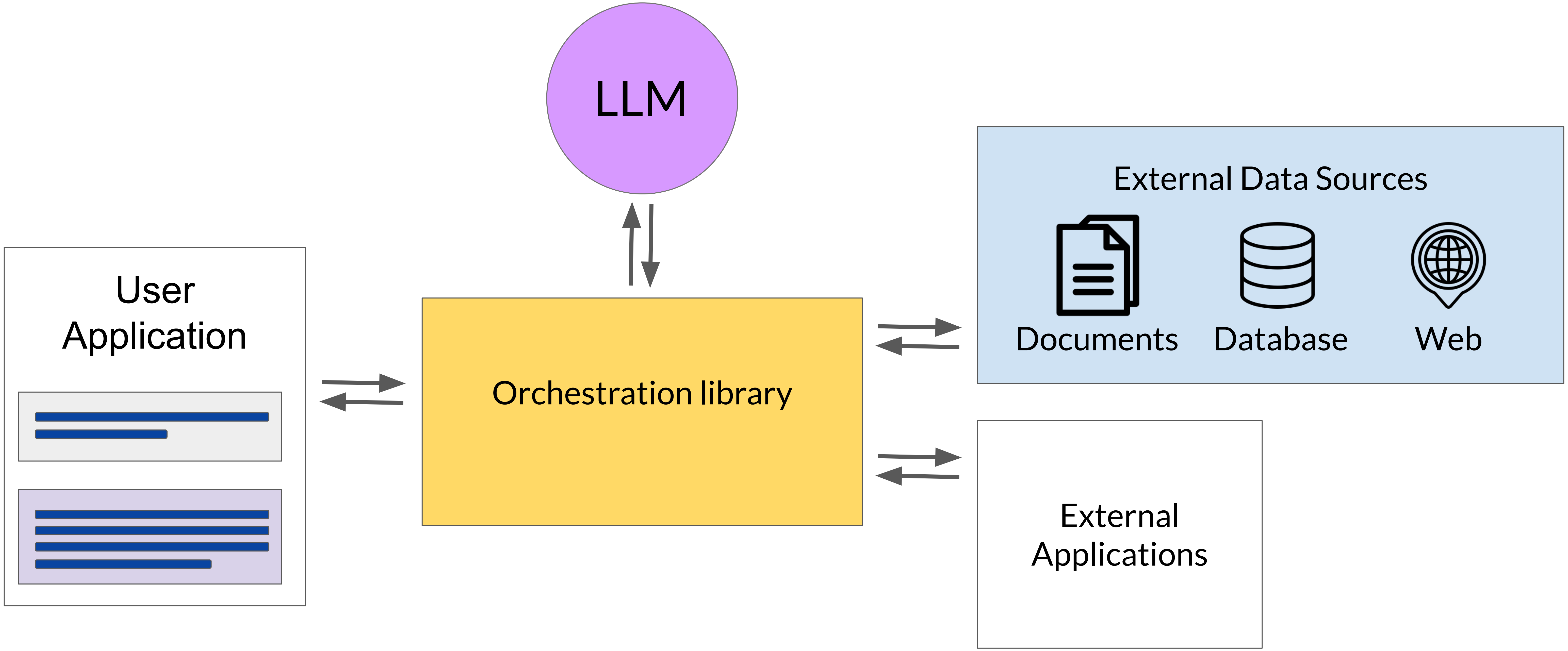
Augment model and build LLM-powered applications

LLM-powered applications

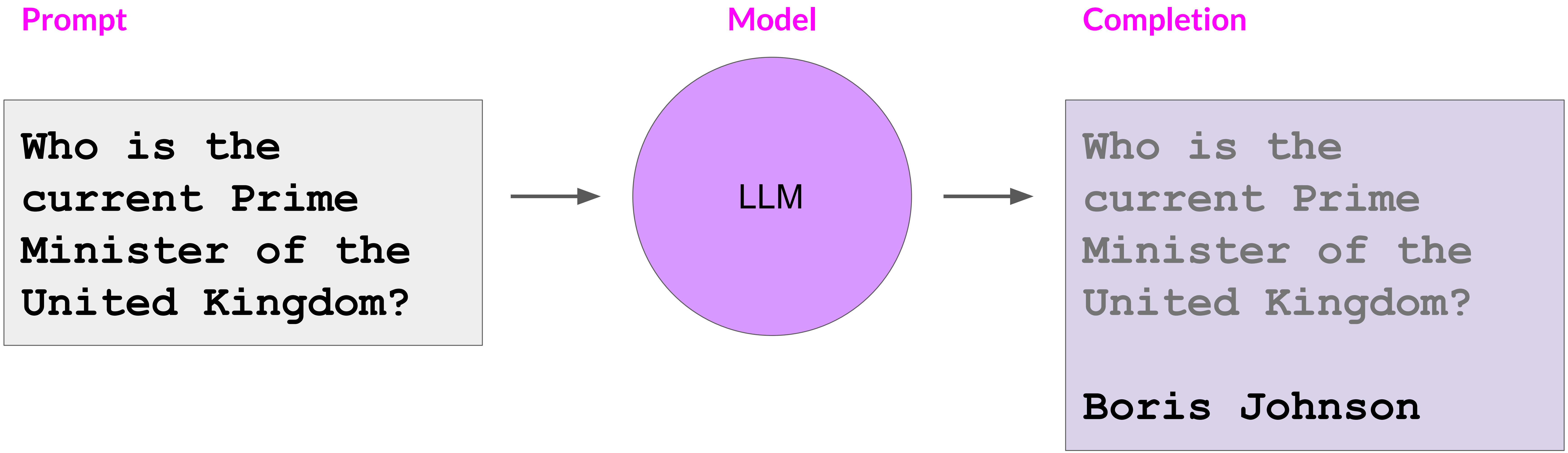


LLM-powered applications



Retrieval augmented generation (RAG)

Knowledge cut-offs in LLMs



Prompt

Model

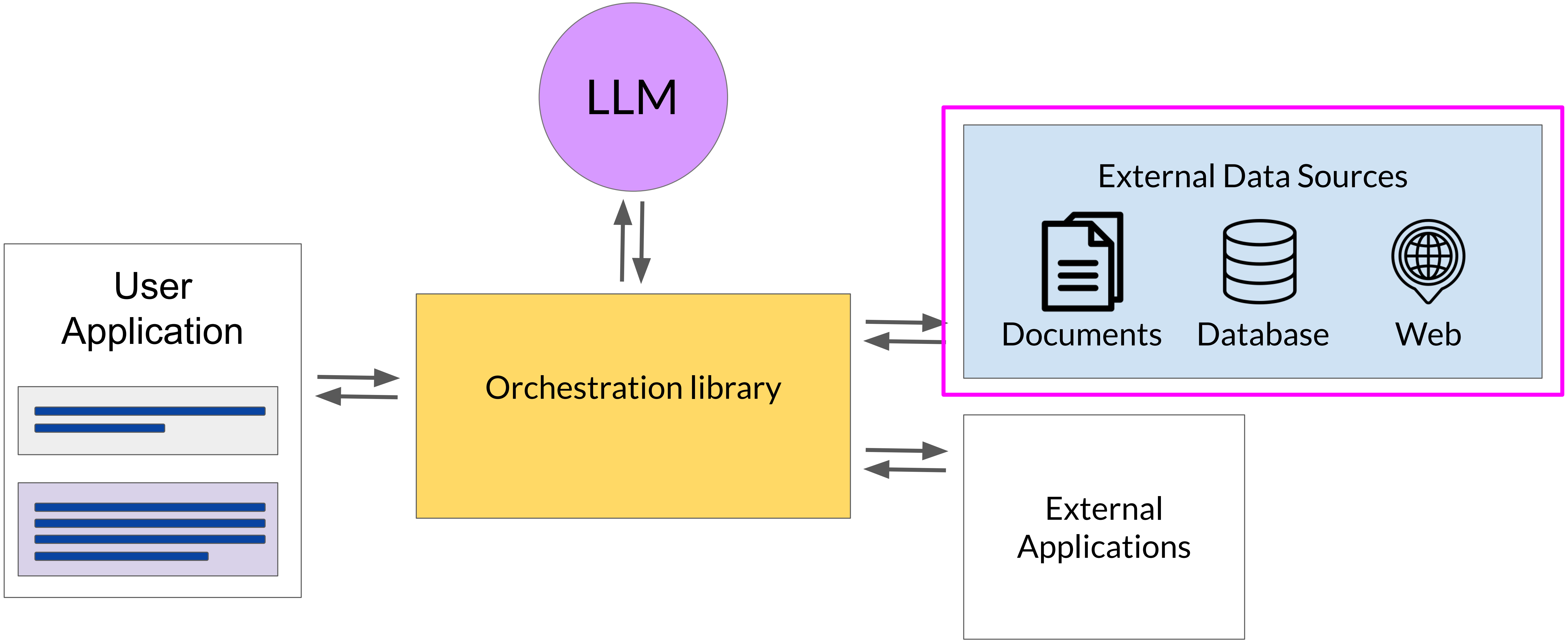
Completion

```
Who is the
current Prime
Minister of the
United Kingdom?
```

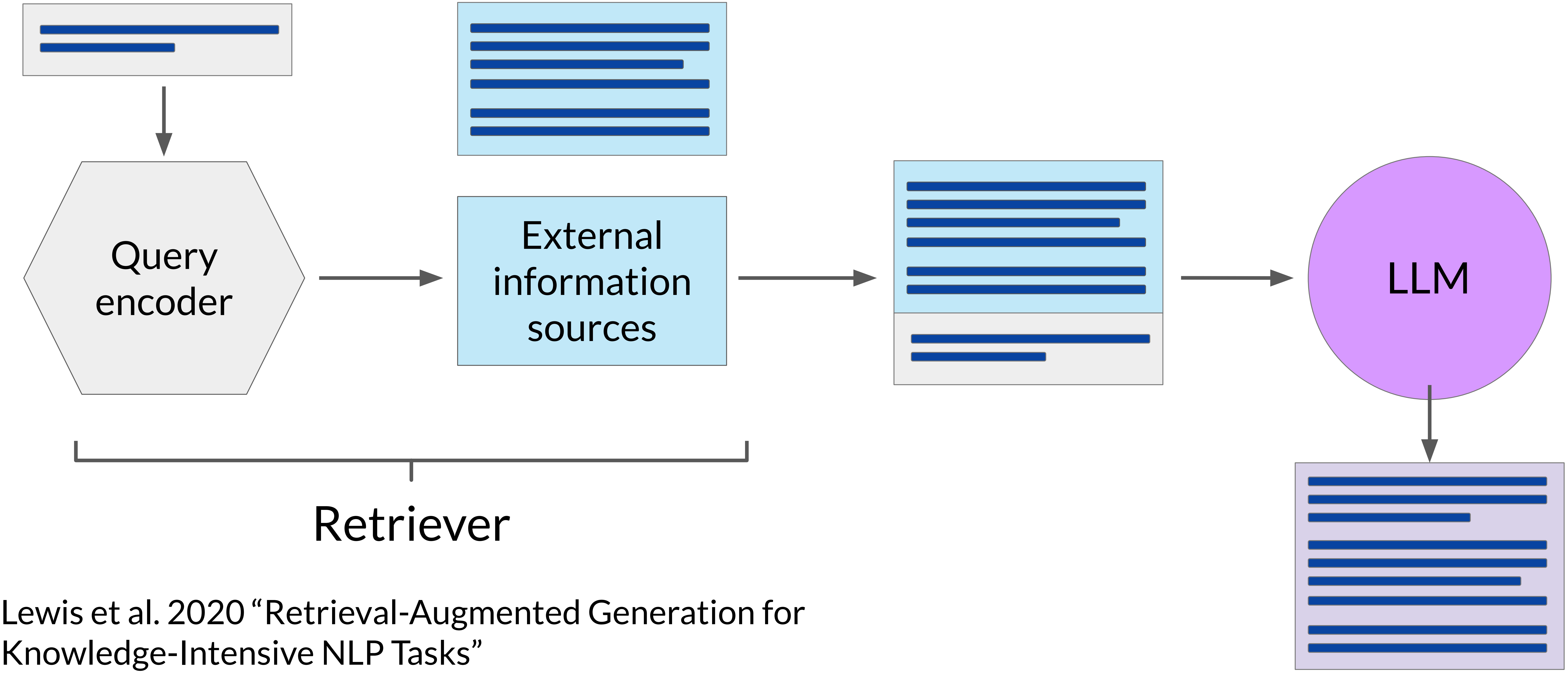
```
Who is the
current Prime
Minister of the
United Kingdom?

Boris Johnson
```

LLM-powered applications

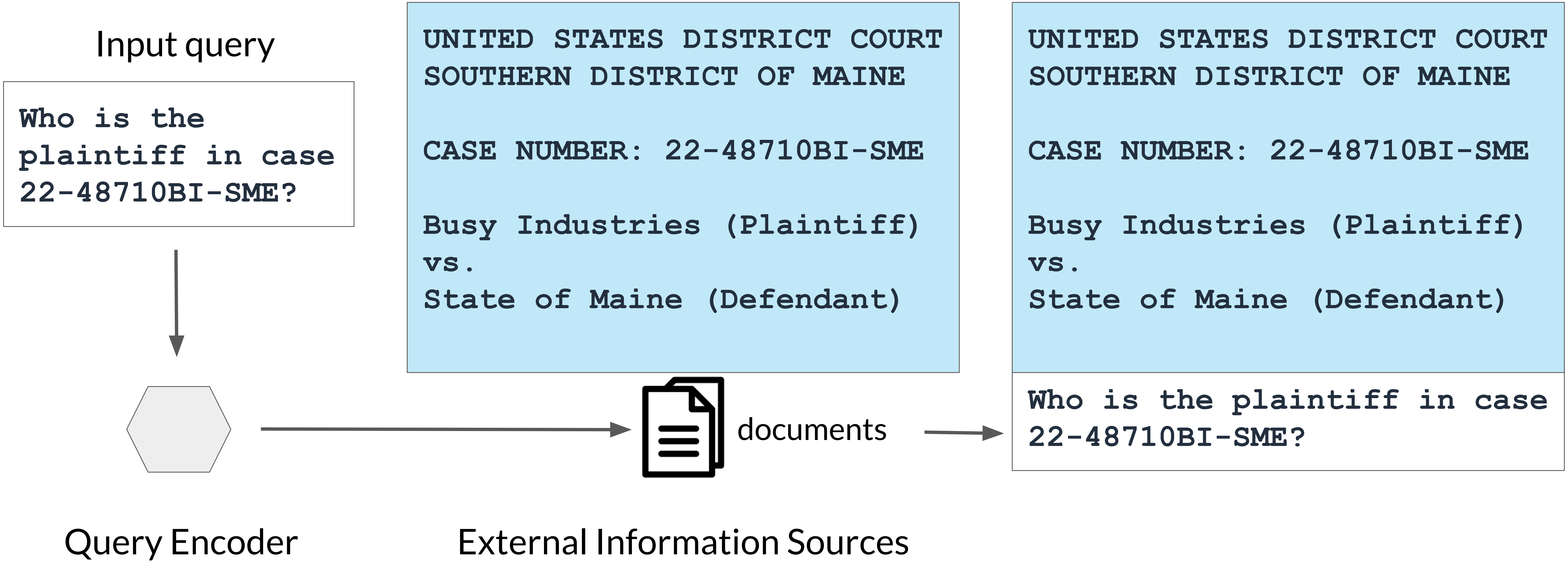


Retrieval Augmented Generation (RAG)



Lewis et al. 2020 “Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks”

Example: Searching legal documents



Who is the plaintiff in case 22-48710BI-SME?

UNITED STATES DISTRICT COURT
SOUTHERN DISTRICT OF MAINE

CASE NUMBER: 22-48710BI-SME

Busy Industries (Plaintiff)
vs.
State of Maine (Defendant)

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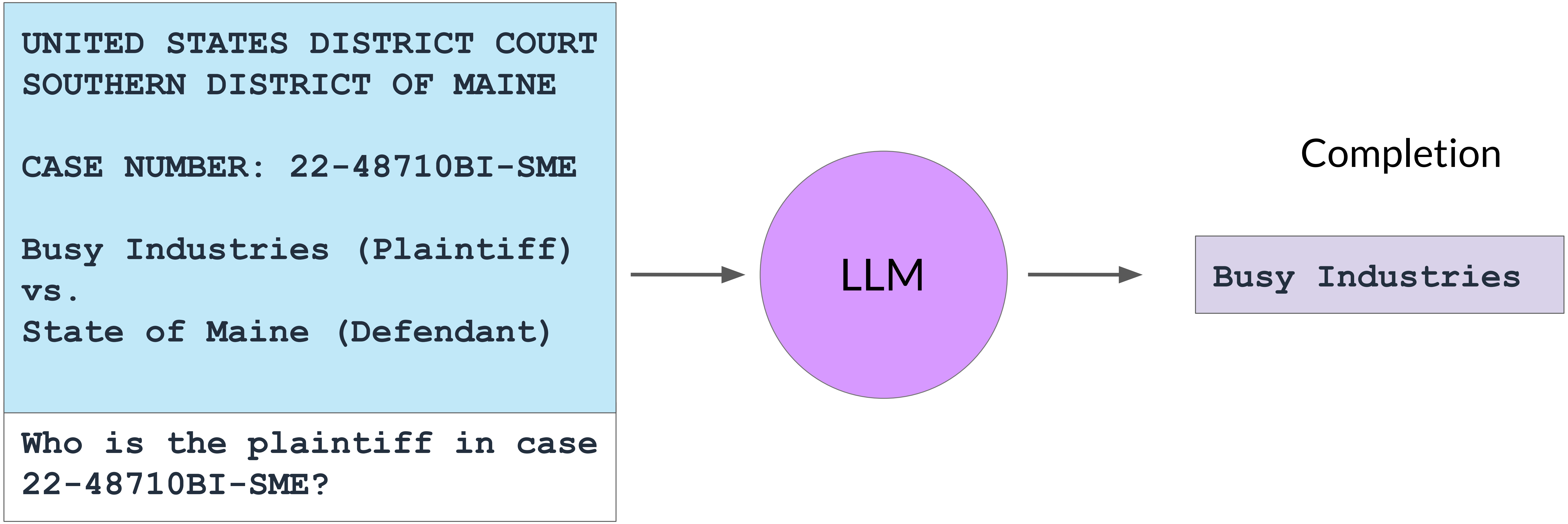

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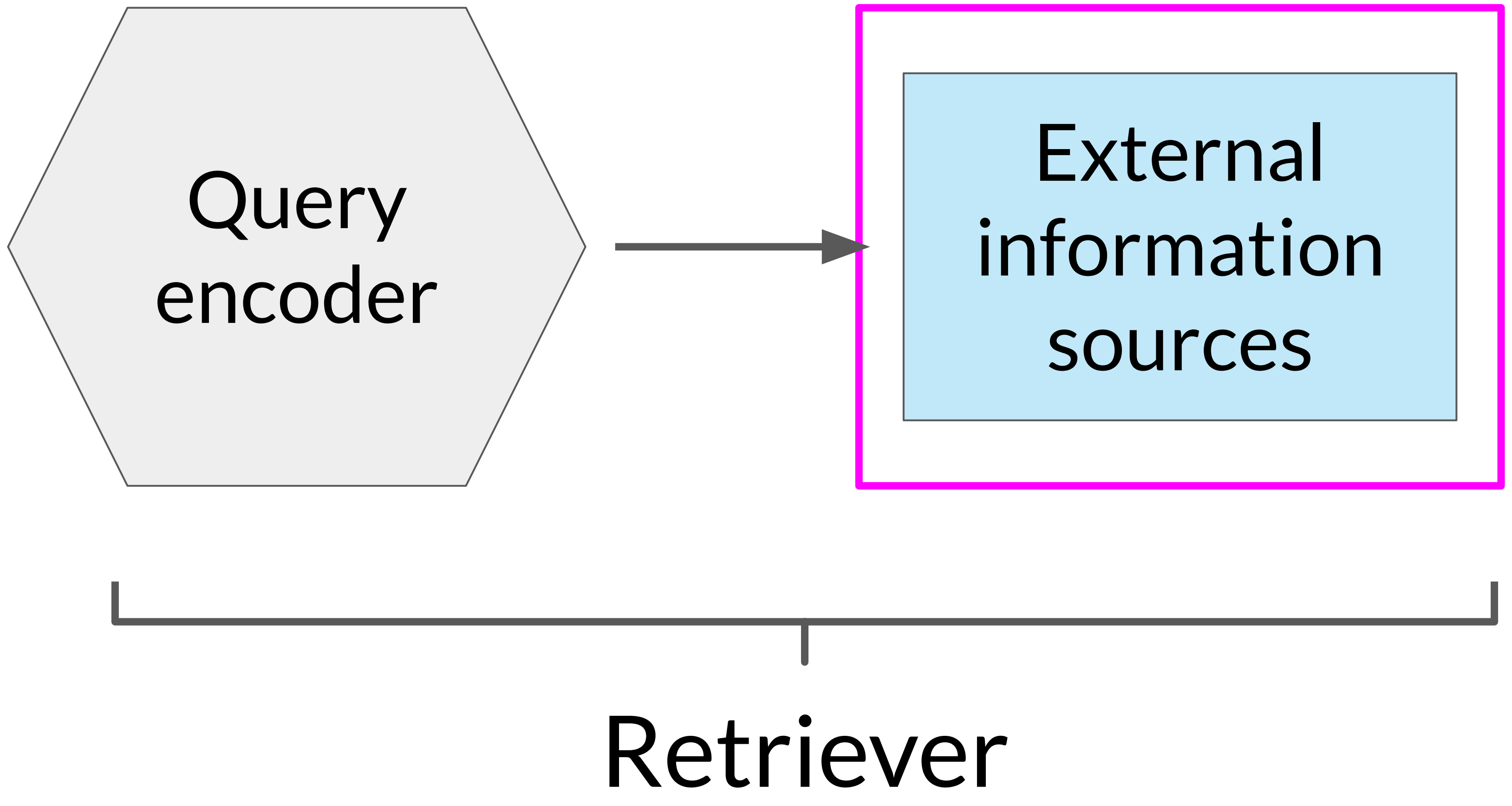
Who is the plaintiff in case 22-48710BI-SME?

RAG integrates with many types of data sources



External Information Sources

- Documents
- Wikis
- Expert Systems
- Web pages
- Databases
- Vector Store

Data preparation for vector store for RAG

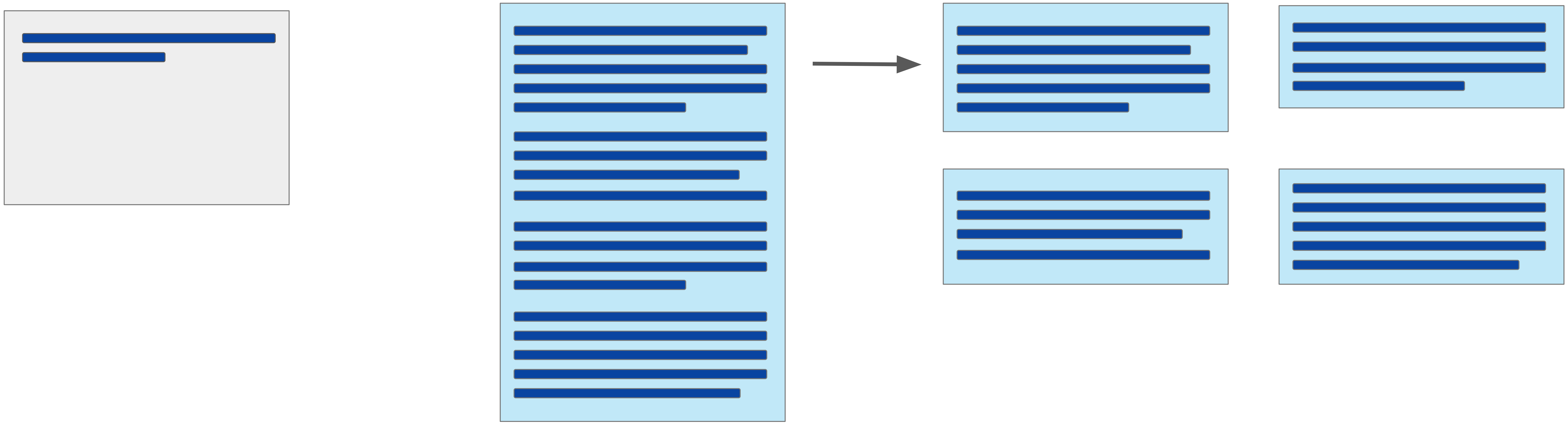
Two considerations for using external data in RAG:

1. Data must fit inside context window

Prompt context limit few 1000 tokens

Single document too large to fit in window

Split long sources into short chunks

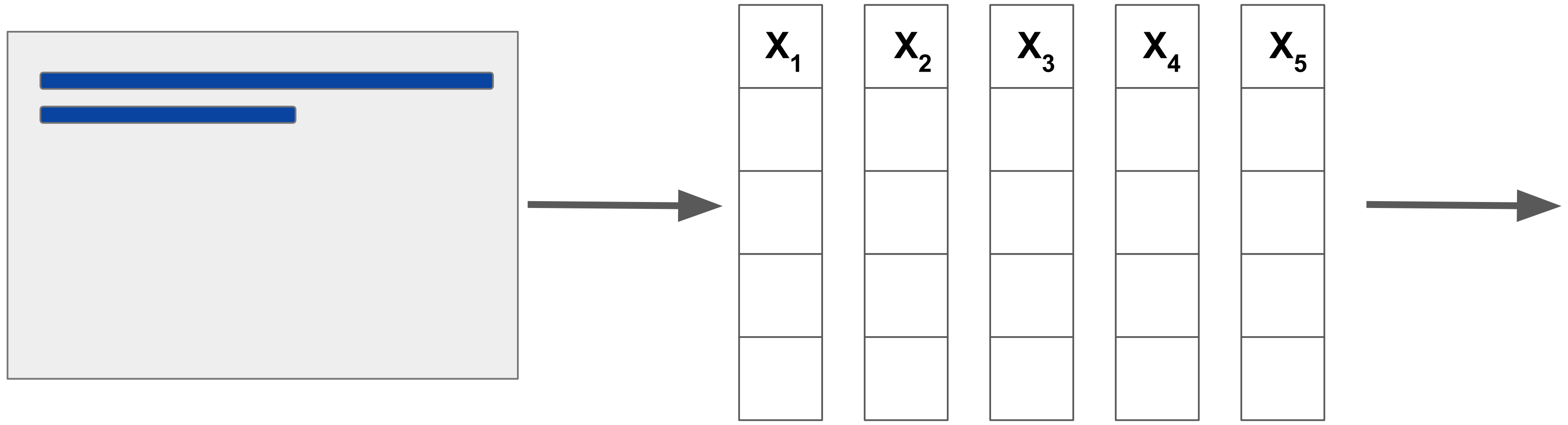


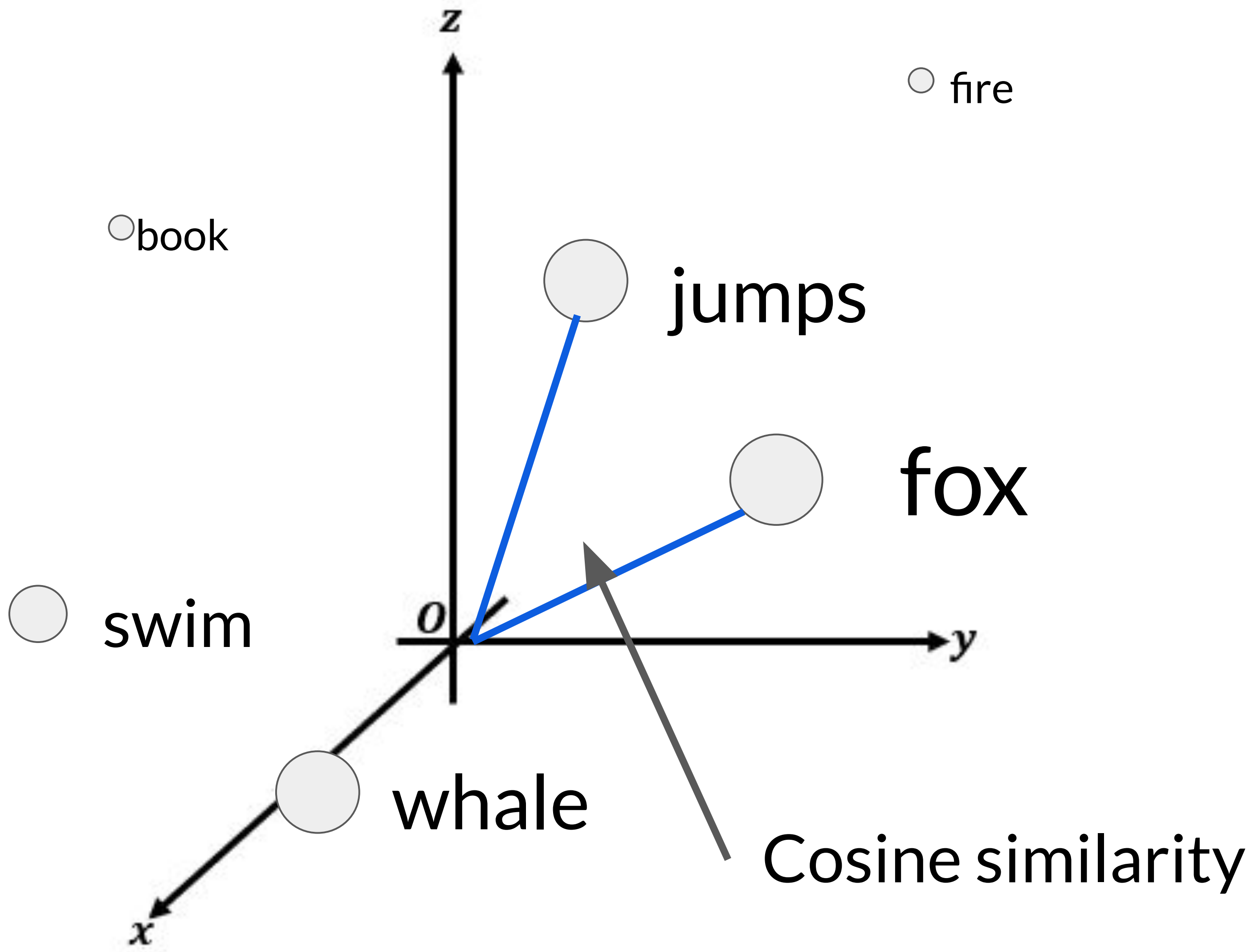
Data preparation for RAG

Two considerations for using external data in RAG:

1. Data must fit inside context window
2. Data must be in format that allows its relevance to be assessed at inference time: **Embedding vectors**

Prompt text converted to embedding vectors



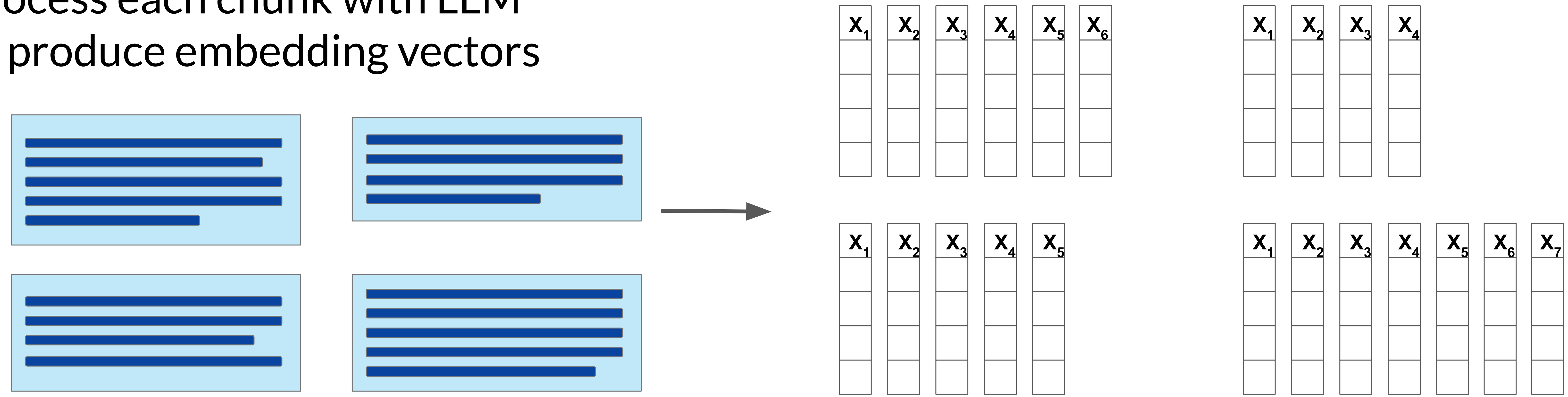


Data preparation for RAG

Two considerations for using external data in RAG:

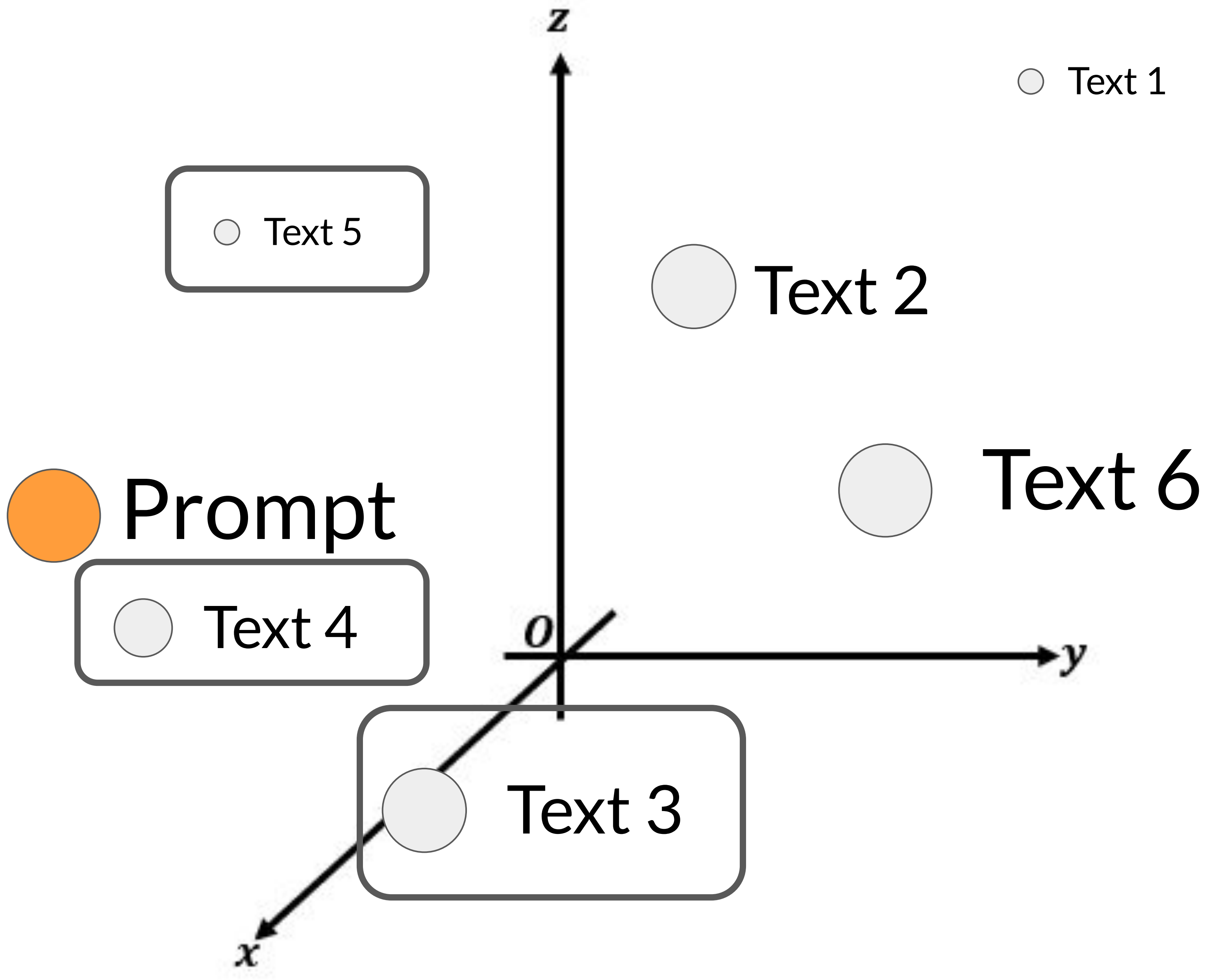
1. Data must fit inside context window
2. Data must be in format that allows its relevance to be assessed at inference time: **Embedding vectors**

Process each chunk with LLM to produce embedding vectors



x_1 x_2 x_3 x_4 x_5 x_6
x_1 x_2 x_3 x_4
x_1 x_2 x_3 x_4 x_5
x_1 x_2 x_3 x_4 x_5 x_6 x_7

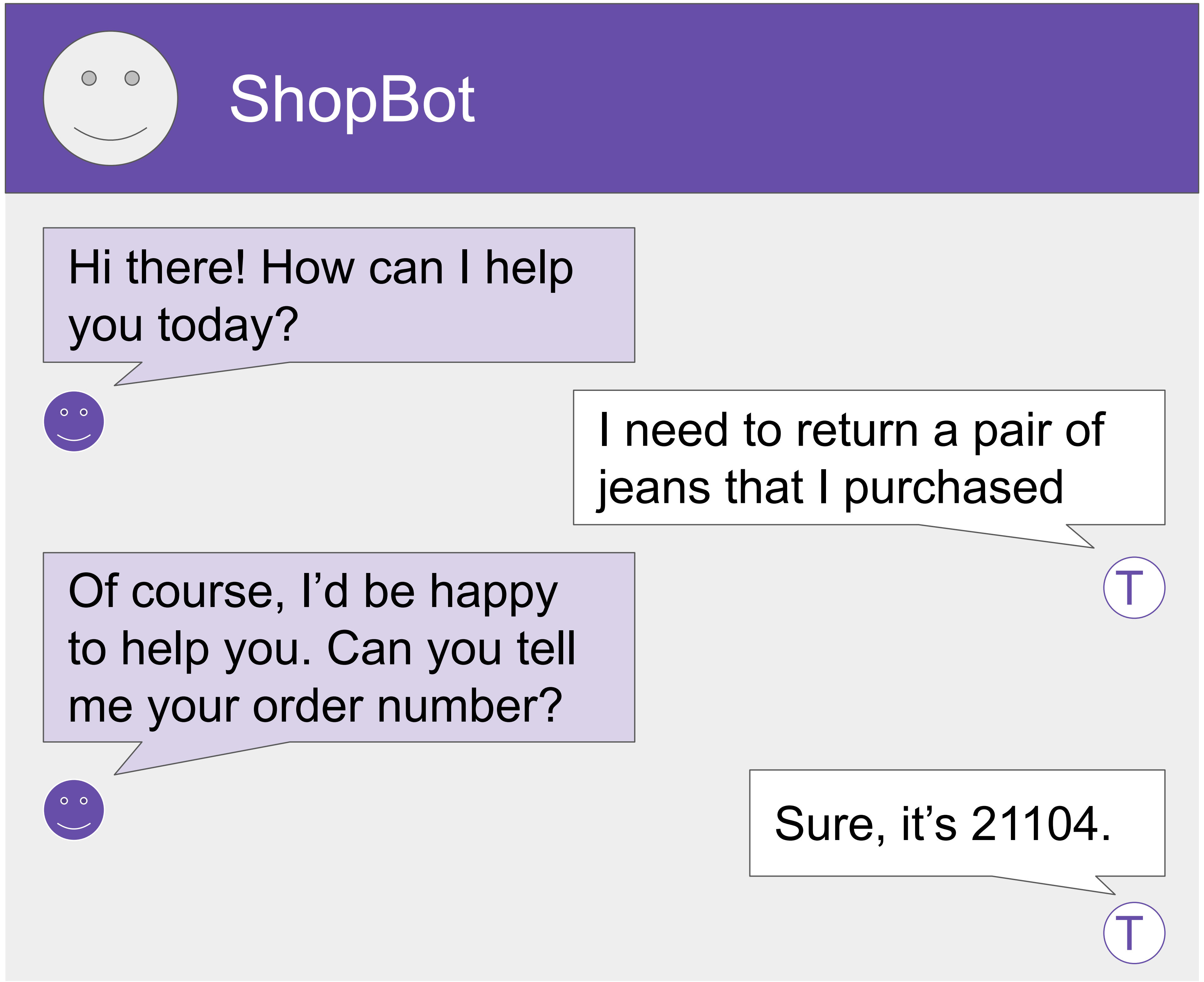
Vector database search



- Each text in vector store is identified by a key
- Enables a **citation** to be included in completion

Enabling interactions with external applications

Having an LLM initiate a clothing return



Hi there! How can I help you today?

I need to return a pair of jeans that I purchased

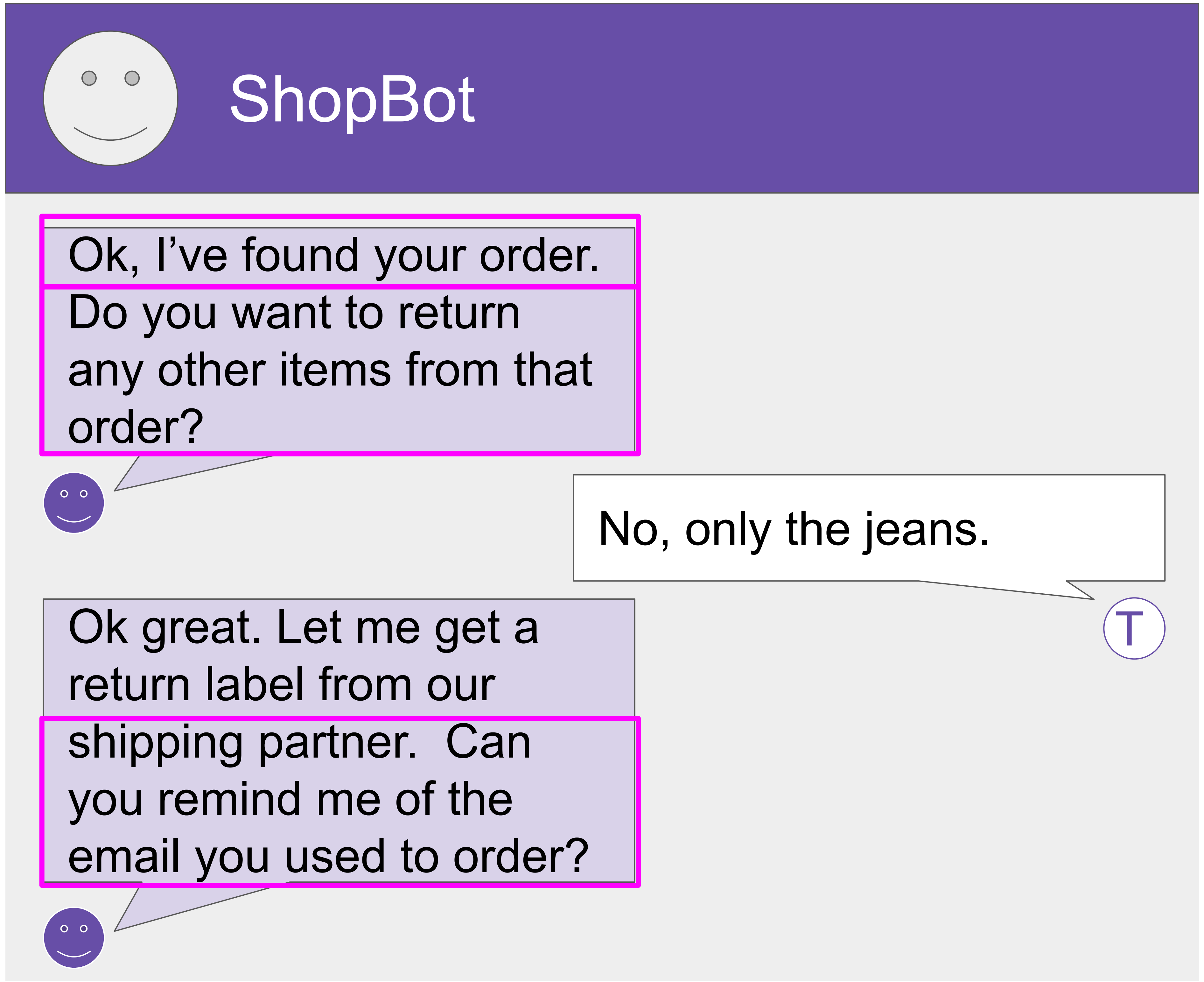
Of course, I'd be happy to help you. Can you tell me your order number?

Sure, it's 21104.

Having an LLM initiate a clothing return

Lookup with RAG

API call



ShopBot

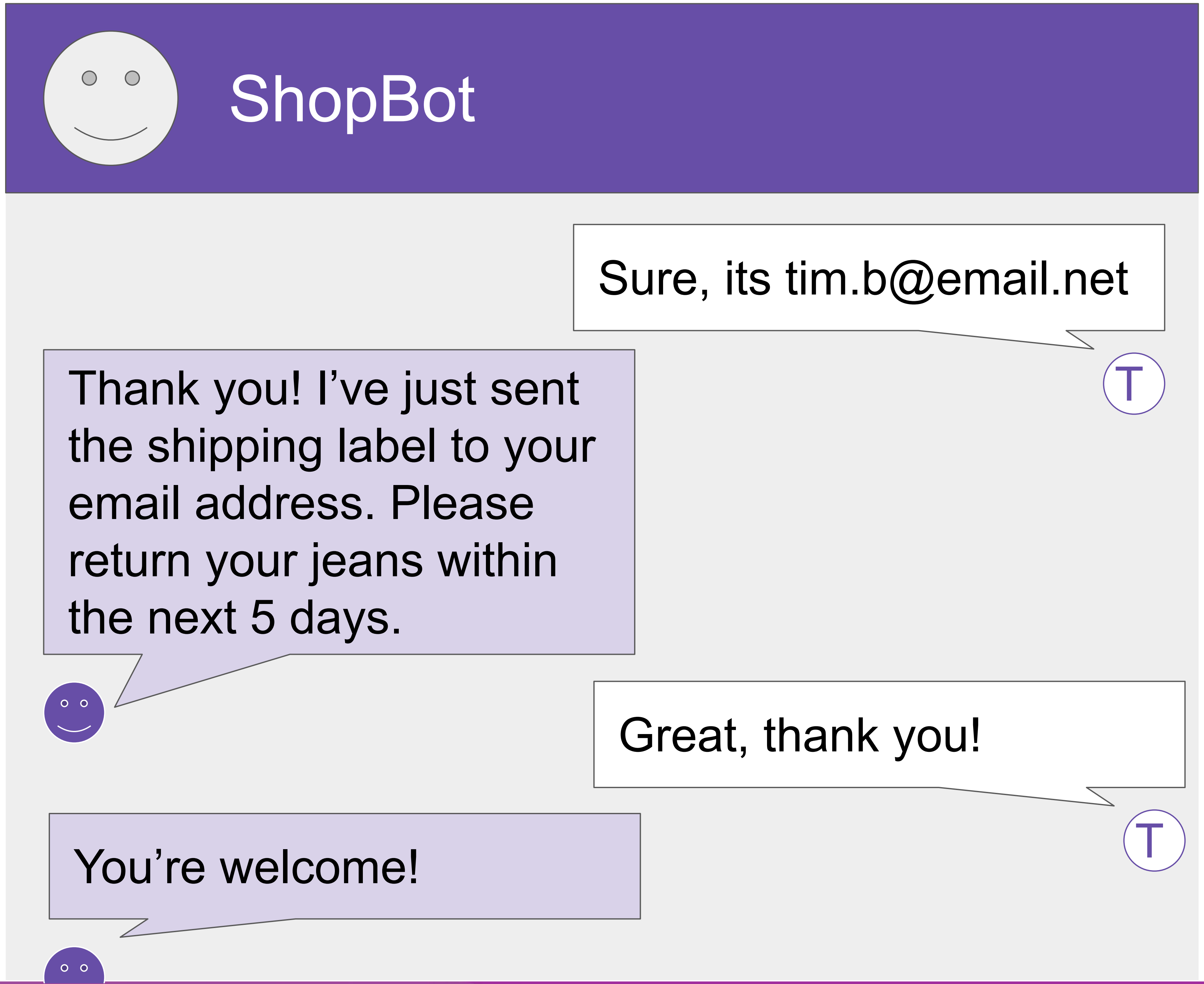
Ok, I've found your order. Do you want to return any other items from that order?

No, only the jeans.

Ok great. Let me get a return label from our shipping partner. Can you remind me of the email you used to order?

Having an LLM initiate a clothing return

API call to the shipper



ShopBot

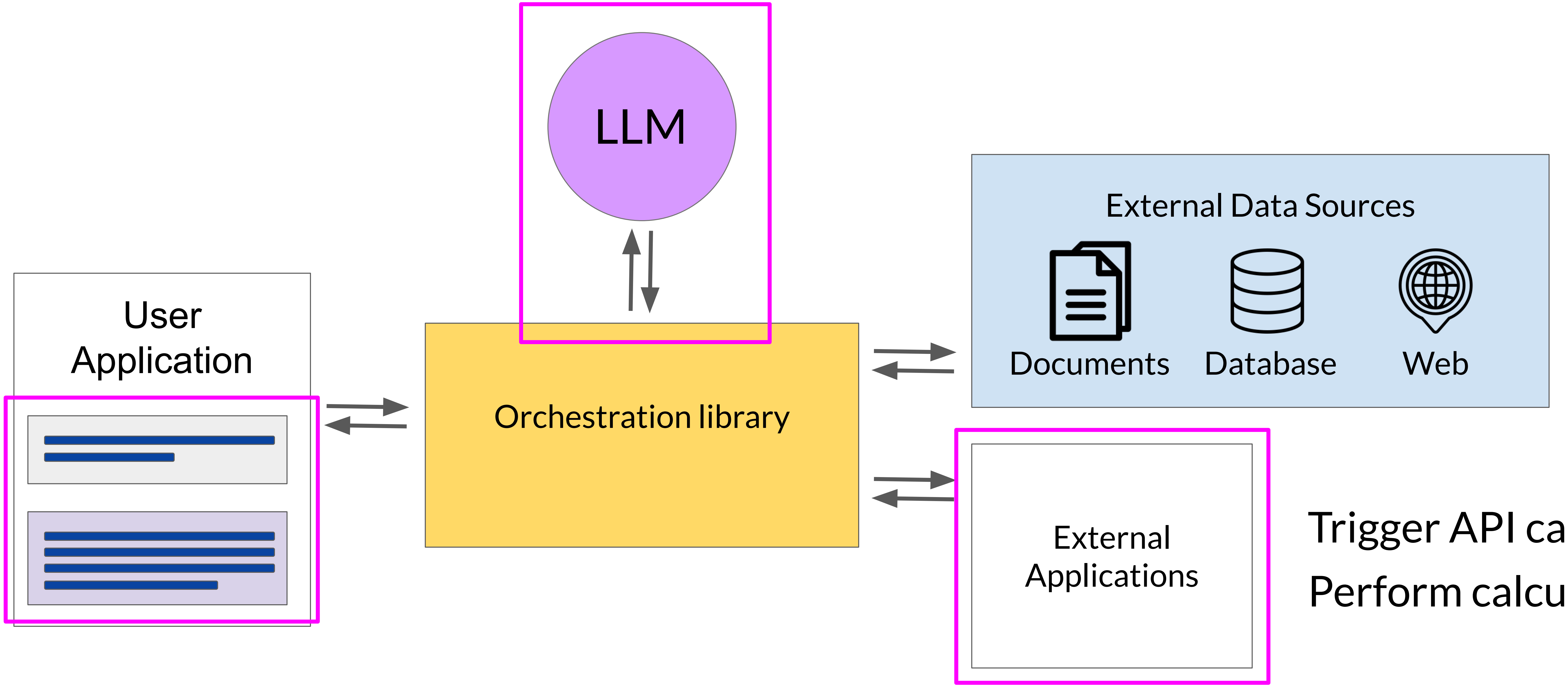
Sure, its tim.b@email.net

Thank you! I’ve just sent the shipping label to your email address. Please return your jeans within the next 5 days.

Great, thank you!

You’re welcome!

LLM-powered applications



Trigger API call

Perform calculations

Requirements for using LLMs to power applications

Plan actions

Steps to process return:

Step 1: Check order ID

Step 2: Request label

Step 3: Verify user email

Step 4: Email user label

Format outputs

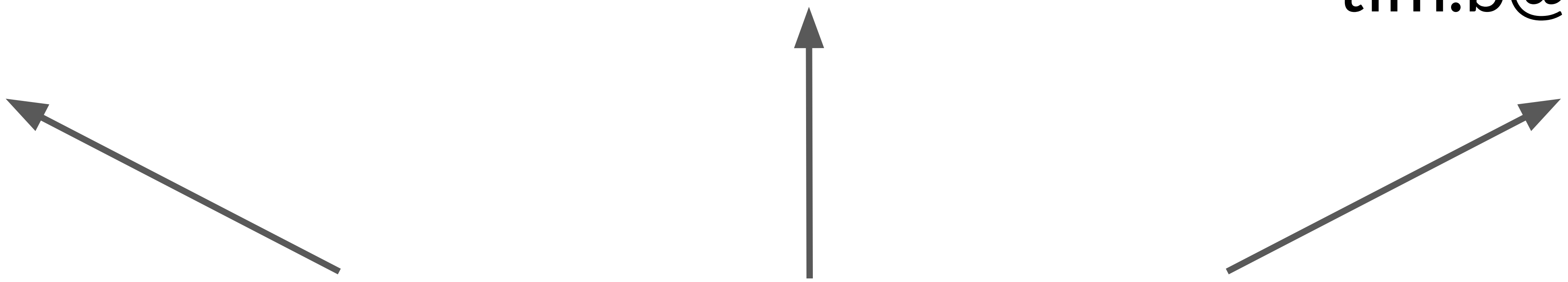
SQL Query:

SELECT COUNT(*)
FROM orders
WHERE order_id = 21104

Validate actions

Collect required user information and make sure it is in the completion

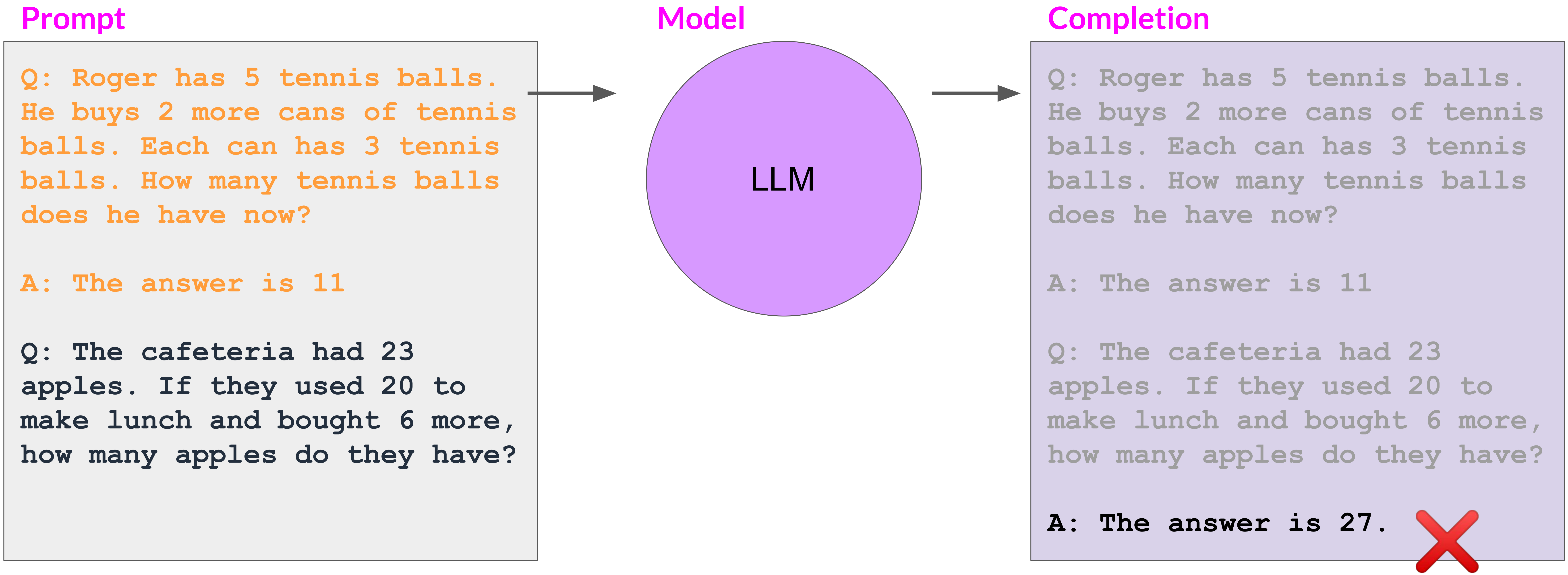
User email:
tim.b@email.net



Prompt structure is important!

Helping LLMs reason and plan with Chain-of-Thought Prompting

LLMs can struggle with complex reasoning problems



Prompt

```
Q: Roger has 5 tennis balls.
He buys 2 more cans of tennis
balls. Each can has 3 tennis
balls. How many tennis balls
does he have now?

A: The answer is 11

Q: The cafeteria had 23
apples. If they used 20 to
make lunch and bought 6 more,
how many apples do they have?
```

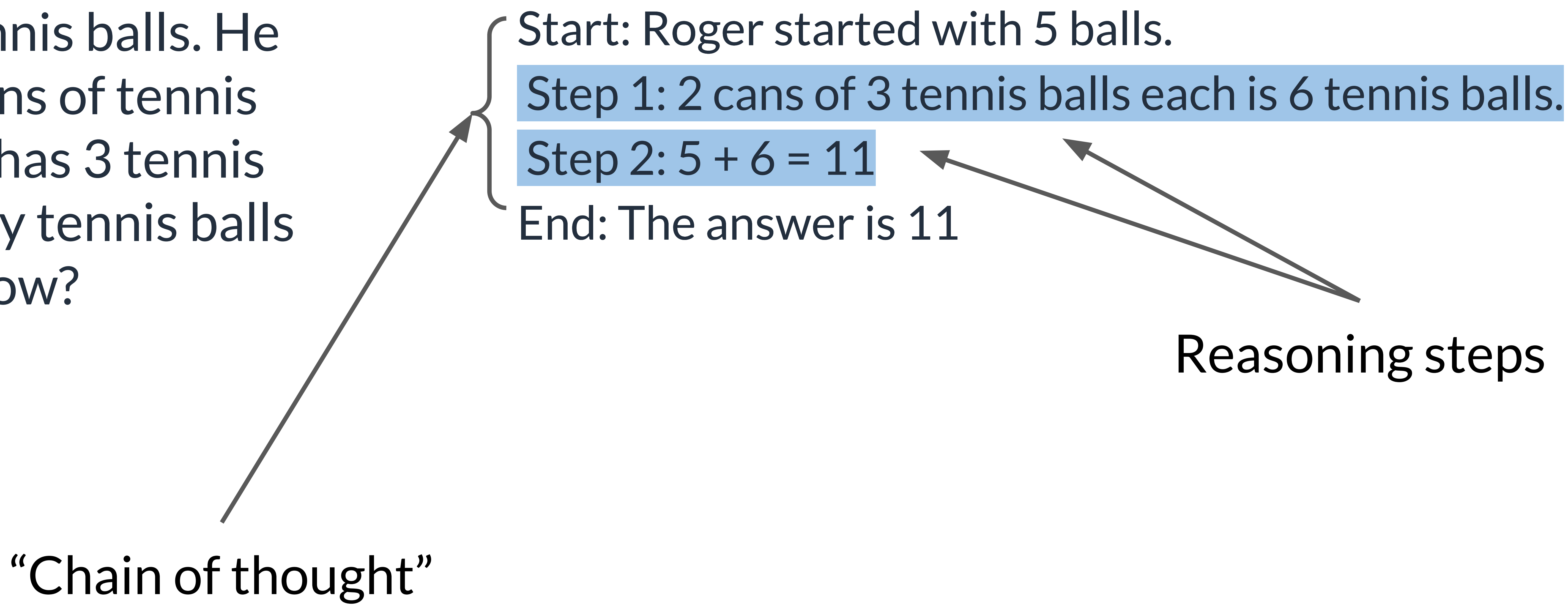
Model

Completion

```
Q: Roger has 5 tennis balls.
He buys 2 more cans of tennis
balls. Each can has 3 tennis
balls. How many tennis balls
does he have now?

A: The answer is 11

Q: The cafeteria had 23
apples. If they used 20 to
make lunch and bought 6 more,
how many apples do they have?

A: The answer is 27. ❌
```

Humans take a step-by-step approach to solving complex problems

Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?



Start: Roger started with 5 balls.

Step 1: 2 cans of 3 tennis balls each is 6 tennis balls.

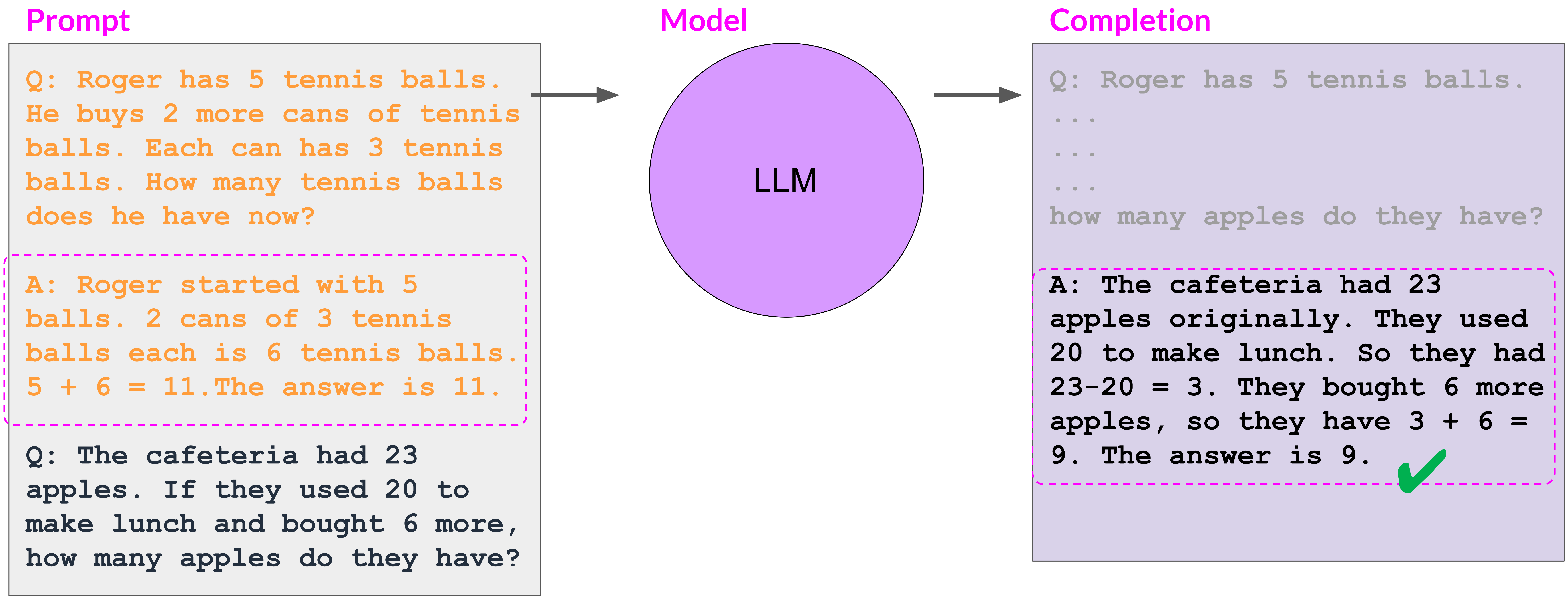
Step 2: 5 + 6 = 11

End: The answer is 11

Reasoning steps

“Chain of thought”

Chain-of-Thought Prompting can help LLMs reason



Prompt

```
Q: Roger has 5 tennis balls.
He buys 2 more cans of tennis
balls. Each can has 3 tennis
balls. How many tennis balls
does he have now?

A: Roger started with 5
balls. 2 cans of 3 tennis
balls each is 6 tennis balls.
5 + 6 = 11.The answer is 11.

Q: The cafeteria had 23
apples. If they used 20 to
make lunch and bought 6 more,
how many apples do they have?
```

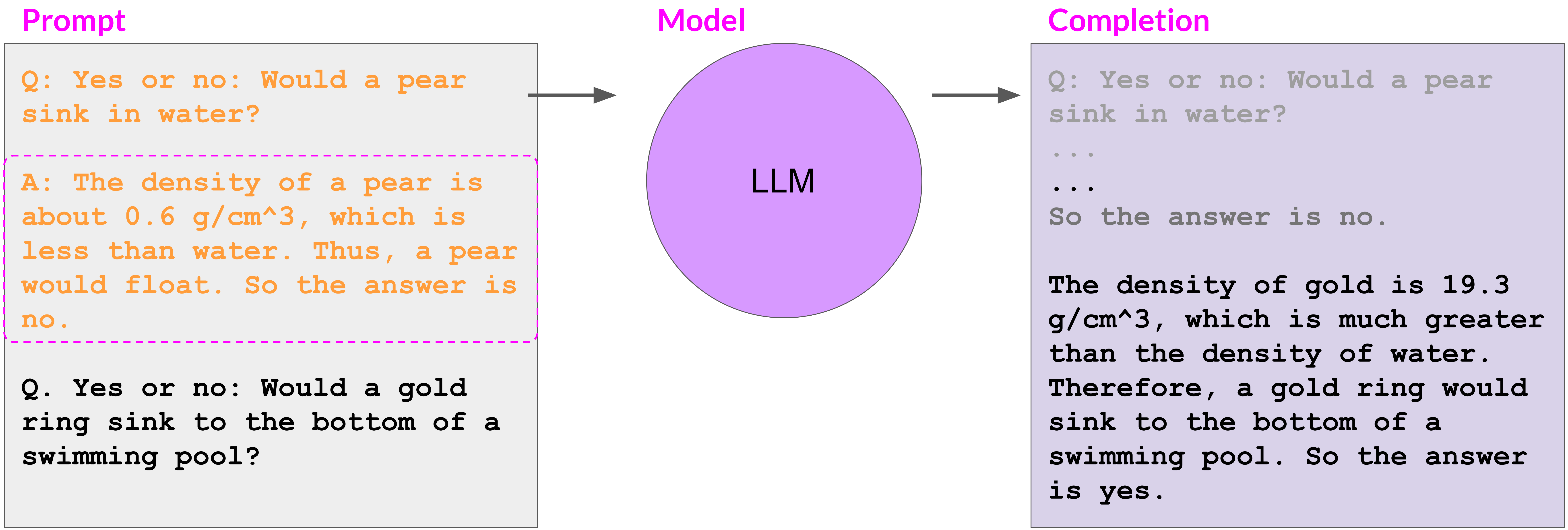
Model

Completion

```
Q: Roger has 5 tennis balls.
...
...
...
how many apples do they have?

A: The cafeteria had 23
apples originally. They used
20 to make lunch. So they had
23-20 = 3. They bought 6 more
apples, so they have 3 + 6 =
9. The answer is 9. ✔
```

Source: Wei et al. 2022, “Chain-of-Thought Prompting Elicits Reasoning in Large Language Models”

Chain-of-Thought Prompting can help LLMs reason



Prompt

Q: Yes or no: Would a pear sink in water?

A: The density of a pear is about 0.6 g/cm^3, which is less than water. Thus, a pear would float. So the answer is no.

Q. Yes or no: Would a gold ring sink to the bottom of a swimming pool?

Model

Completion

Q: Yes or no: Would a pear sink in water?

...

...

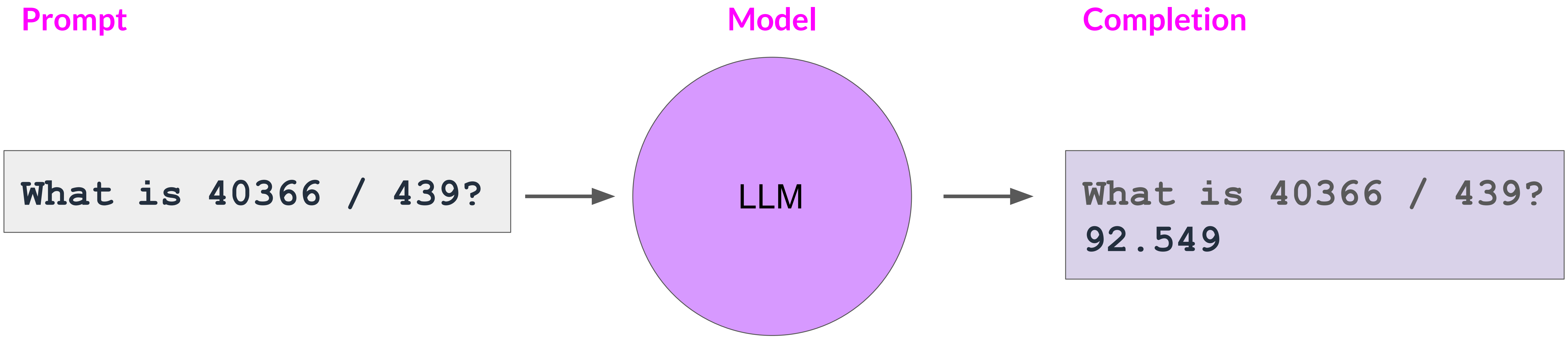
So the answer is no.

The density of gold is 19.3 g/cm^3, which is much greater than the density of water. Therefore, a gold ring would sink to the bottom of a swimming pool. So the answer is yes.

Source: Wei et al. 2022, “Chain-of-Thought Prompting Elicits Reasoning in Large Language Models”

Program-aided Language Models

LLMs can struggle with mathematics



Prompt

Model

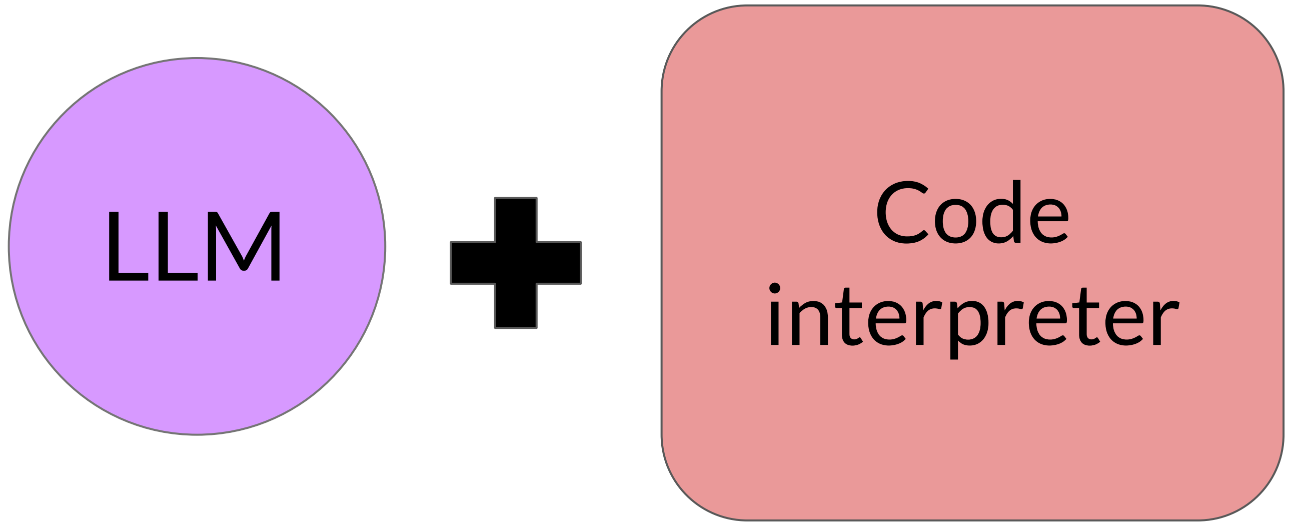
Completion

```
What is 40366 / 439?
```

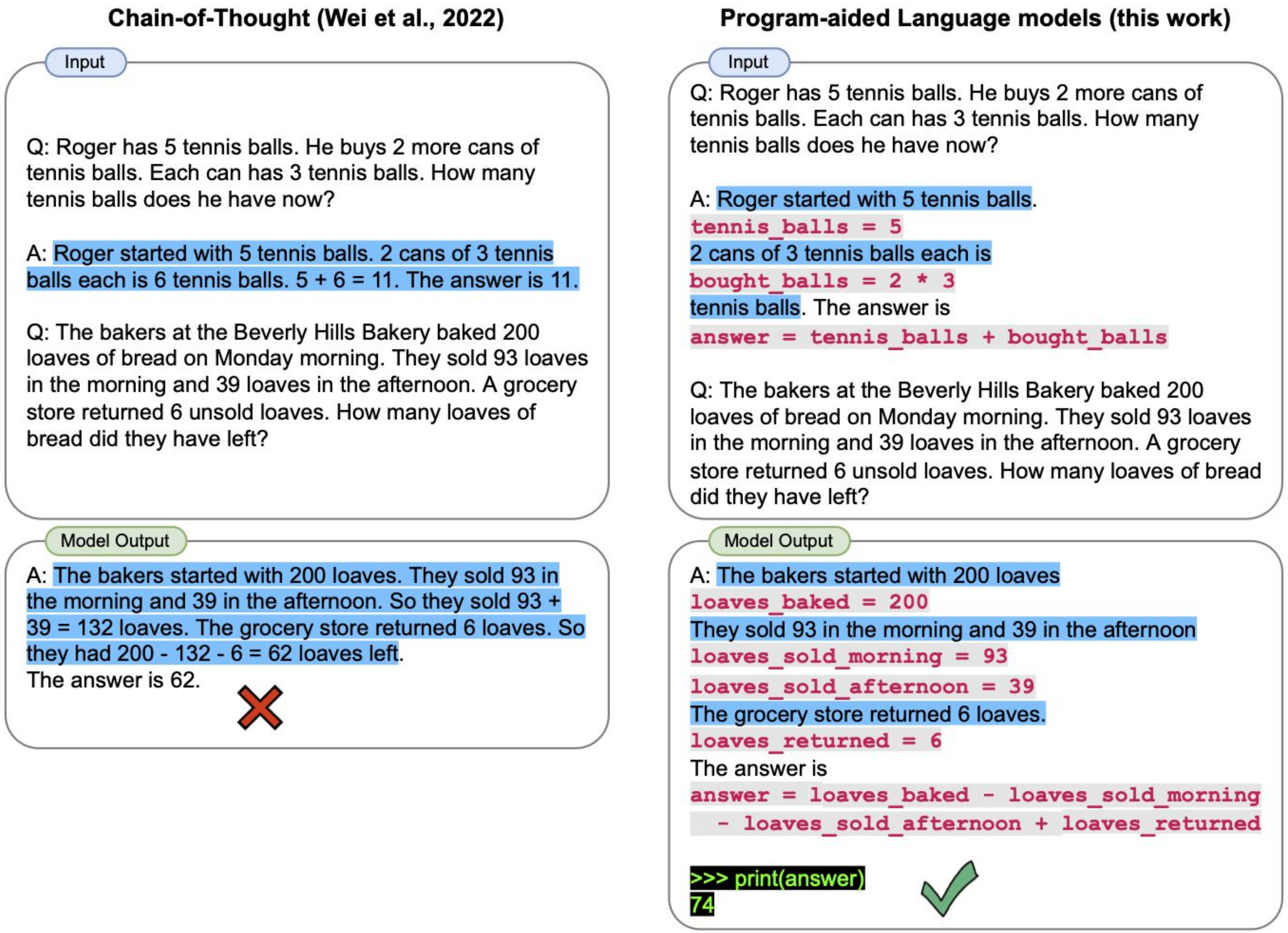
LLM

```
What is 40366 / 439?
92.549
```

Program-aided language (PAL) models



LLM + Code interpreter



Chain-of-Thought (Wei et al., 2022)

Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: Roger started with 5 tennis balls. 2 cans of 3 tennis balls each is 6 tennis balls. 5 + 6 = 11. The answer is 11.

Q: The bakers at the Beverly Hills Bakery baked 200 loaves of bread on Monday morning. They sold 93 loaves in the morning and 39 loaves in the afternoon. A grocery store returned 6 unsold loaves. How many loaves of bread did they have left?

Model Output

A: The bakers started with 200 loaves. They sold 93 in the morning and 39 in the afternoon. So they sold 93 + 39 = 132 loaves. The grocery store returned 6 loaves. So they had 200 - 132 - 6 = 62 loaves left.
The answer is 62. ✗

Program-aided Language models (this work)

Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: Roger started with 5 tennis balls.
```
tennis_balls = 5
```
2 cans of 3 tennis balls each is
```
bought_balls = 2 * 3
```
tennis balls. The answer is
```
answer = tennis_balls + bought_balls
```

Q: The bakers at the Beverly Hills Bakery baked 200 loaves of bread on Monday morning. They sold 93 loaves in the morning and 39 loaves in the afternoon. A grocery store returned 6 unsold loaves. How many loaves of bread did they have left?

Model Output

A: The bakers started with 200 loaves
```
loaves_baked = 200
```
They sold 93 in the morning and 39 in the afternoon
```
loaves_sold_morning = 93
loaves_sold_afternoon = 39
```
The grocery store returned 6 loaves.
```
loaves_returned = 6
```
The answer is
```
answer = loaves_baked - loaves_sold_morning
  - loaves_sold_afternoon + loaves_returned
```

```
>>> print(answer)
74
```
✓

Source: Gao et al. 2022, "PAL: Program-aided Language Models"

PAL example

Prompt with one-shot example

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

Answer:

```
# Roger started with 5 tennis balls
tennis_balls = 5
# 2 cans of tennis balls each is
bought_balls = 2 * 3
# tennis balls. The answer is
answer = tennis_balls + bought_balls
```

Q: The bakers at the Beverly Hills Bakery baked 200 loaves of bread on Monday morning. They sold 93 loaves in the morning and 39 loaves in the afternoon. A grocery store returned 6 unsold loaves. How many loaves did they have left?

PAL example

Prompt with one-shot example

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

Answer:

```
# Roger started with 5 tennis balls
tennis_balls = 5
# 2 cans of tennis balls each is
bought_balls = 2 * 3
# tennis balls. The answer is
answer = tennis_balls + bought_balls
```

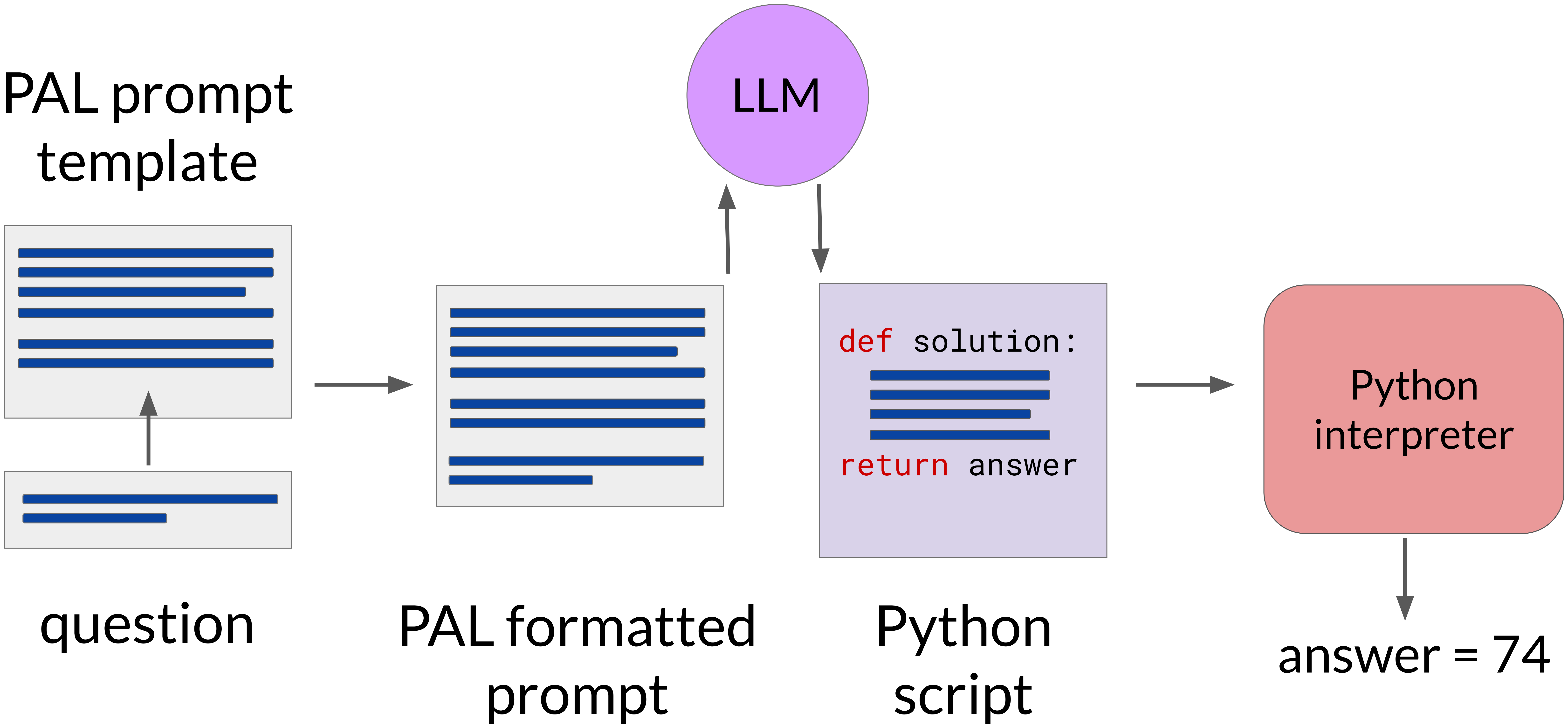
Q: The bakers at the Beverly Hills Bakery baked 200 loaves of bread on Monday morning. They sold 93 loaves in the morning and 39 loaves in the afternoon. A grocery store returned 6 unsold loaves. How many loaves did they have left?

Completion, CoT reasoning (blue) , and PAL execution (pink)

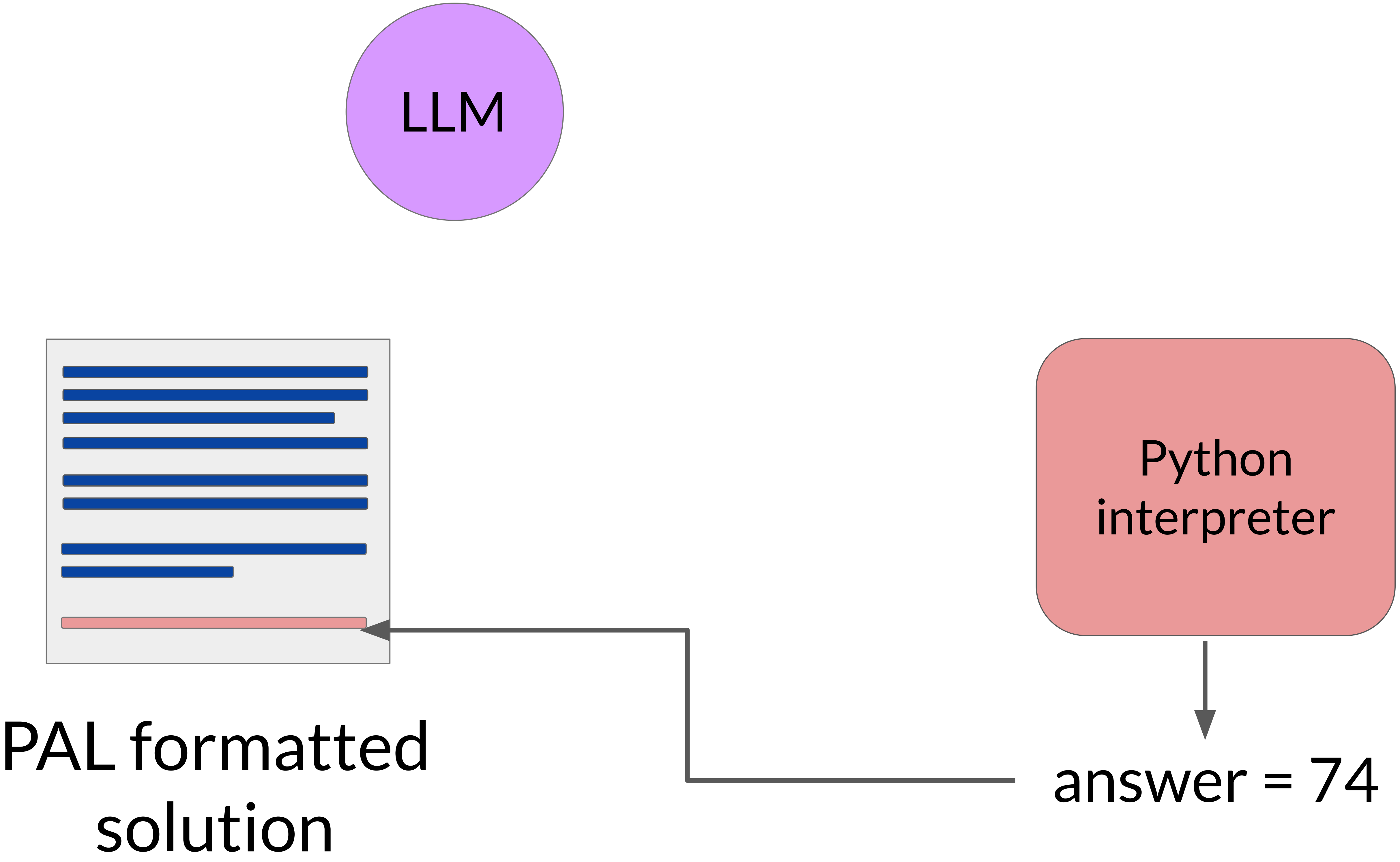
Answer:

```
# The bakers started with 200 loaves
loaves_baked = 200
# They sold 93 in the morning and 39 in the
afternoon
loaves_sold_morning = 93
loaves_sold_afternoon = 39
# The grocery store returned 6 loaves.
loaves_returned = 6
# The answer is
answer = loaves_baked
  - loaves_sold_morning
  - loaves_sold_afternoon
  + loaves_returned
```

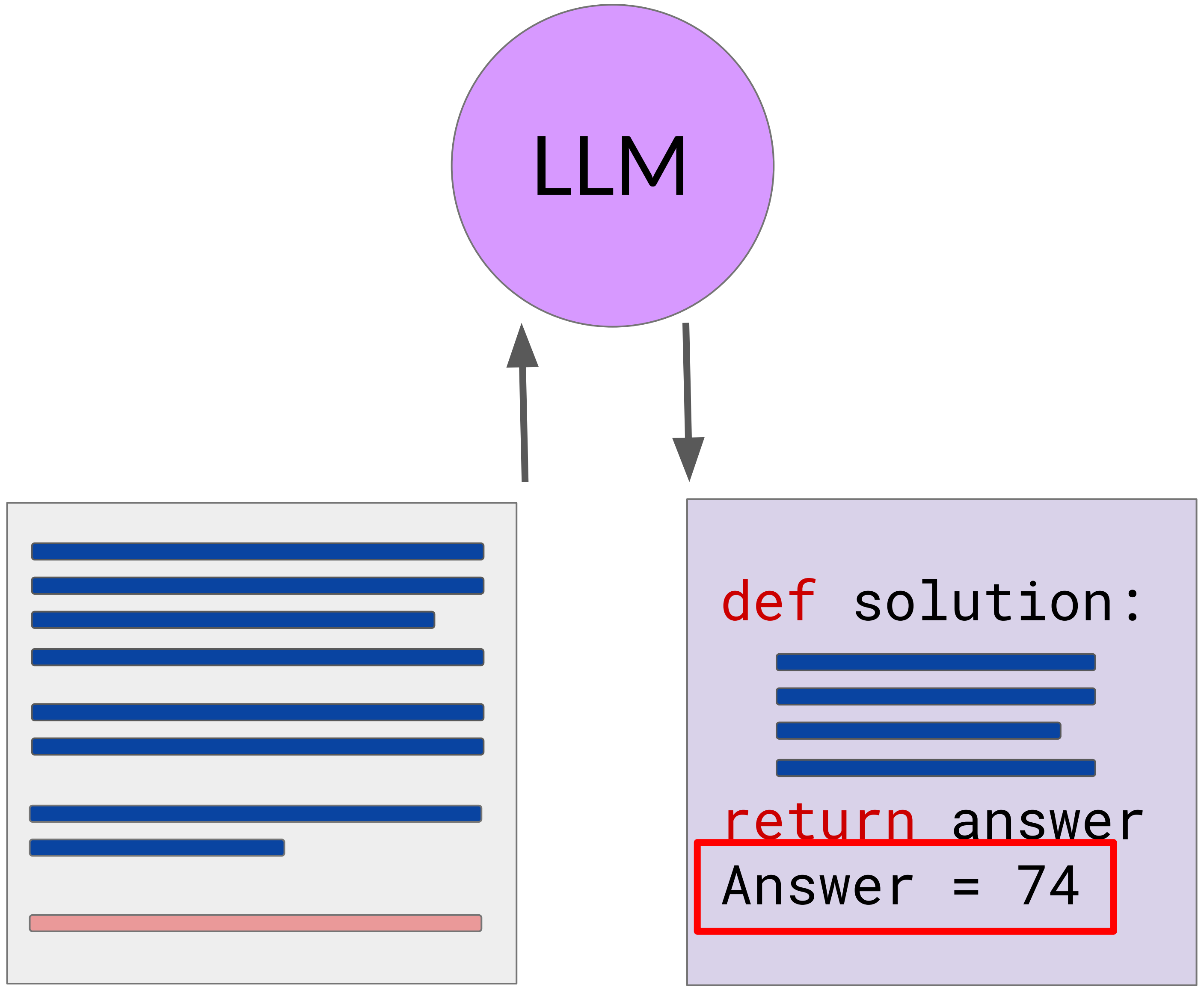
Program-aided language (PAL) models



Program-aided language (PAL) models



Program-aided language (PAL) models

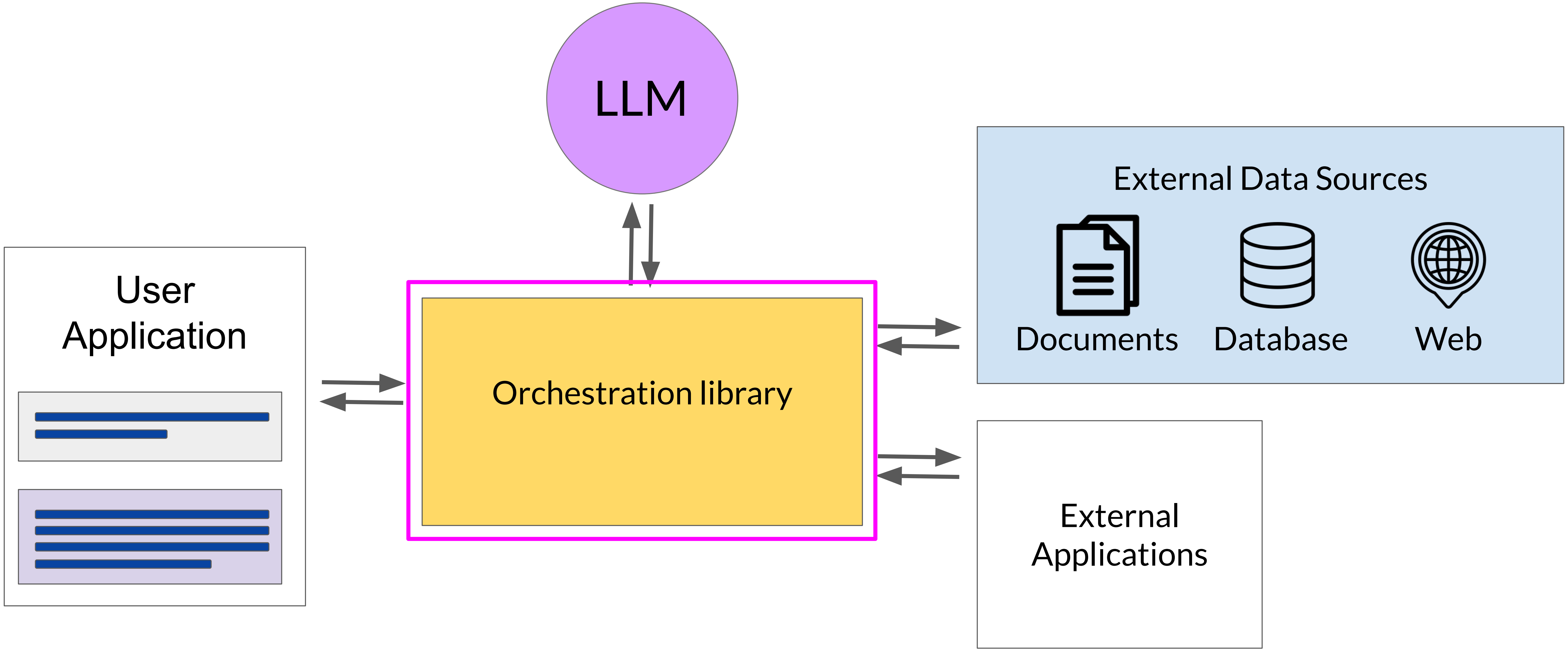


```
def solution:

return answer
Answer = 74
```

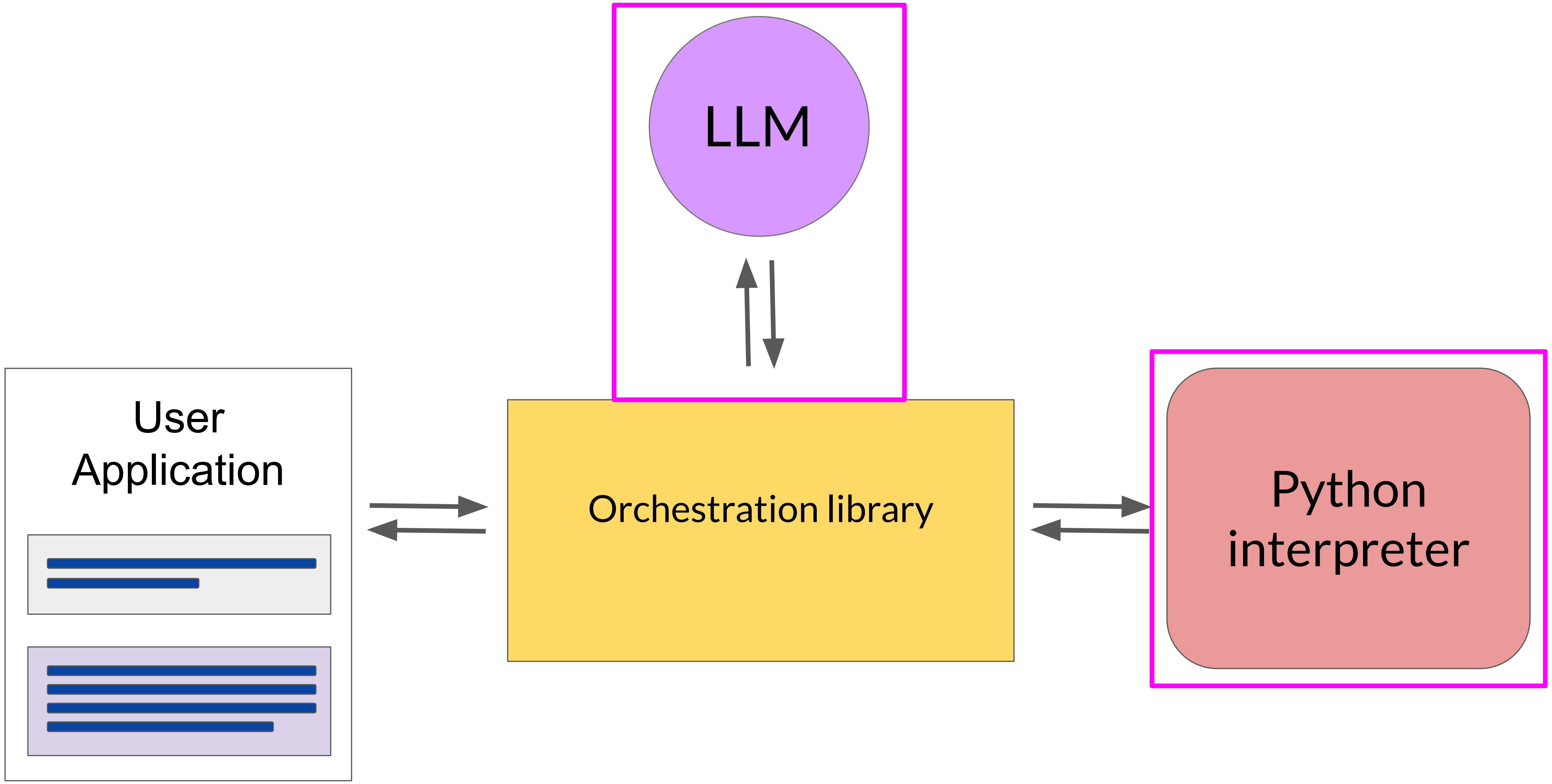
Completion with correct answer

PAL formatted solution

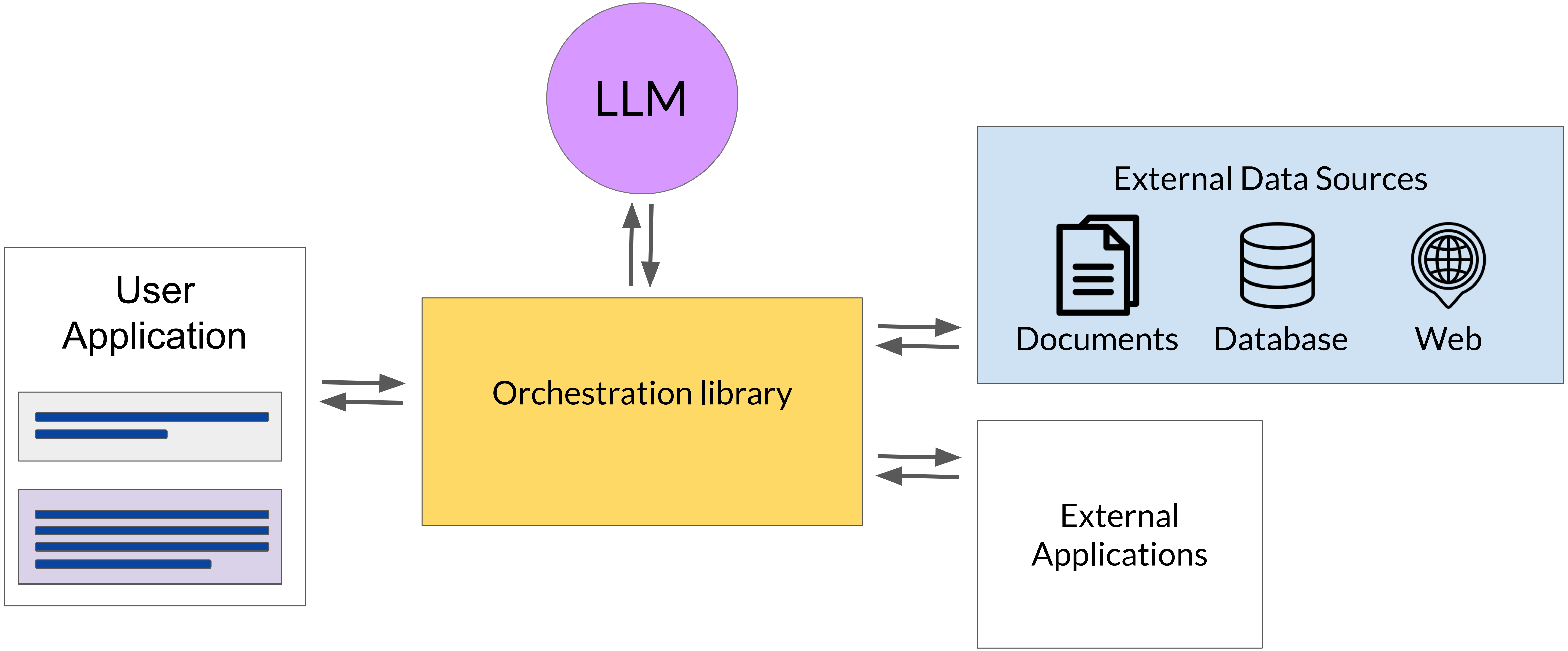
LLM-powered applications



PAL architecture

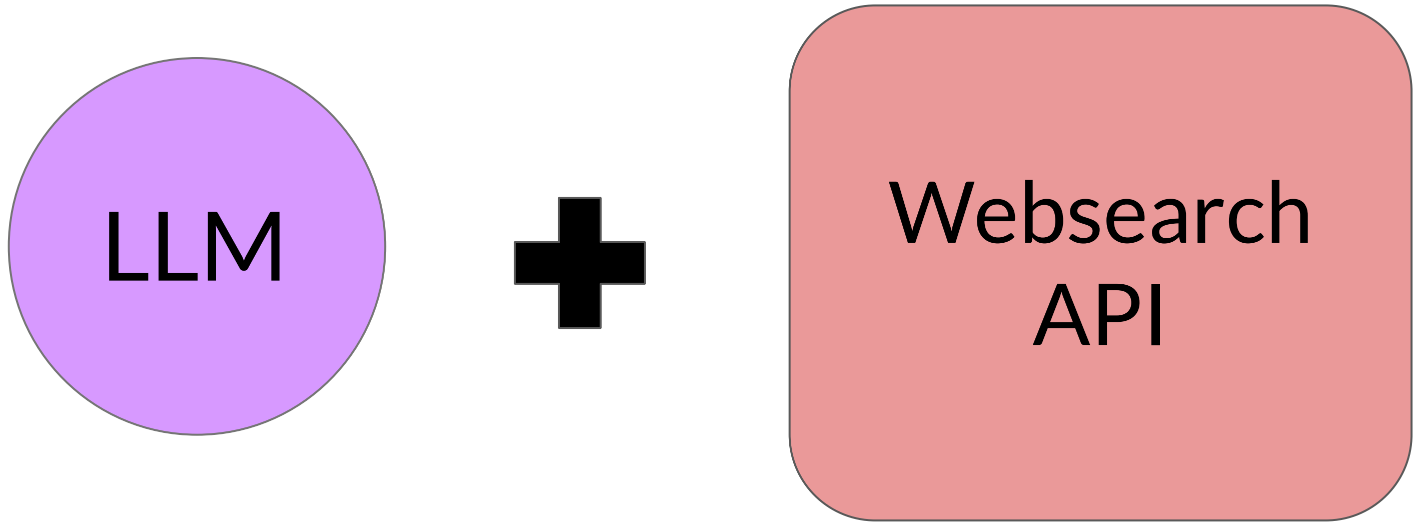


LLM-powered applications

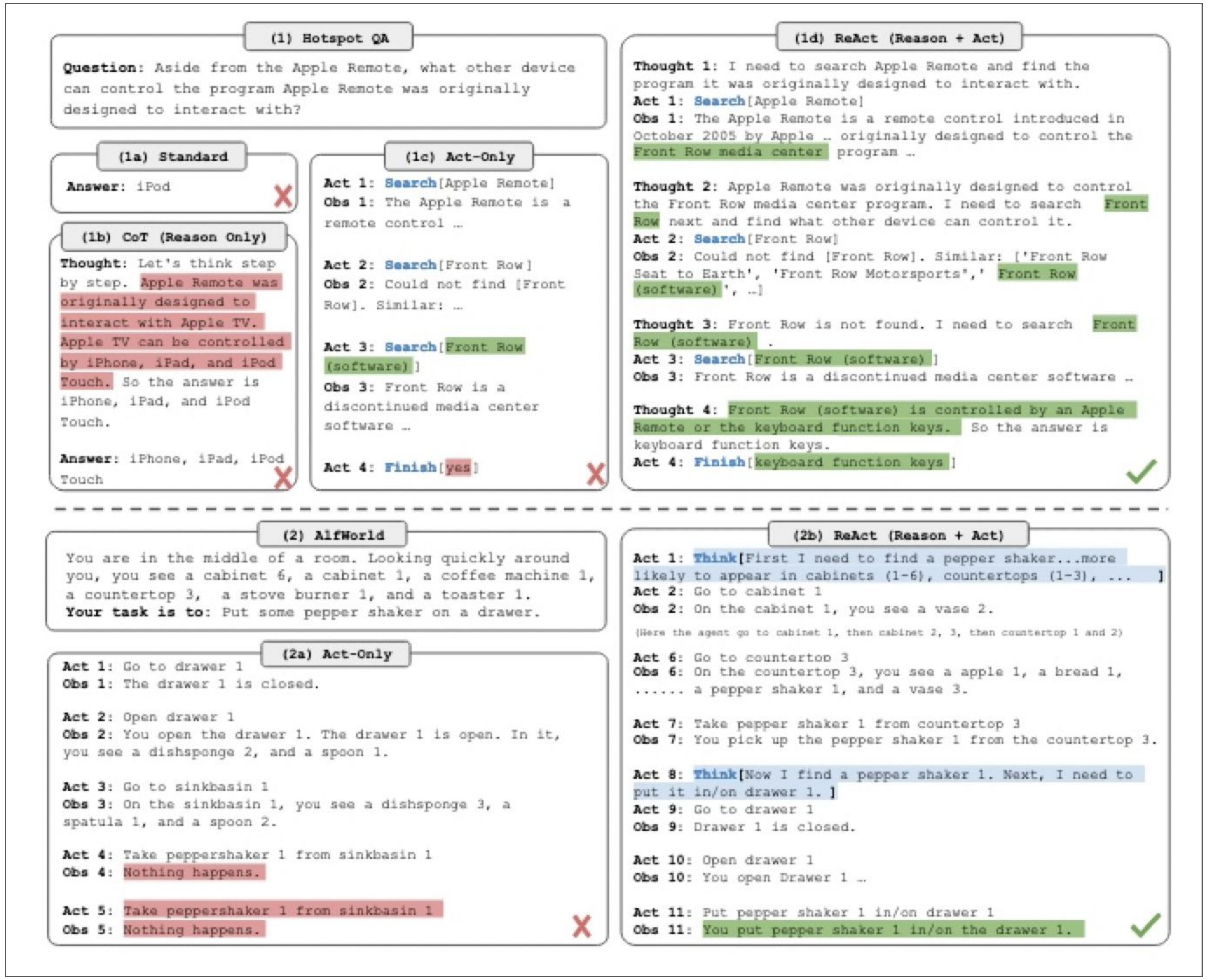


ReAct: Combining reasoning and action in LLMs

ReAct: Synergizing Reasoning and Action in LLMs



HotPot QA: multi-step question answering
Fever: Fact verification



(1) Hotspot QA

Question: Aside from the Apple Remote, what other device can control the program Apple Remote was originally designed to interact with?

(1a) Standard

Answer: iPod ✗

(1b) CoT (Reason Only)

Thought: Let's think step by step. Apple Remote was originally designed to interact with Apple TV. Apple TV can be controlled by iPhone, iPad, and iPod Touch. So the answer is iPhone, iPad, and iPod Touch.

Answer: iPhone, iPad, iPod Touch ✗

(1c) Act-Only

Act 1: Search[Apple Remote]
Obs 1: The Apple Remote is a remote control …

Act 2: Search[Front Row]
Obs 2: Could not find [Front Row]. Similar: …

Act 3: Search[Front Row (software)]
Obs 3: Front Row is a discontinued media center software …

Act 4: Finish[yes] ✗

(1d) ReAct (Reason + Act)

Thought 1: I need to search Apple Remote and find the program it was originally designed to interact with.
Act 1: Search[Apple Remote]
Obs 1: The Apple Remote is a remote control introduced in October 2005 by Apple … originally designed to control the Front Row media center program …

Thought 2: Apple Remote was originally designed to control the Front Row media center program. I need to search Front Row next and find what other device can control it.
Act 2: Search[Front Row]
Obs 2: Could not find [Front Row]. Similar: ['Front Row Seat to Earth', 'Front Row Motorsports',' Front Row (software) ', …]

Thought 3: Front Row is not found. I need to search Front Row (software) .
Act 3: Search[Front Row (software)]
Obs 3: Front Row is a discontinued media center software …

Thought 4: Front Row (software) is controlled by an Apple Remote or the keyboard function keys. So the answer is keyboard function keys.
Act 4: Finish[keyboard function keys] ✓

(2) AlfWorld

You are in the middle of a room. Looking quickly around you, you see a cabinet 6, a cabinet 1, a coffee machine 1, a countertop 3, a stove burner 1, and a toaster 1.
Your task is to: Put some pepper shaker on a drawer.

(2a) Act-Only

Act 1: Go to drawer 1
Obs 1: The drawer 1 is closed.

Act 2: Open drawer 1
Obs 2: You open the drawer 1. The drawer 1 is open. In it, you see a dishsponge 2, and a spoon 1.

Act 3: Go to sinkbasin 1
Obs 3: On the sinkbasin 1, you see a dishsponge 3, a spatula 1, and a spoon 2.

Act 4: Take peppershaker 1 from sinkbasin 1
Obs 4: Nothing happens.

Act 5: Take peppershaker 1 from sinkbasin 1
Obs 5: Nothing happens. ✗

(2b) ReAct (Reason + Act)

Act 1: Think[First I need to find a pepper shaker...more likely to appear in cabinets (1-6), countertops (1-3), ...]
Act 2: Go to cabinet 1
Obs 2: On the cabinet 1, you see a vase 2.

(Here the agent go to cabinet 1, then cabinet 2, 3, then countertop 1 and 2)

Act 6: Go to countertop 3
Obs 6: On the countertop 3, you see a apple 1, a bread 1, ... a pepper shaker 1, and a vase 3.

Act 7: Take pepper shaker 1 from countertop 3
Obs 7: You pick up the pepper shaker 1 from the countertop 3.

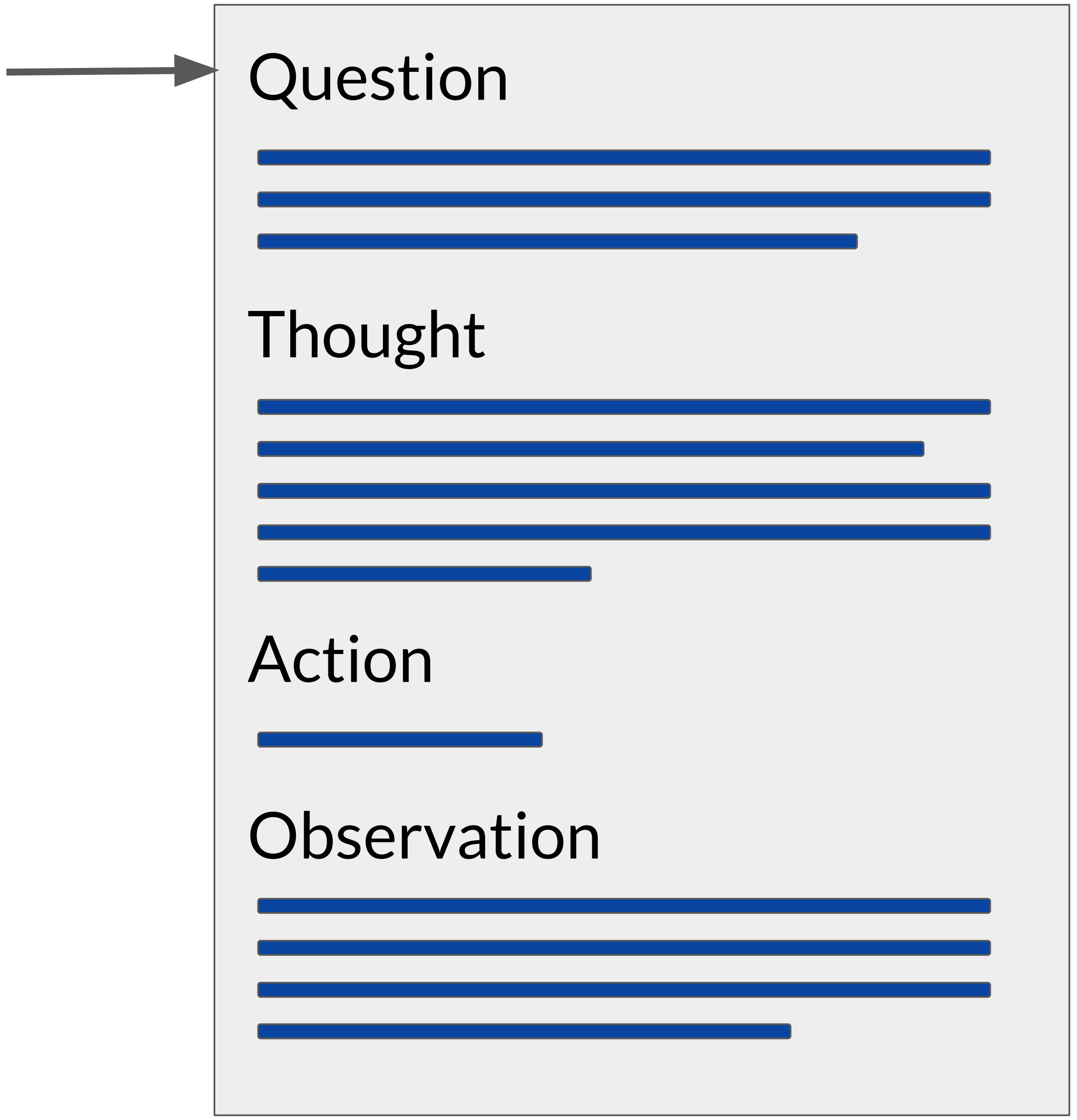
Act 8: Think[Now I find a pepper shaker 1. Next, I need to put it in/on drawer 1.]
Act 9: Go to drawer 1
Obs 9: Drawer 1 is closed.

Act 10: Open drawer 1
Obs 10: You open Drawer 1 …

Act 11: Put pepper shaker 1 in/on drawer 1
Obs 11: You put pepper shaker 1 in/on the drawer 1. ✓

Source: Yao et al. 2022, "ReAct: Synergizing Reasoning and Acting in Language Models"

ReAct: Synergizing Reasoning and Action in LLMs

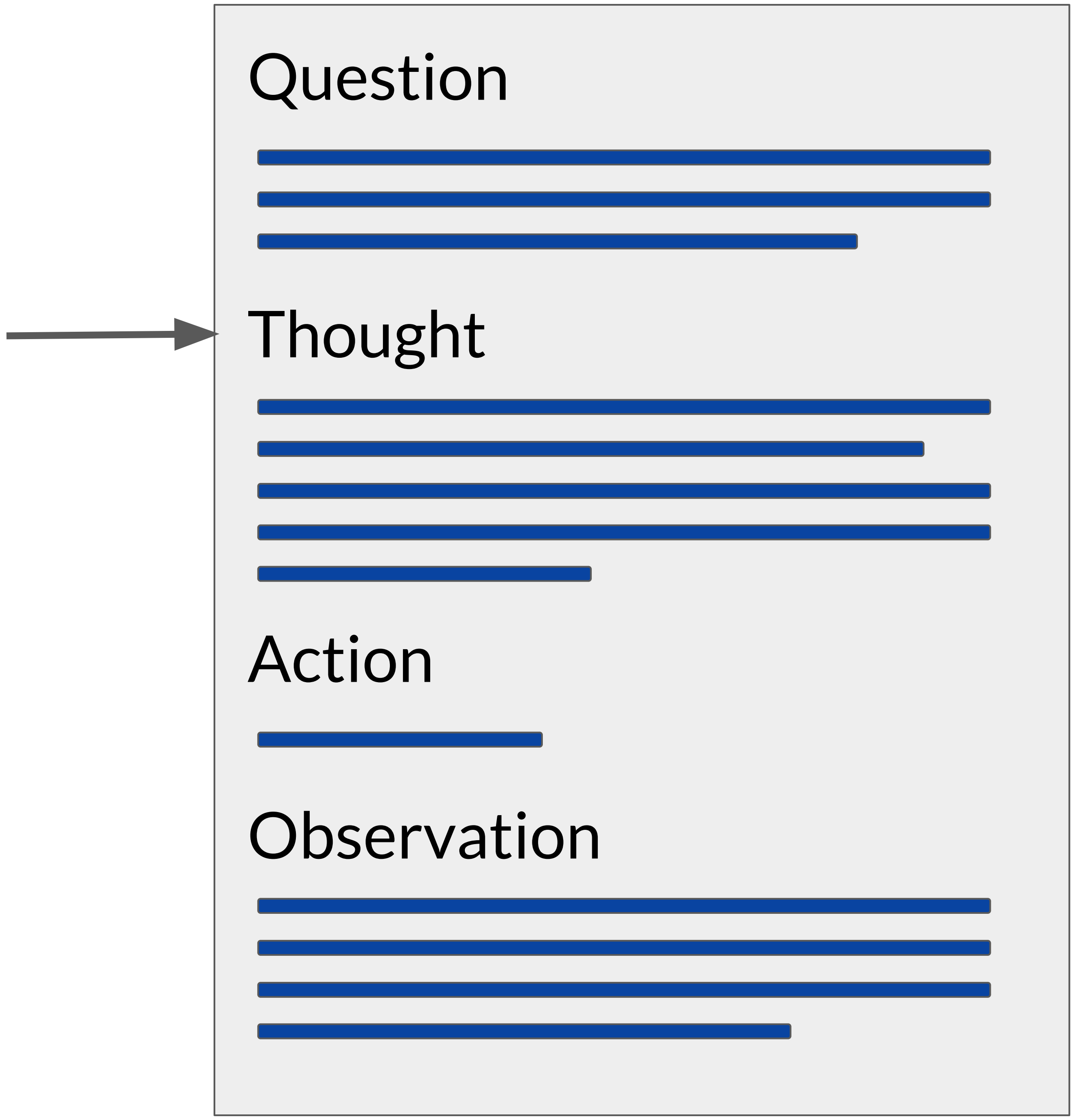


Question: Problem that requires advanced reasoning and multiple steps to solve.

E.g.
"Which magazine was started first, *Arthur's Magazine* or *First for Women*?"

Source: Yao et al. 2022, "ReAct: Synergizing Reasoning and Acting in Language Models"

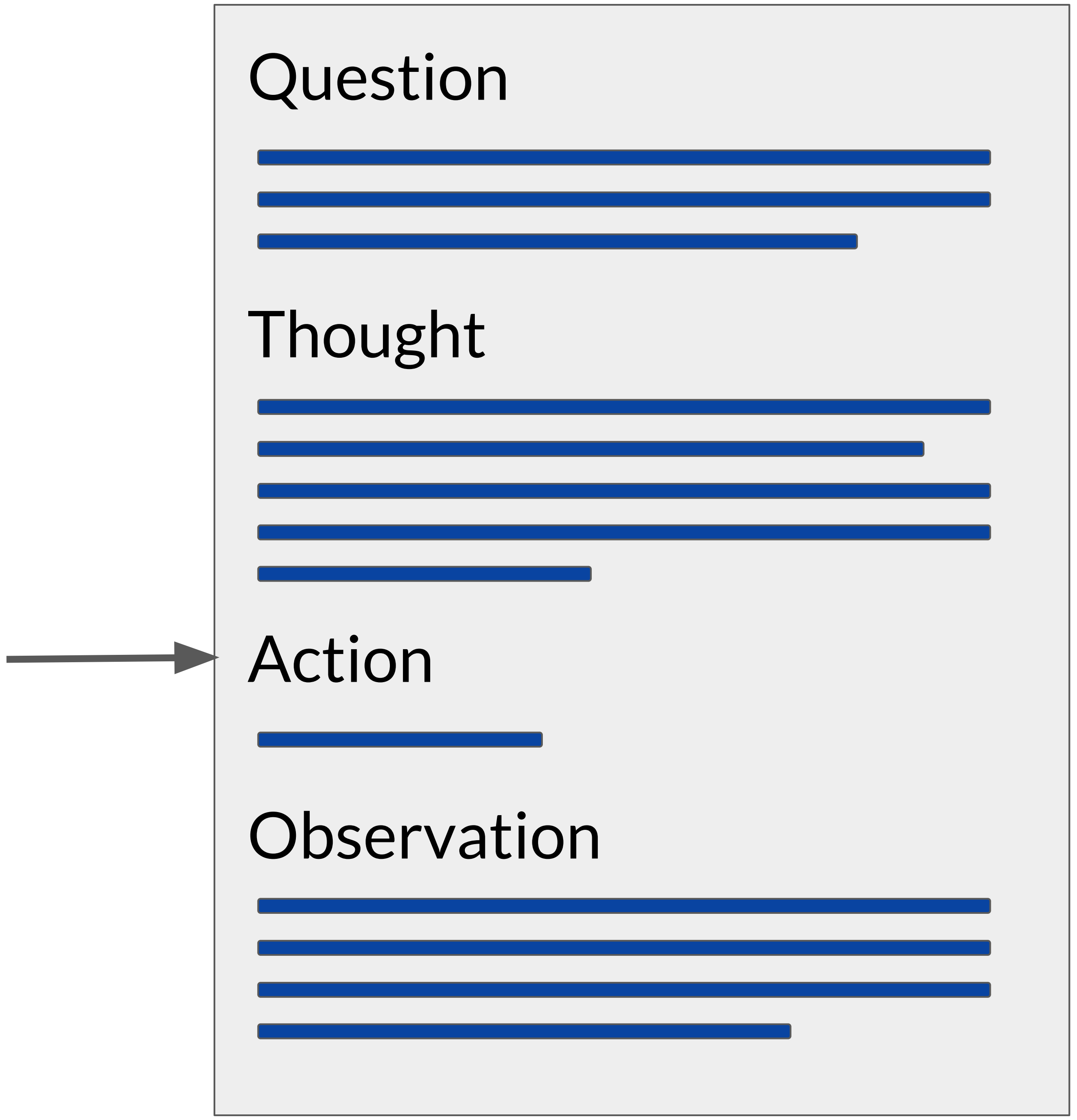
ReAct: Synergizing Reasoning and Action in LLMs



Thought: A reasoning step that identifies how the model will tackle the problem and identify an action to take.

“I need to search Arthur’s Magazine and First for Women, and find which one was started first.”

ReAct: Synergizing Reasoning and Action in LLMs



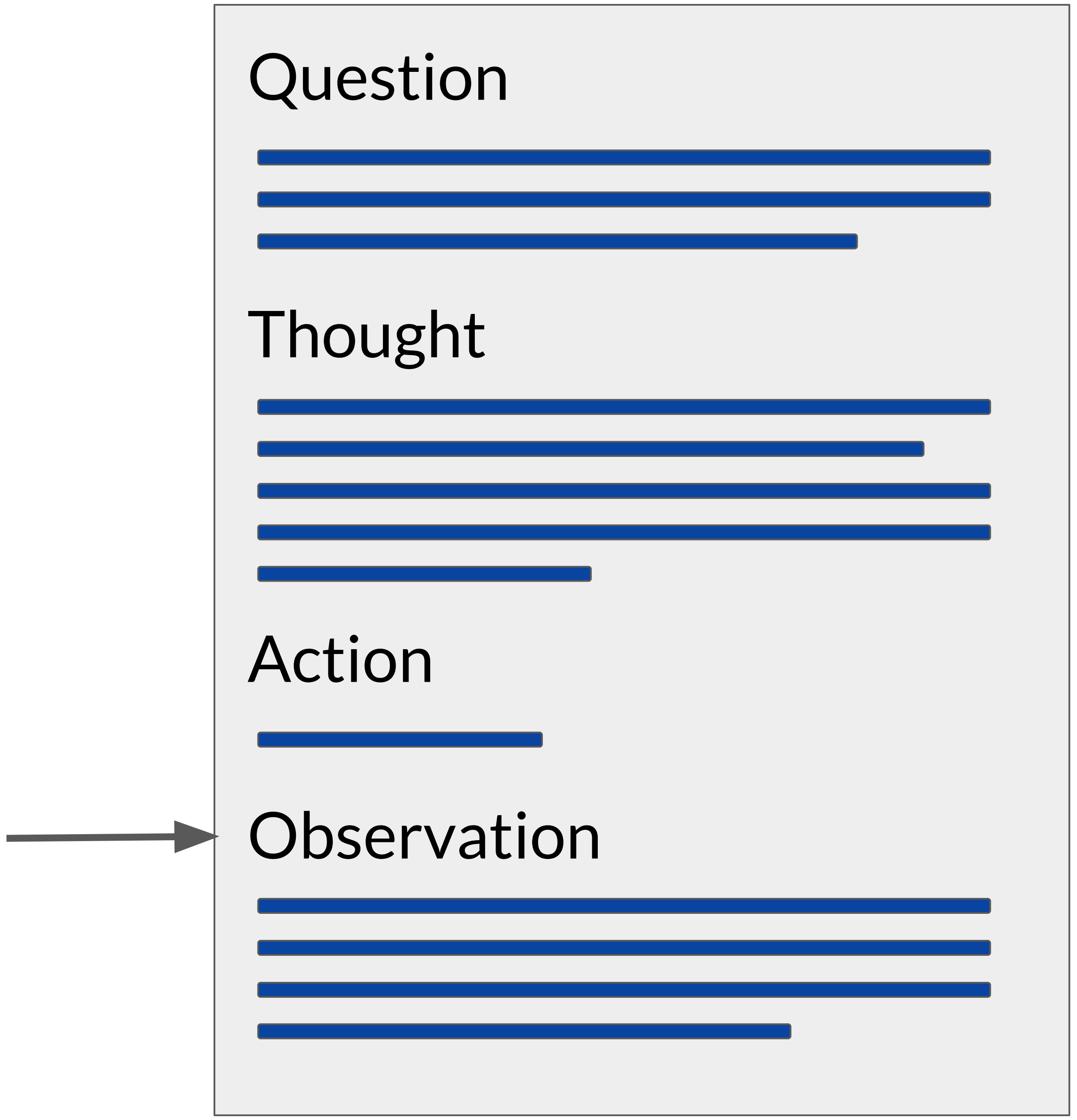
Action: An external task that the model can carry out from an allowed set of actions.

E.g.
search[entity]
lookup[string]
finish[answer]

Which one to choose is determined by the information in the preceding thought.

search[Arthur's Magazine]

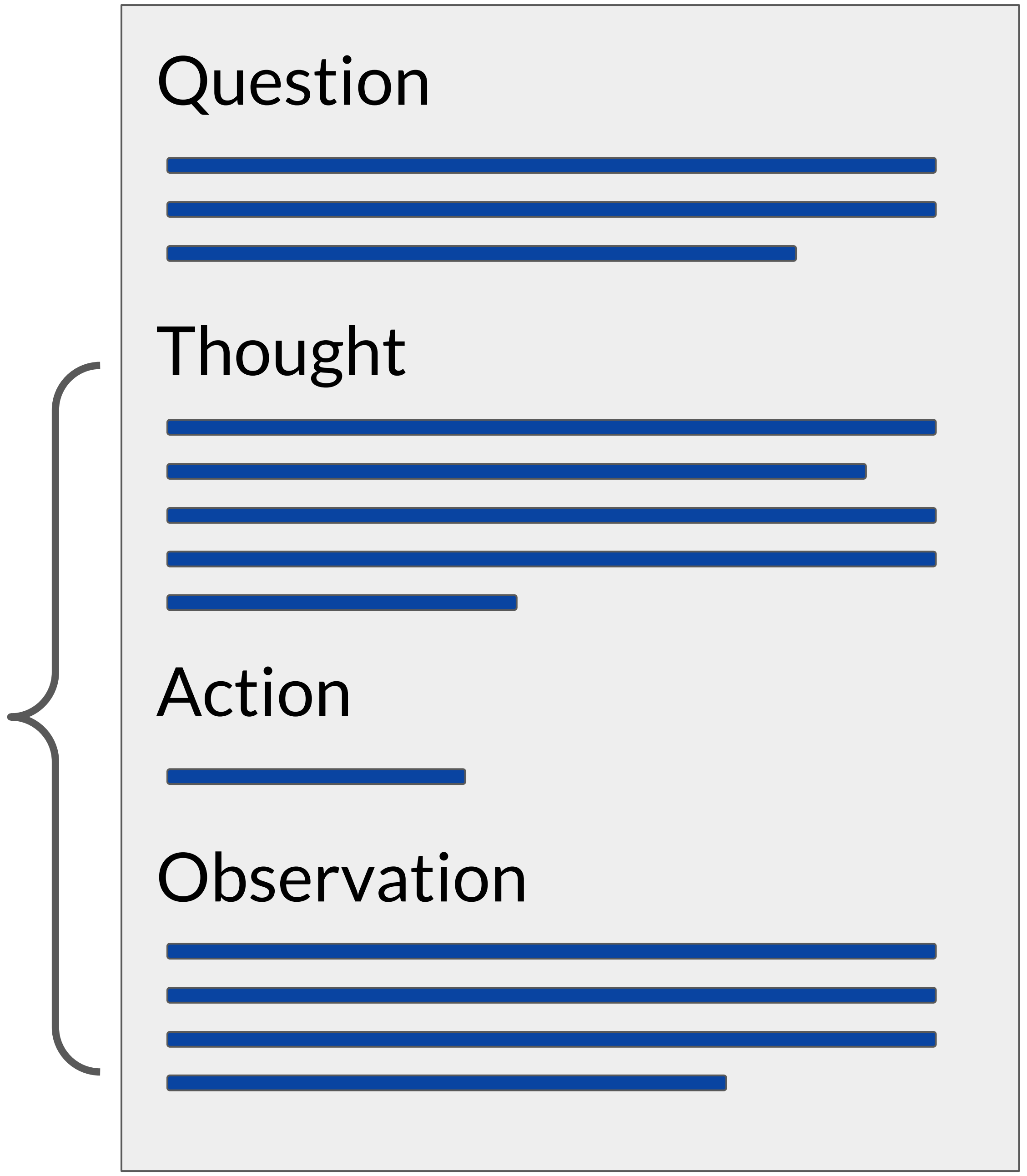
ReAct: Synergizing Reasoning and Action in LLMs



Observation: the result of carrying out the action

E.g.
“Arthur’s Magazine (1844-1846) was an American literary periodical published in Philadelphia in the 19th century.”

ReAct: Synergizing Reasoning and Action in LLMs

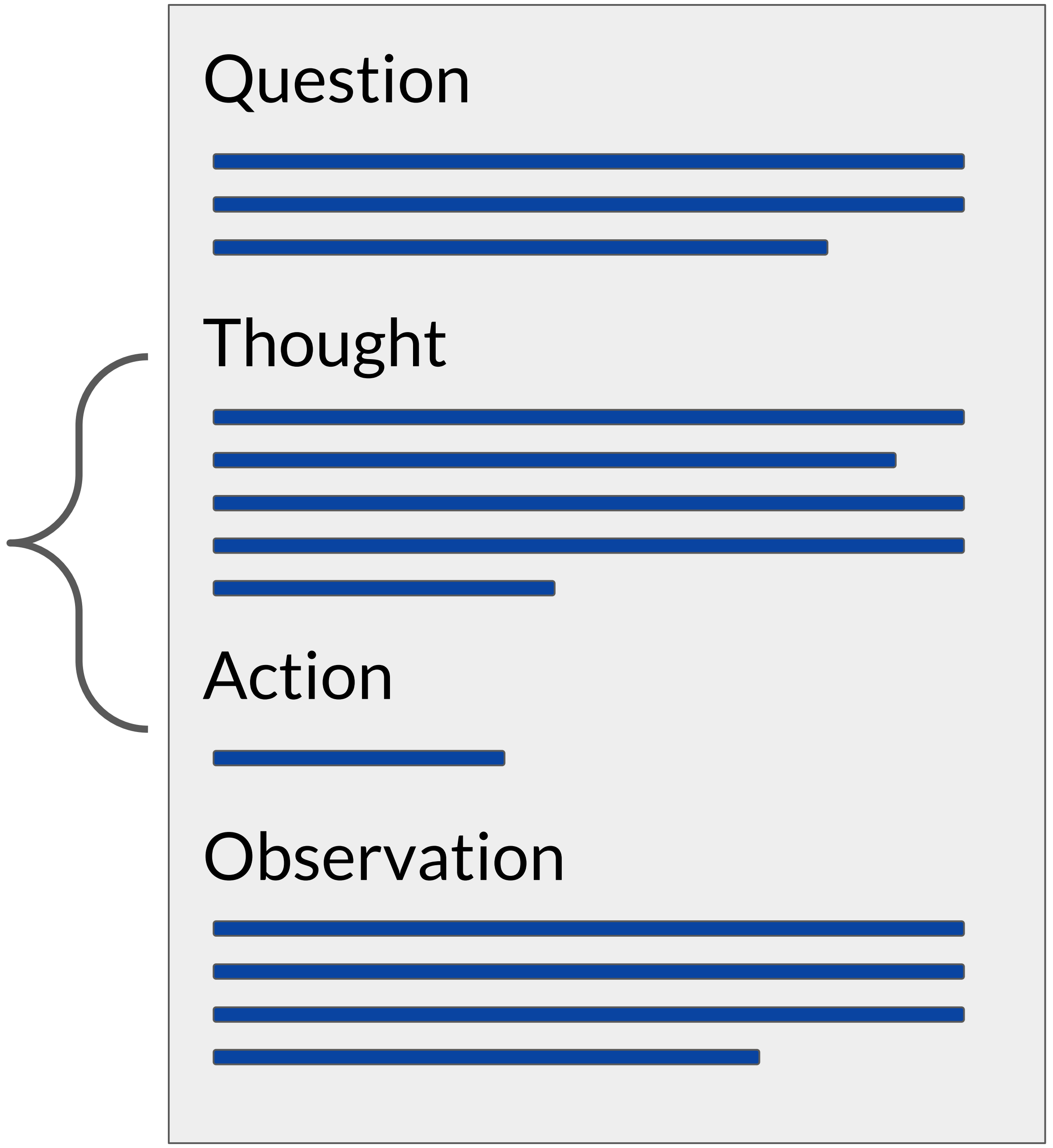


Thought 2:
“Arthur’s magazine was started in 1844. I need to search First for Women next.”

Action 2:
`search[First for Women]`

Observation 2:
“First for Women is a woman’s magazine published by Bauer Media Group in the USA.[1] The magazine was started in 1989.”

ReAct: Synergizing Reasoning and Action in LLMs



Thought 3:
“First for Women was started in 1989. 1844 (Arthur’s Magazine) < 1989 (First for Women), so Arthur’s Magazine as started first”

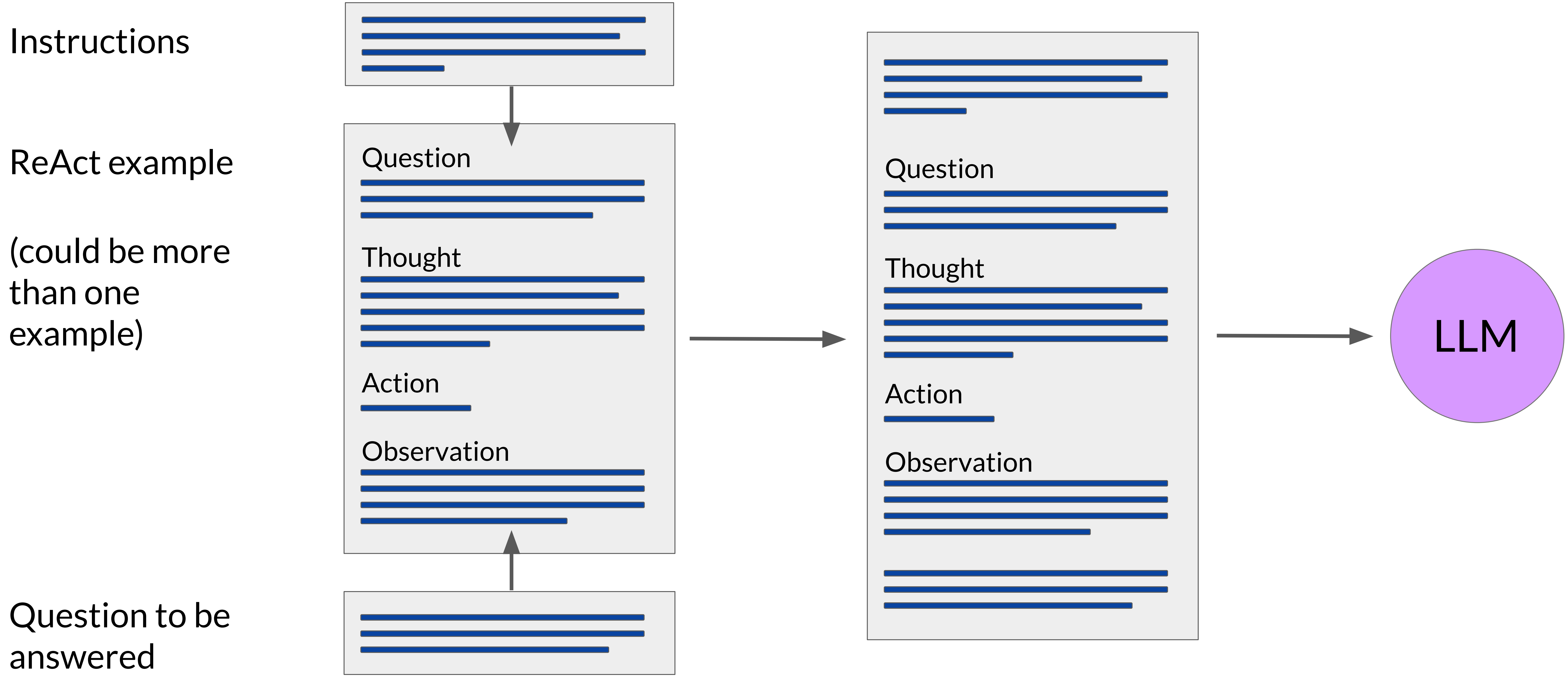
Action 2:
`finish``[Arthur’s Magazine]`

ReAct instructions define the action space

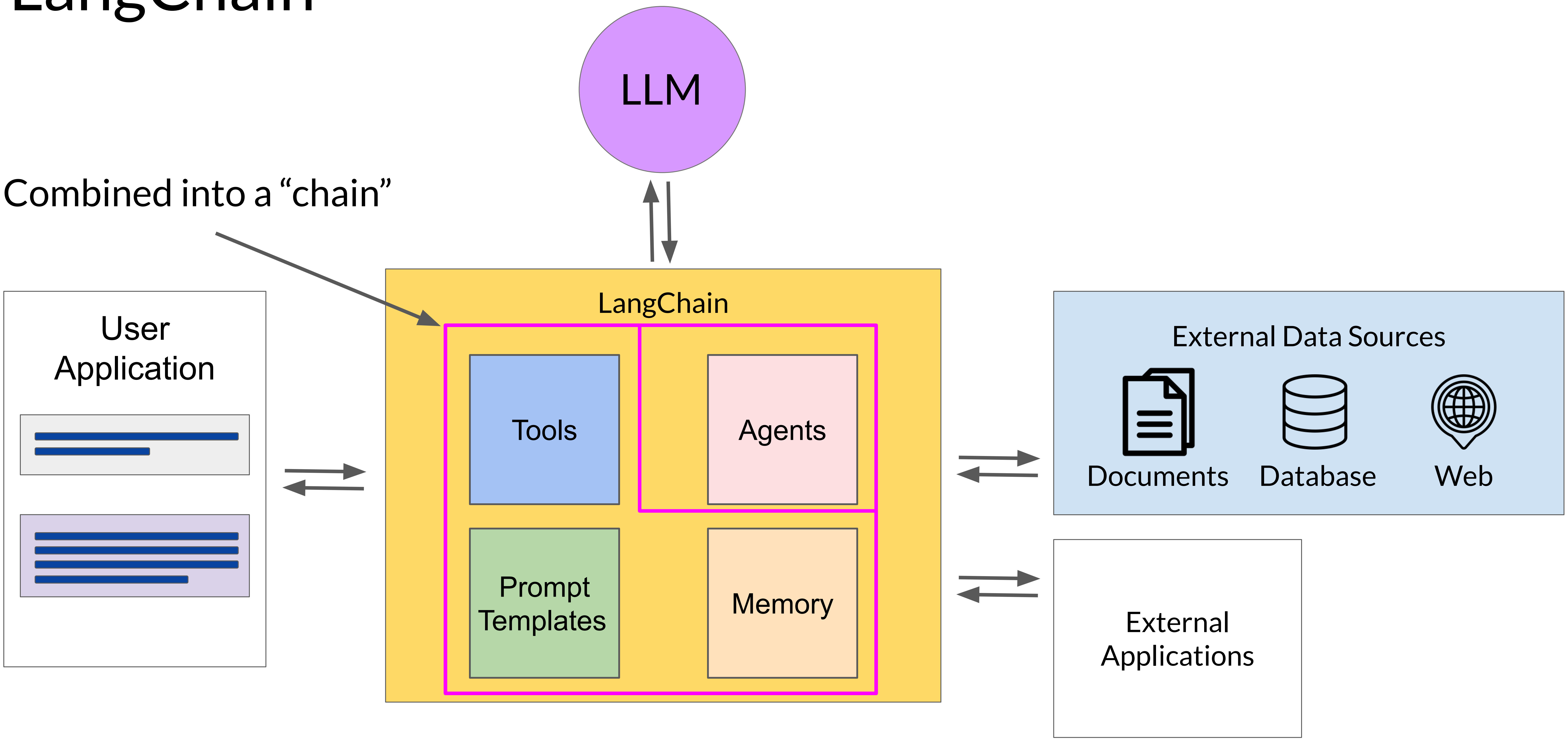
Solve a question answering task with interleaving Thought, Action, Observation steps.

Thought can reason about the current situation, and Action can be three types:
(1) Search[entity], which searches the exact entity on Wikipedia and returns the first paragraph if it exists. If not, it will return some similar entities to search.
(2) Lookup[keyword], which returns the next sentence containing keyword in the current passage.
(3) Finish[answer], which returns the answer and finishes the task.
Here are some examples.

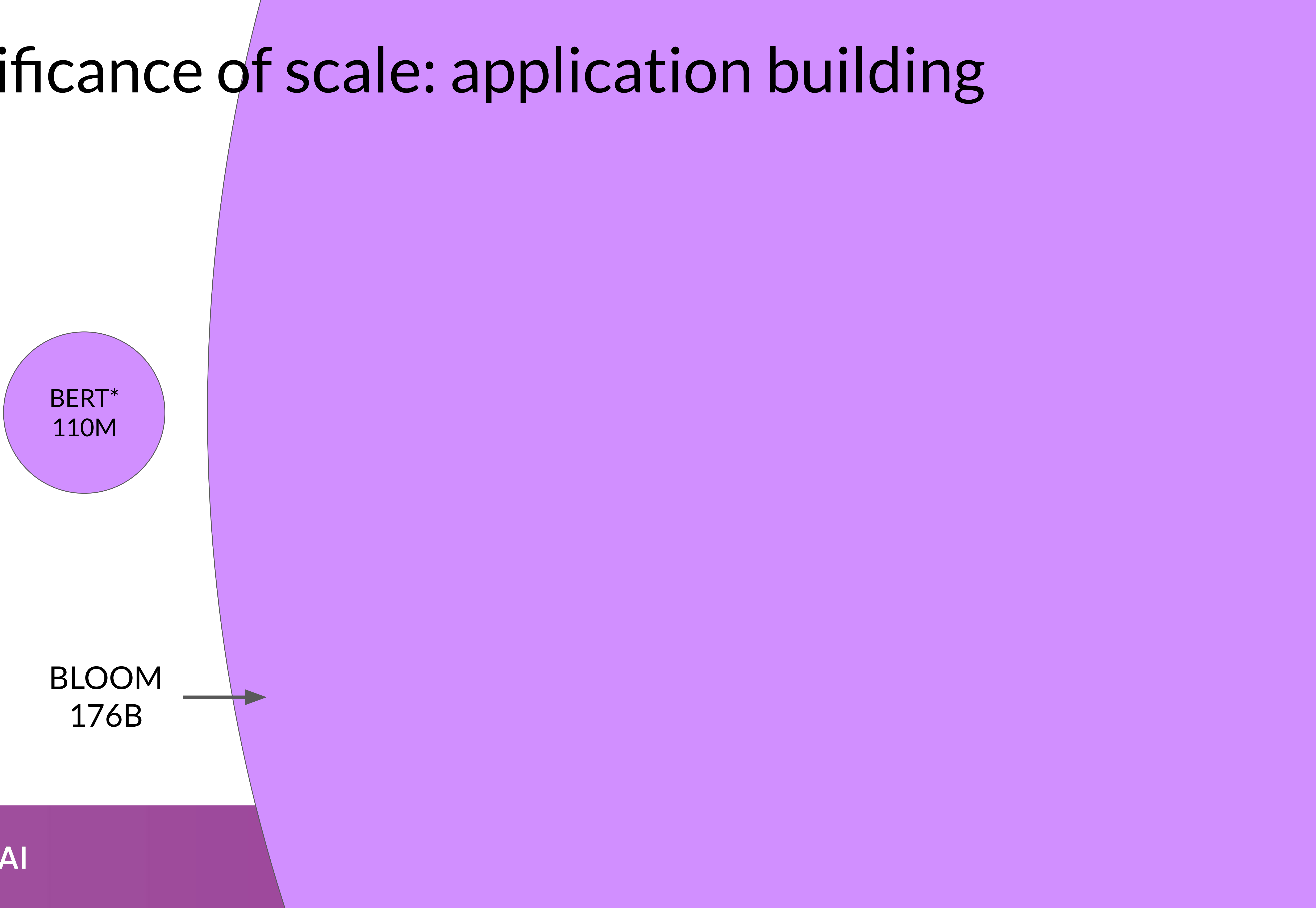
Building up the ReAct prompt



LangChain


LLM
Combined into a "chain"
User Application
LangChain
Tools
Agents
Prompt Templates
Memory
External Data Sources
Documents
Database
Web
External Applications

The significance of scale: application building



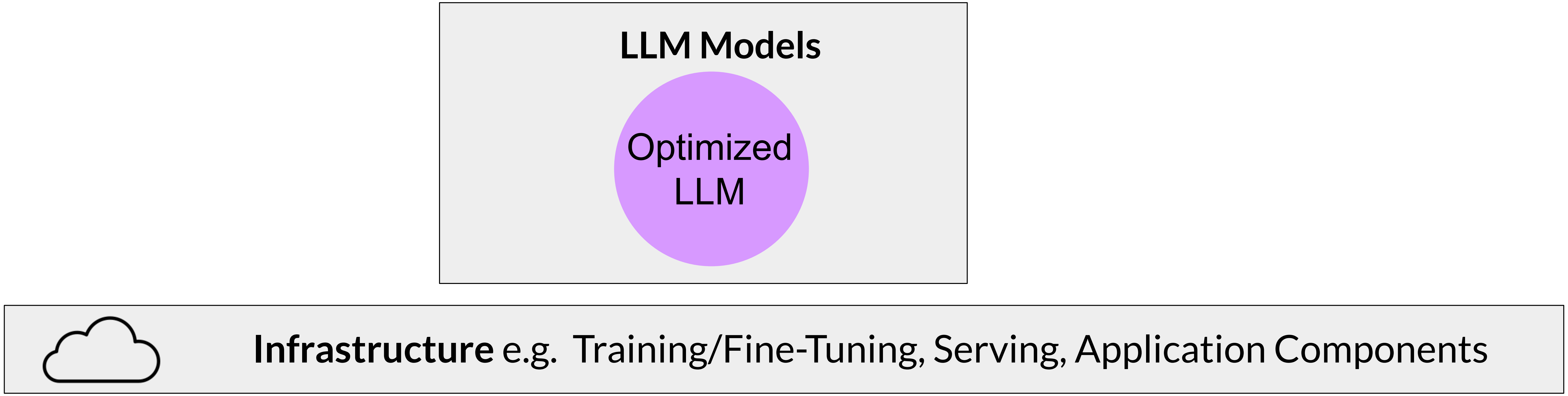
*Bert-base

LLM powered application architectures

Building generative applications

Infrastructure e.g. Training/Fine-Tuning, Serving, Application Components

Building generative applications

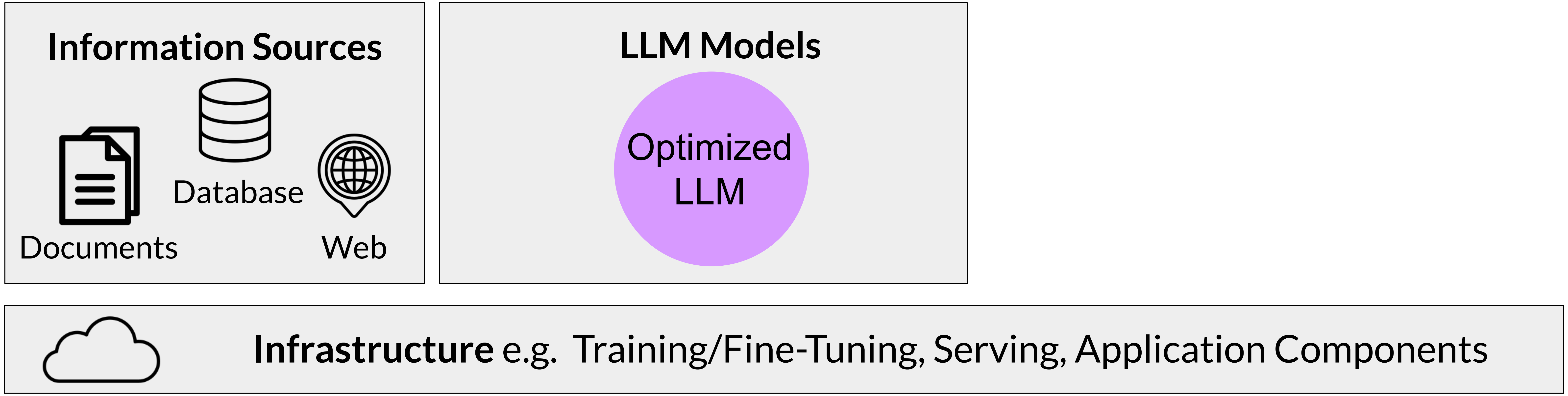


LLM Models

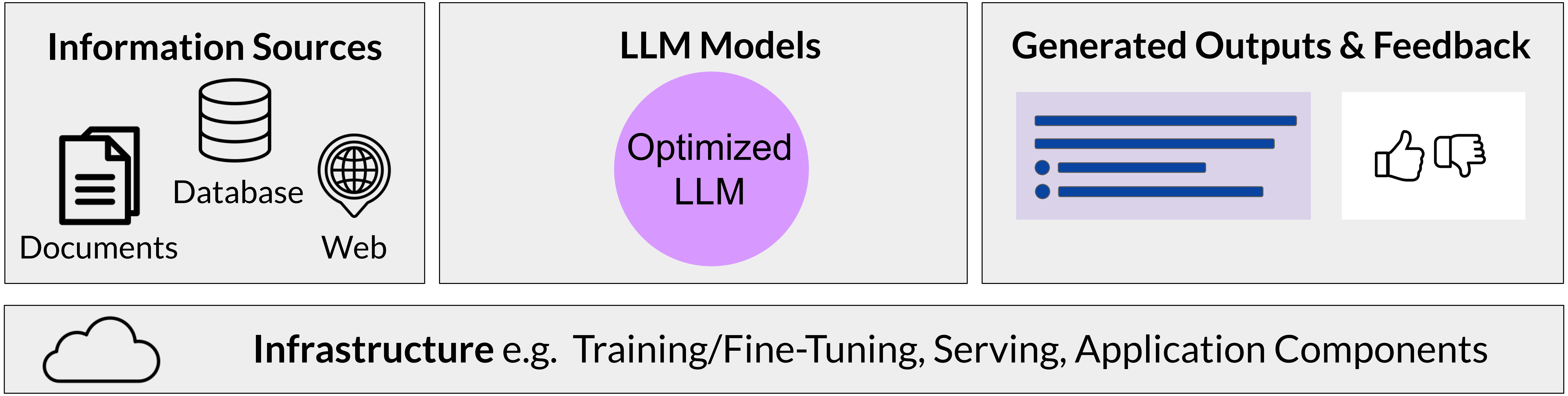
Optimized LLM

Infrastructure e.g. Training/Fine-Tuning, Serving, Application Components

Building generative applications


Information Sources
Documents
Database
Web
LLM Models
Optimized LLM
Infrastructure e.g. Training/Fine-Tuning, Serving, Application Components

Building generative applications


Information Sources
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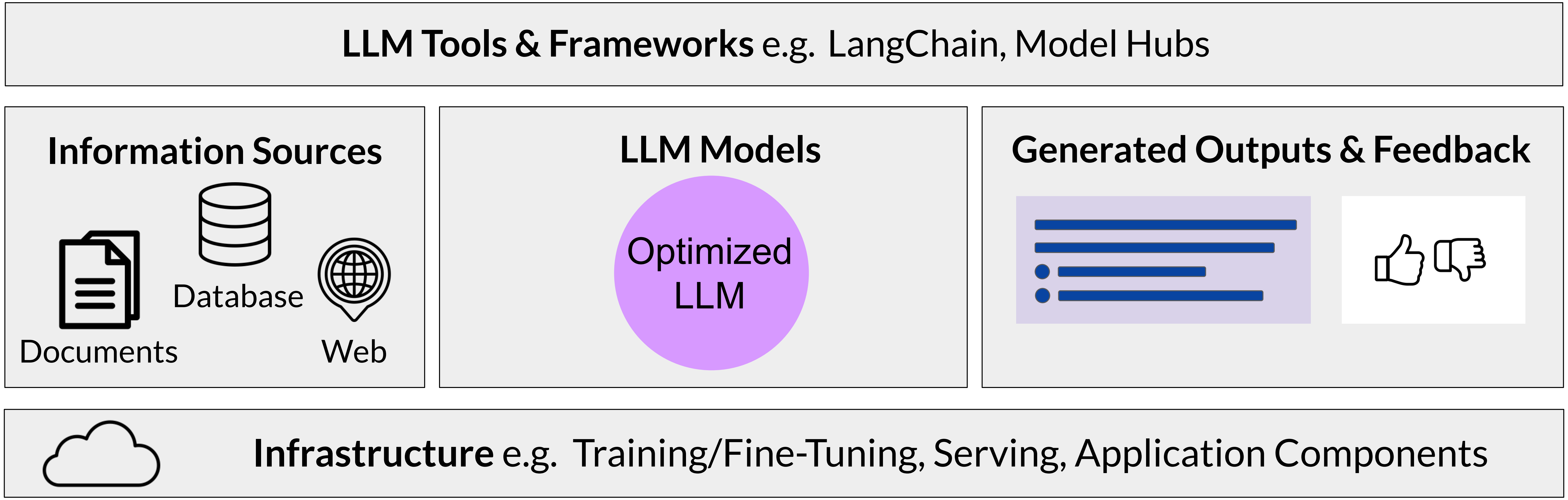
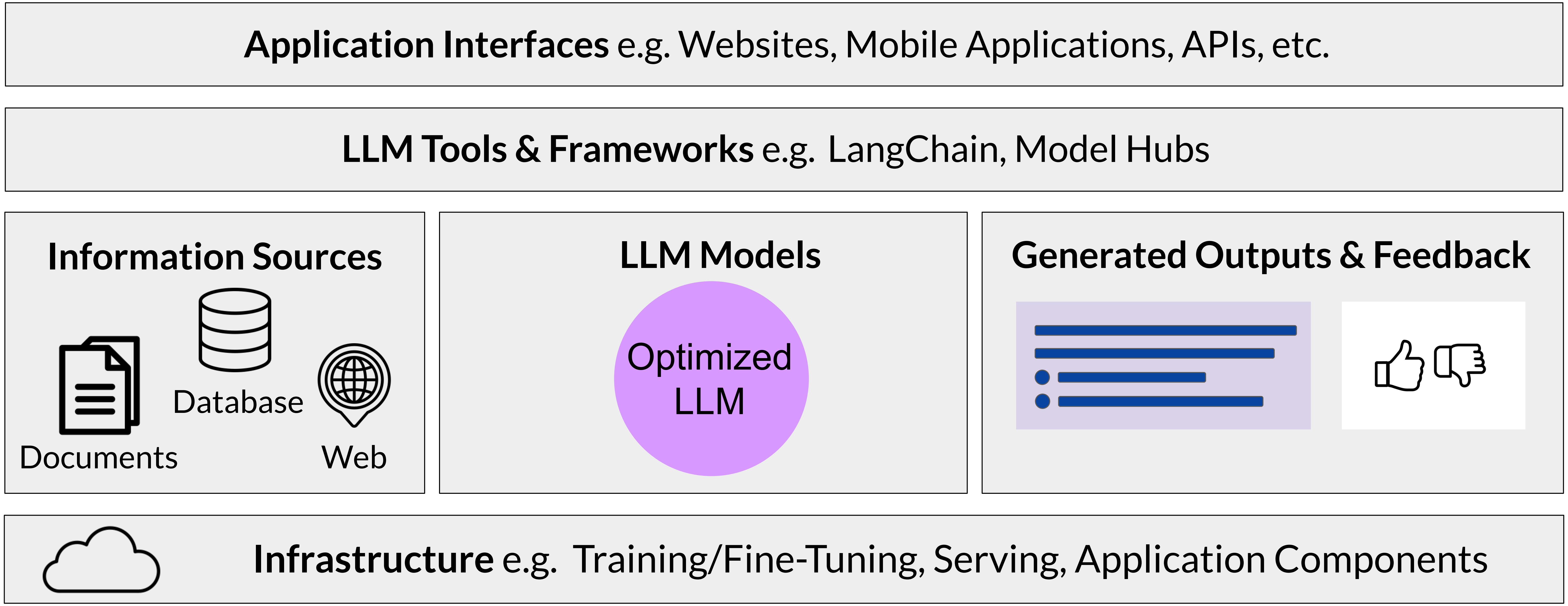
Optimized LLM
Generated Outputs & Feedback
Infrastructure e.g. Training/Fine-Tuning, Serving, Application Components

Building generative applications



LLM Tools & Frameworks e.g. LangChain, Model Hubs
Information Sources
Database
Documents
Web
LLM Models
Optimized LLM
Generated Outputs & Feedback
Infrastructure e.g. Training/Fine-Tuning, Serving, Application Components

Building generative applications



Application Interfaces e.g. Websites, Mobile Applications, APIs, etc.

LLM Tools & Frameworks e.g. LangChain, Model Hubs

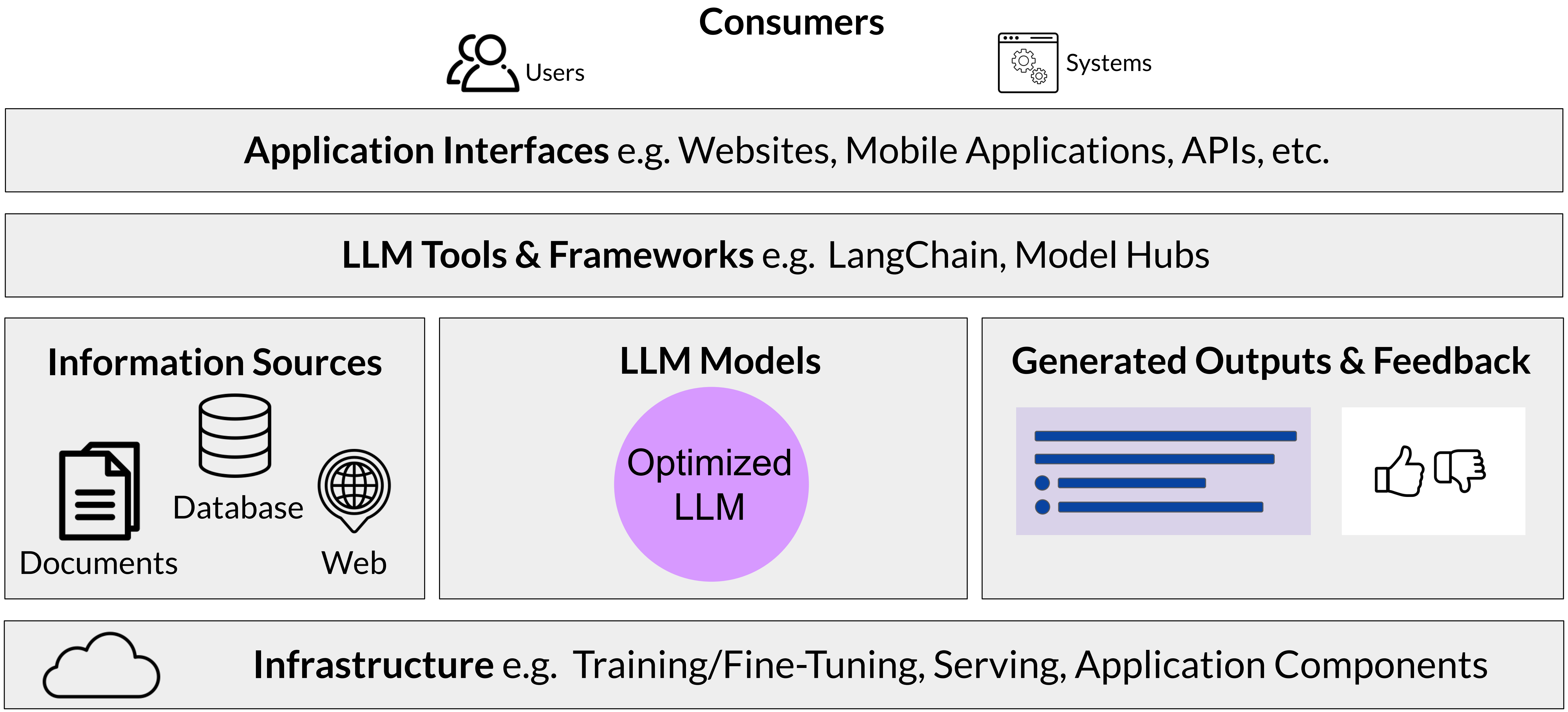
Information Sources

LLM Models

Generated Outputs & Feedback

Infrastructure e.g. Training/Fine-Tuning, Serving, Application Components

Building generative applications



Consumers

Users

Systems

Application Interfaces e.g. Websites, Mobile Applications, APIs, etc.

LLM Tools & Frameworks e.g. LangChain, Model Hubs

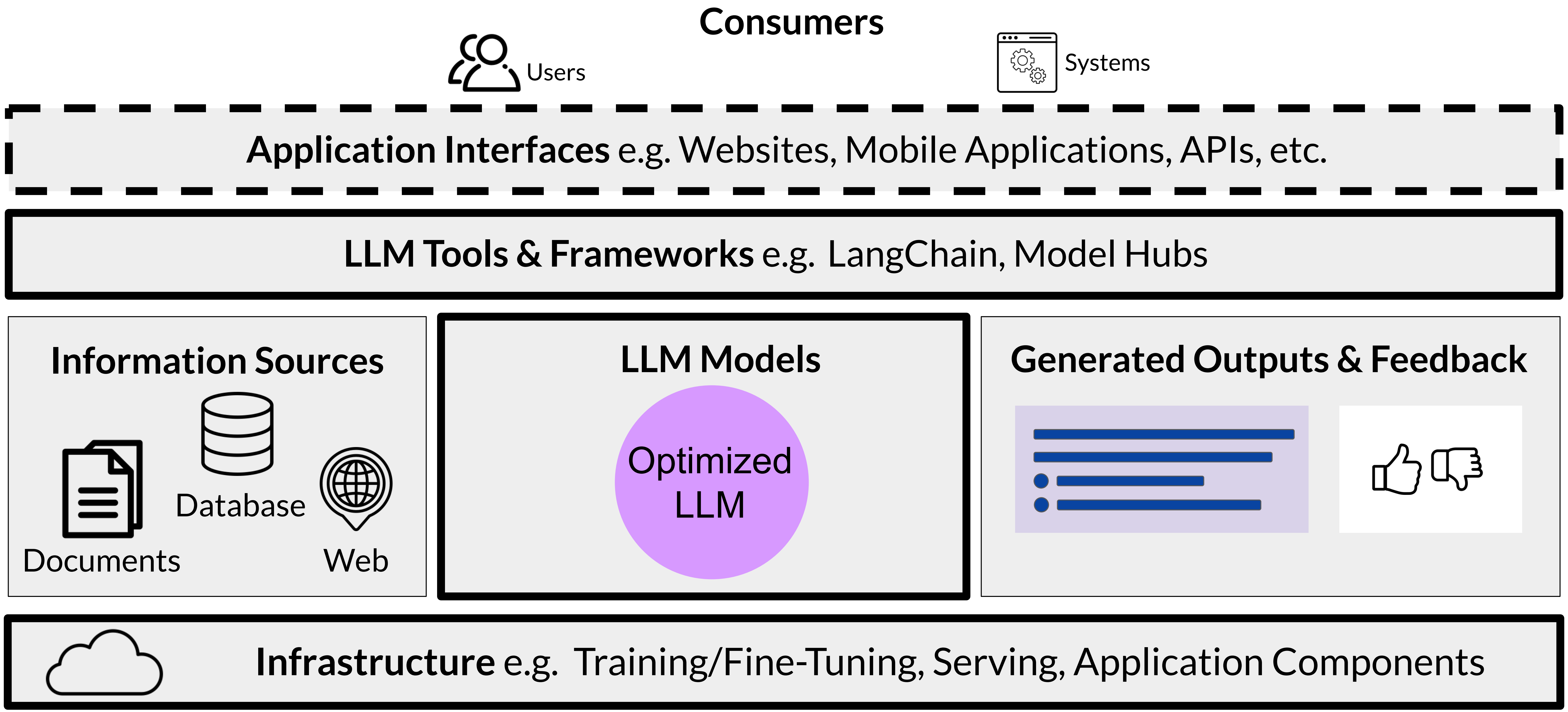
Information Sources

LLM Models

Generated Outputs & Feedback

Infrastructure e.g. Training/Fine-Tuning, Serving, Application Components

Building generative applications



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Optimized LLM

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Conclusion, Responsible AI, and on-going research

Responsible AI

Dr. Nashlie Sephus

Responsible AI
Dr. Nashlie Sephus

Responsible AI

Dr. Nashlie Sephus

On-going research

- Responsible AI

Responsible AI

Special challenges of responsible generative AI

- Toxicity
- Hallucinations
- Intellectual Property

Toxicity

LLM returns responses that can be potentially harmful or discriminatory towards protected groups or protected attributes

How to mitigate?

- Careful curation of training data
- Train guardrail models to filter out unwanted content
- Diverse group of human annotators

Hallucinations

LLM generates factually incorrect content

How to mitigate?

- Educate users about how generative AI works
- Add disclaimers
- Augment LLMs with independent, verified citation databases
- Define intended/unintended use cases

Intellectual Property

Ensure people aren't plagiarizing, make sure there aren't any copyright issues

How to mitigate?

- Mix of technology, policy, and legal mechanisms
- Machine "unlearning"
- Filtering and blocking approaches

Responsibly build and use generative AI models

- Define use cases: the more specific/narrow, the better
- Assess risks for each use case
- Evaluate performance for each use case
- Iterate over entire AI lifecycle

On-going research

- Responsible AI
- Scale models and predict performance
- More efficiencies across model development lifecycle
- Increased and emergent LLM capabilities