

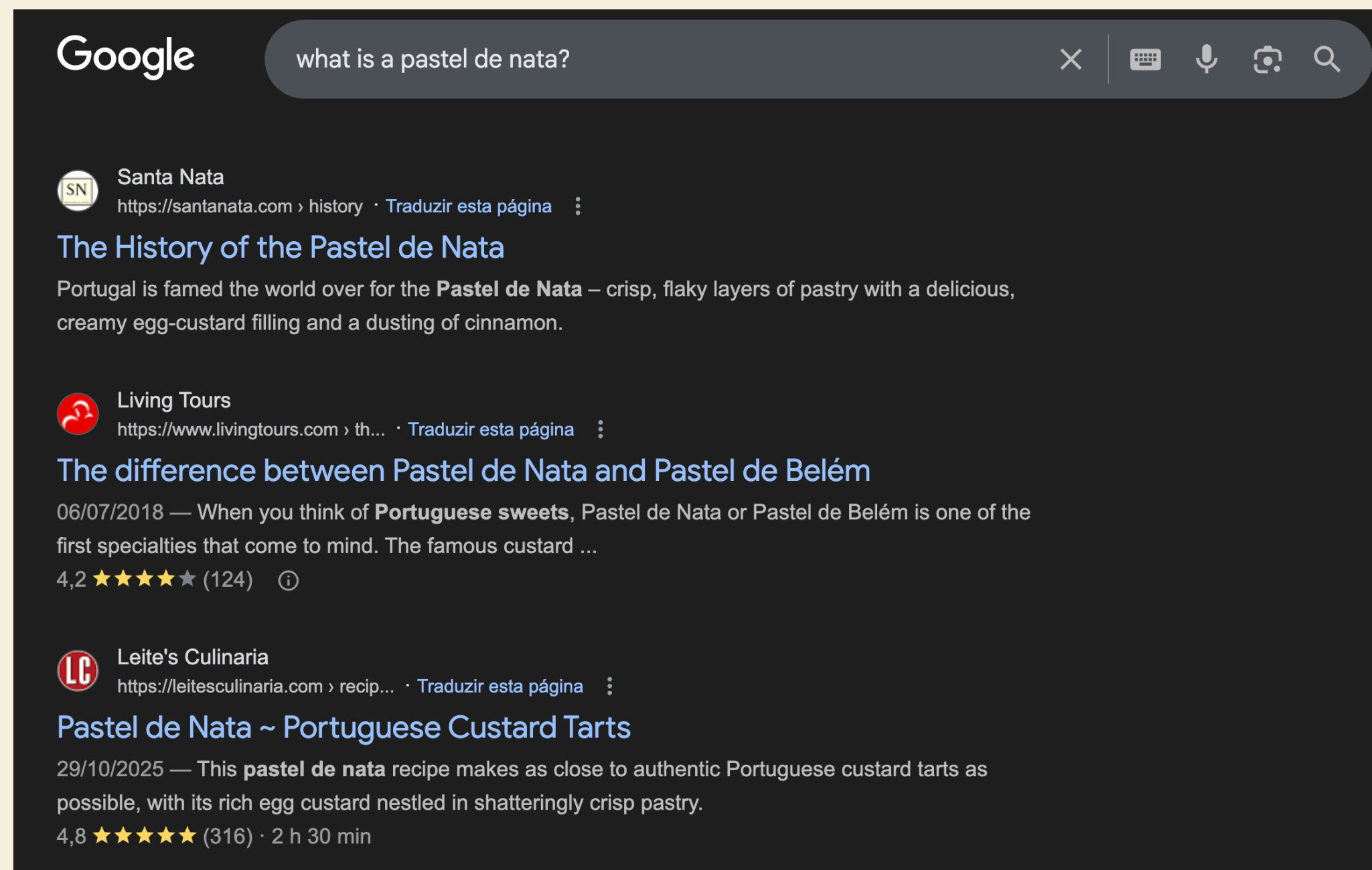
Building Open LLMs

Or how to build ChatGPT at home?

If I asked you “what is a pastel de nata?”
What would you do?

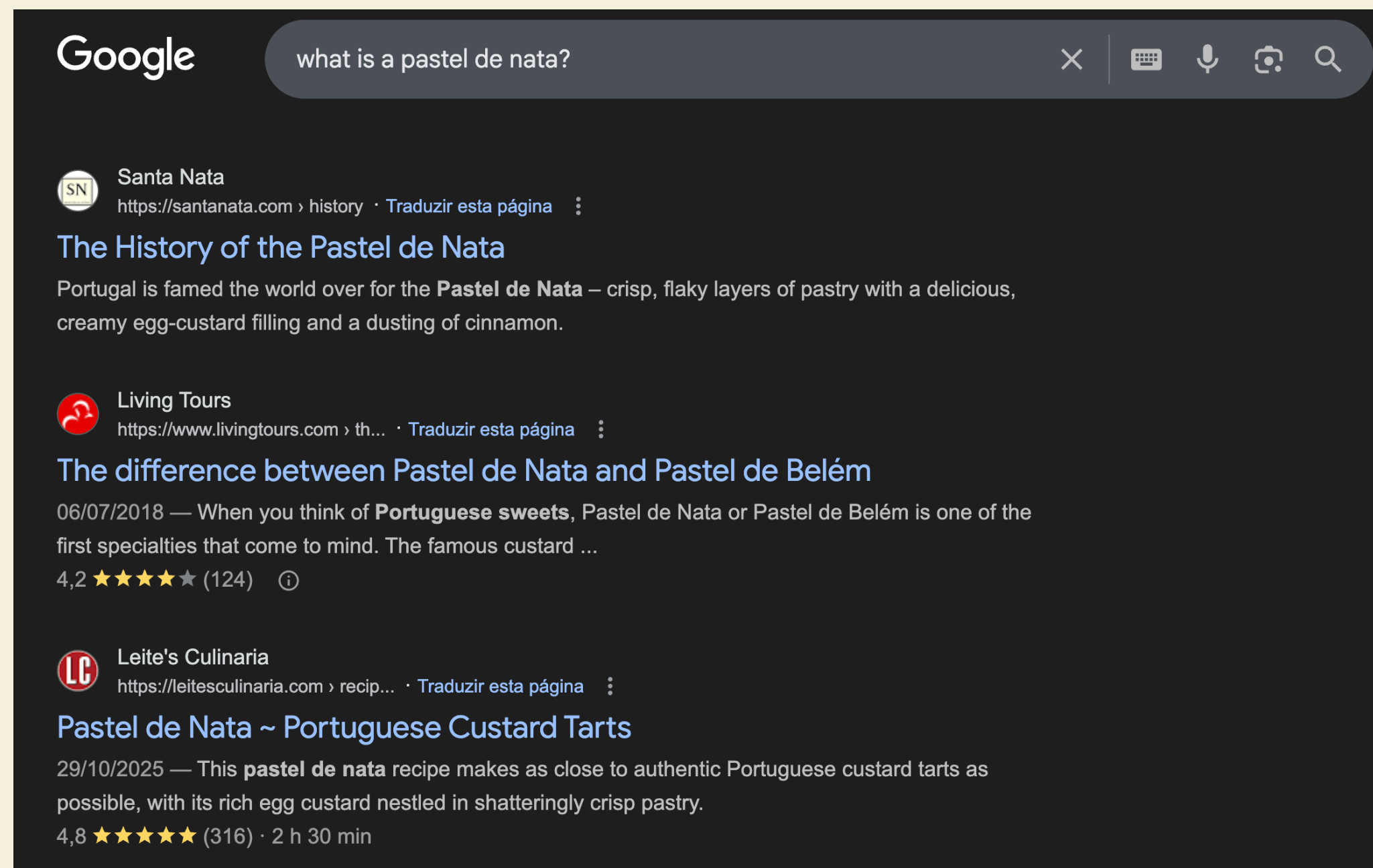
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3 years ago, you would probably Google it...

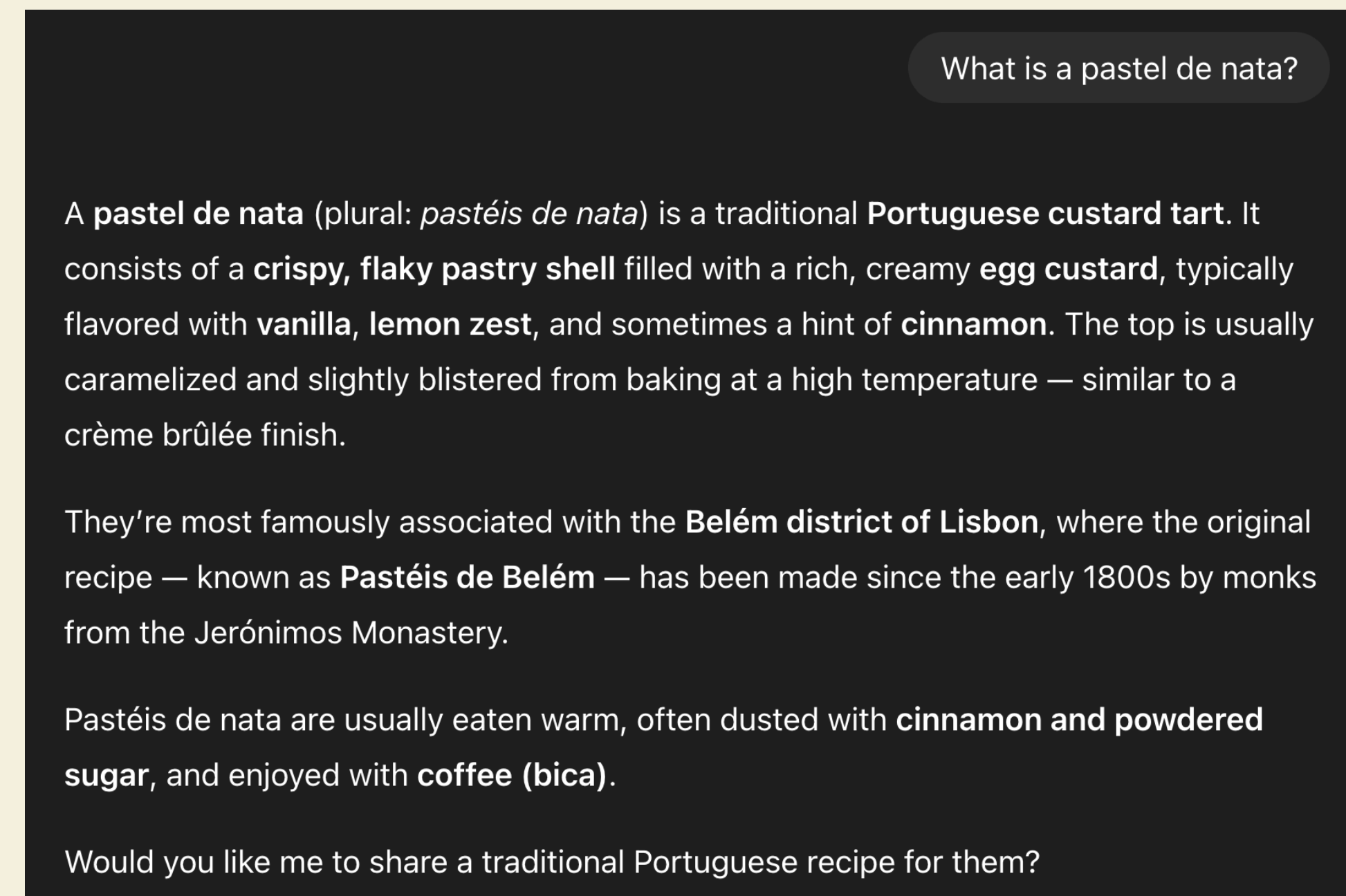


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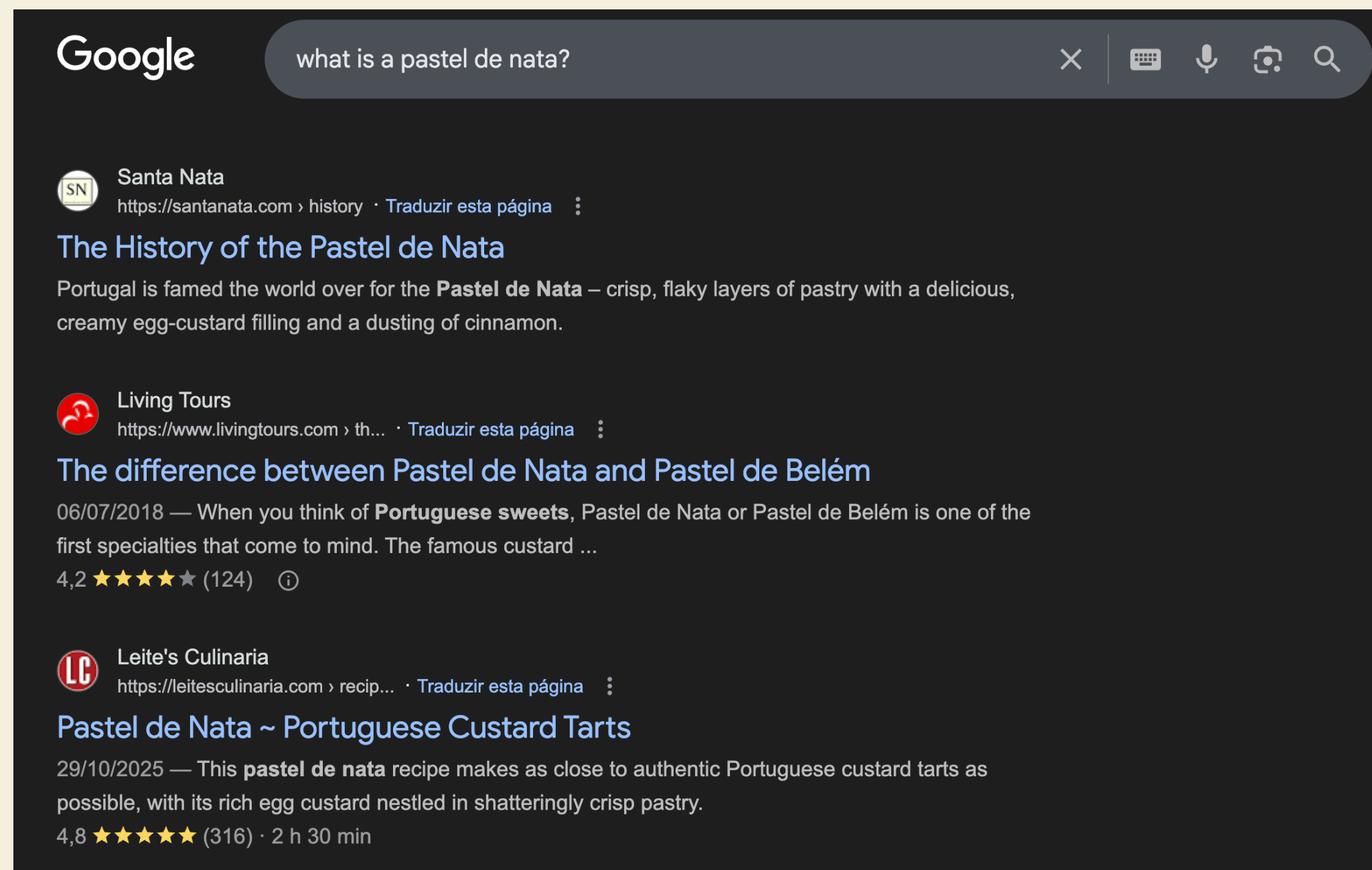


Today, maybe you would ask ChatGPT

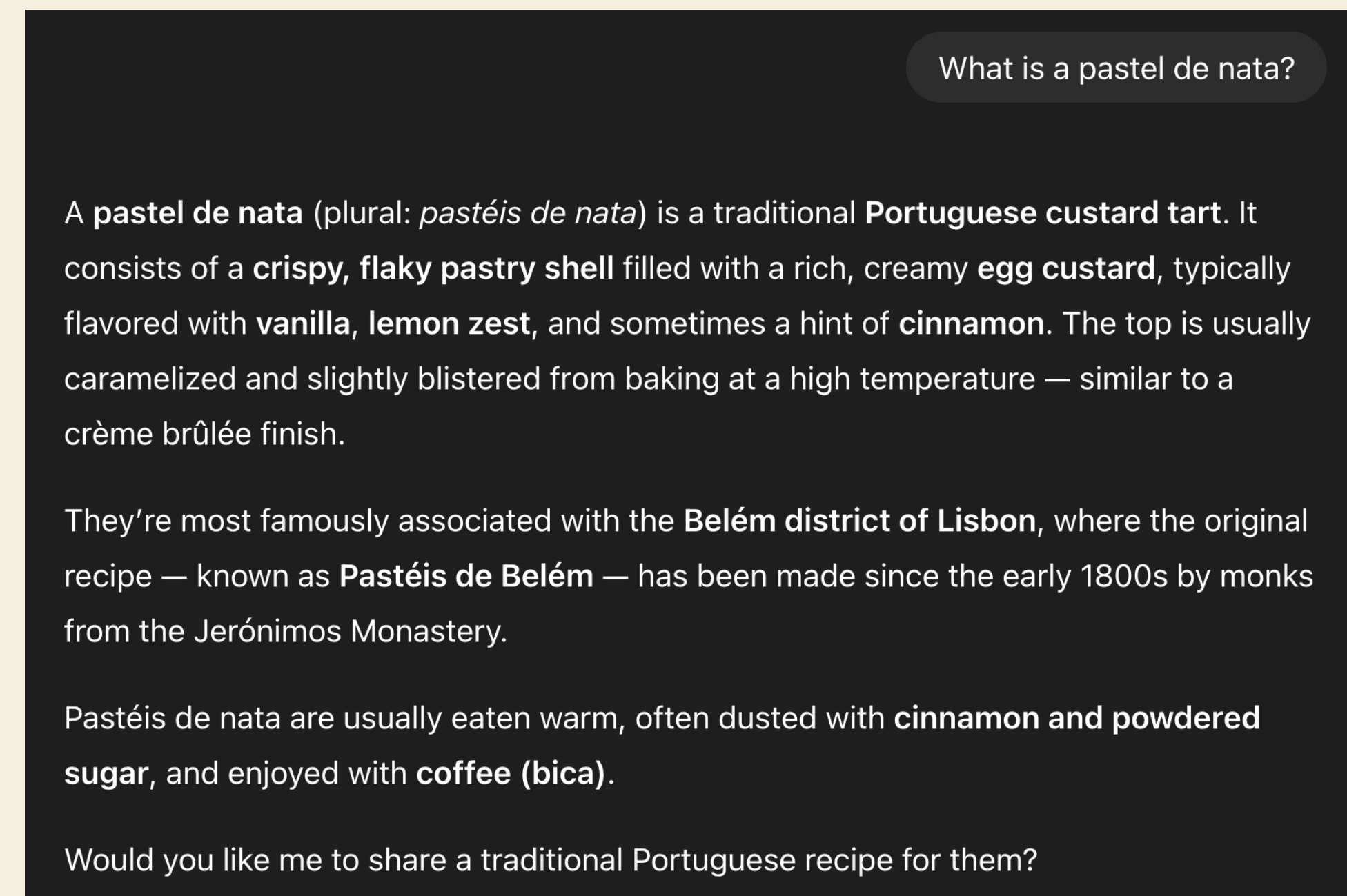


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Today, maybe you would ask ChatGPT



This seems much nicer....

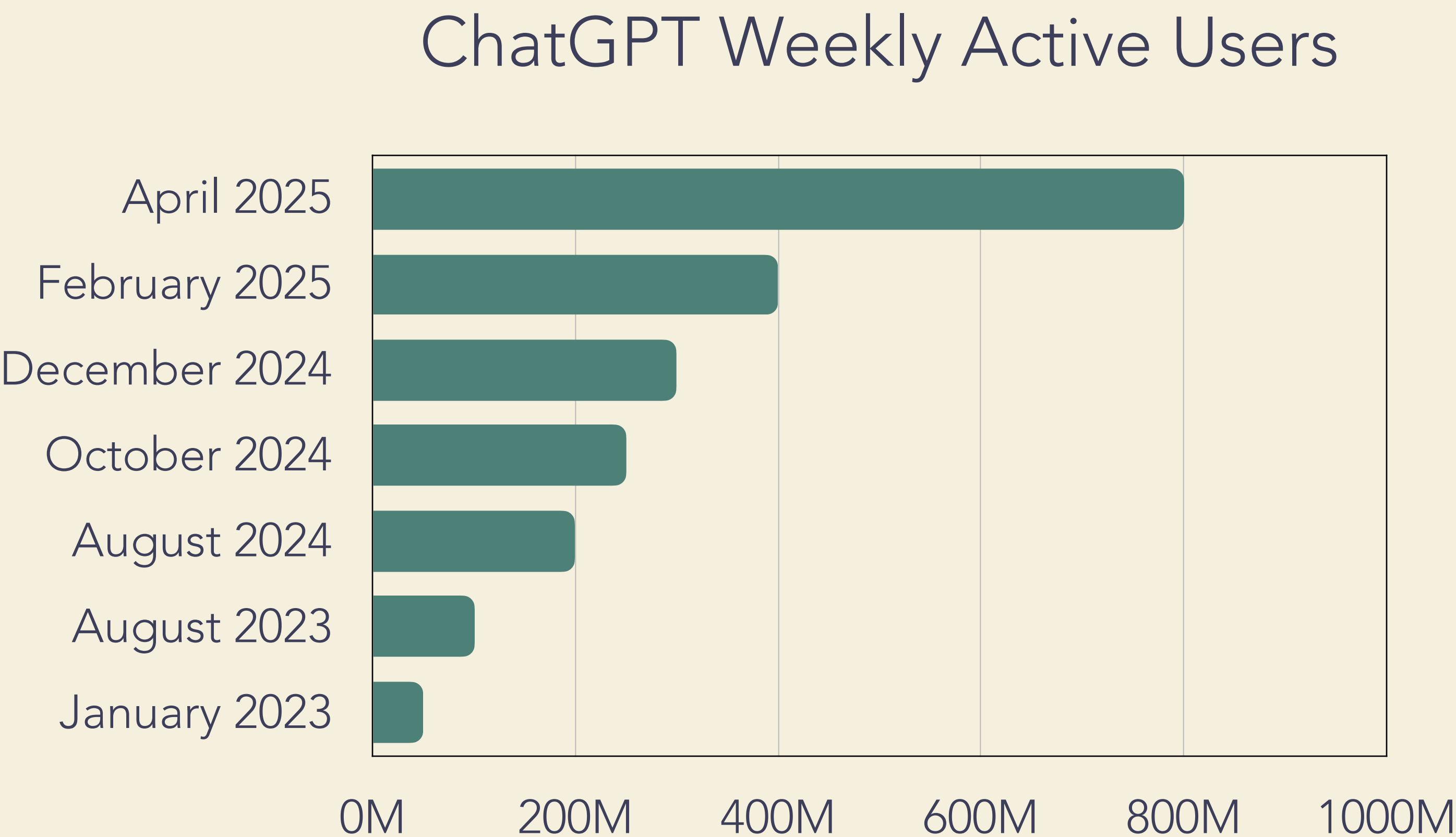
What is a pastel de nata?

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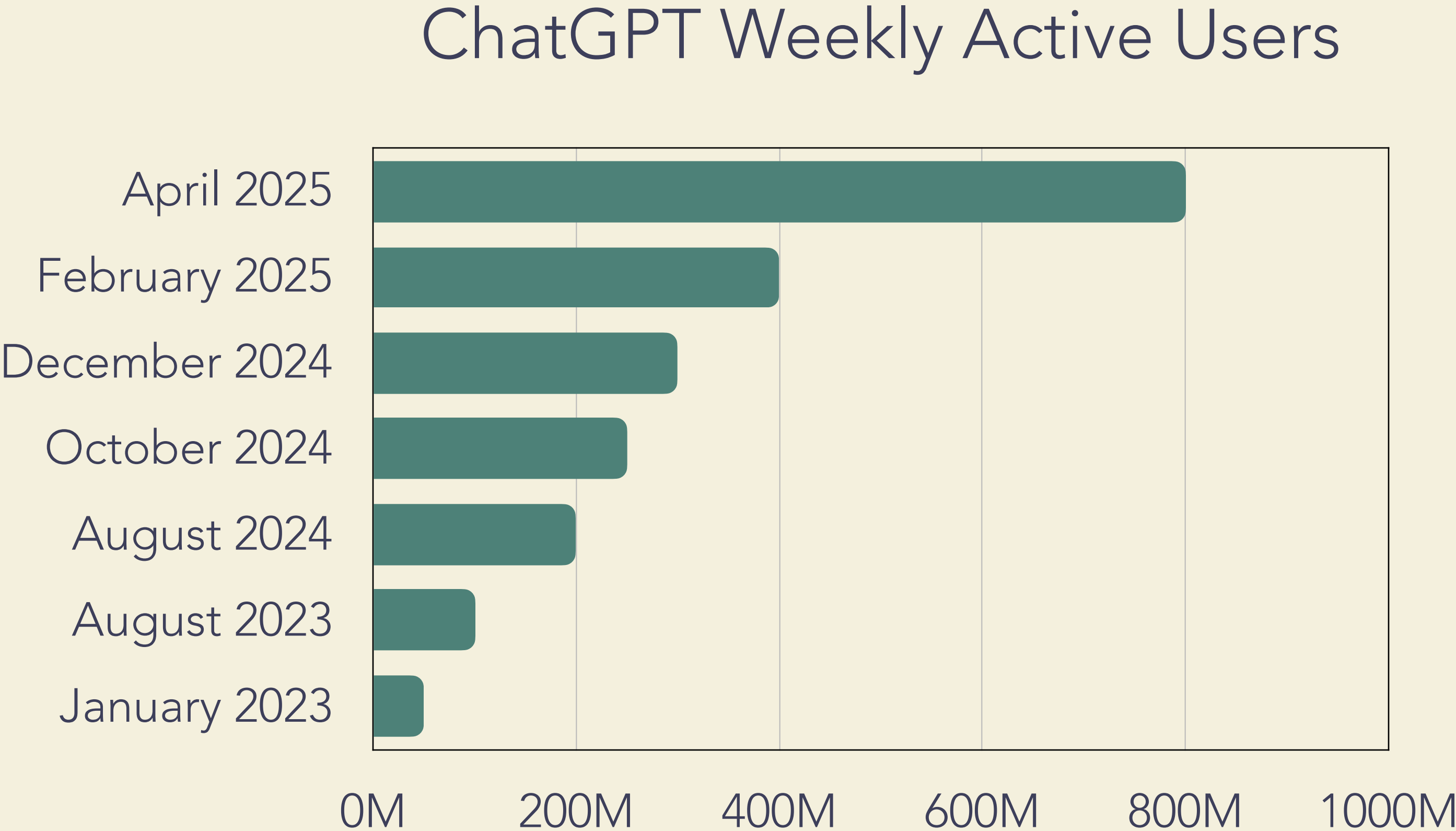


Find out in Portugal 😊

Going back to ChatGPT



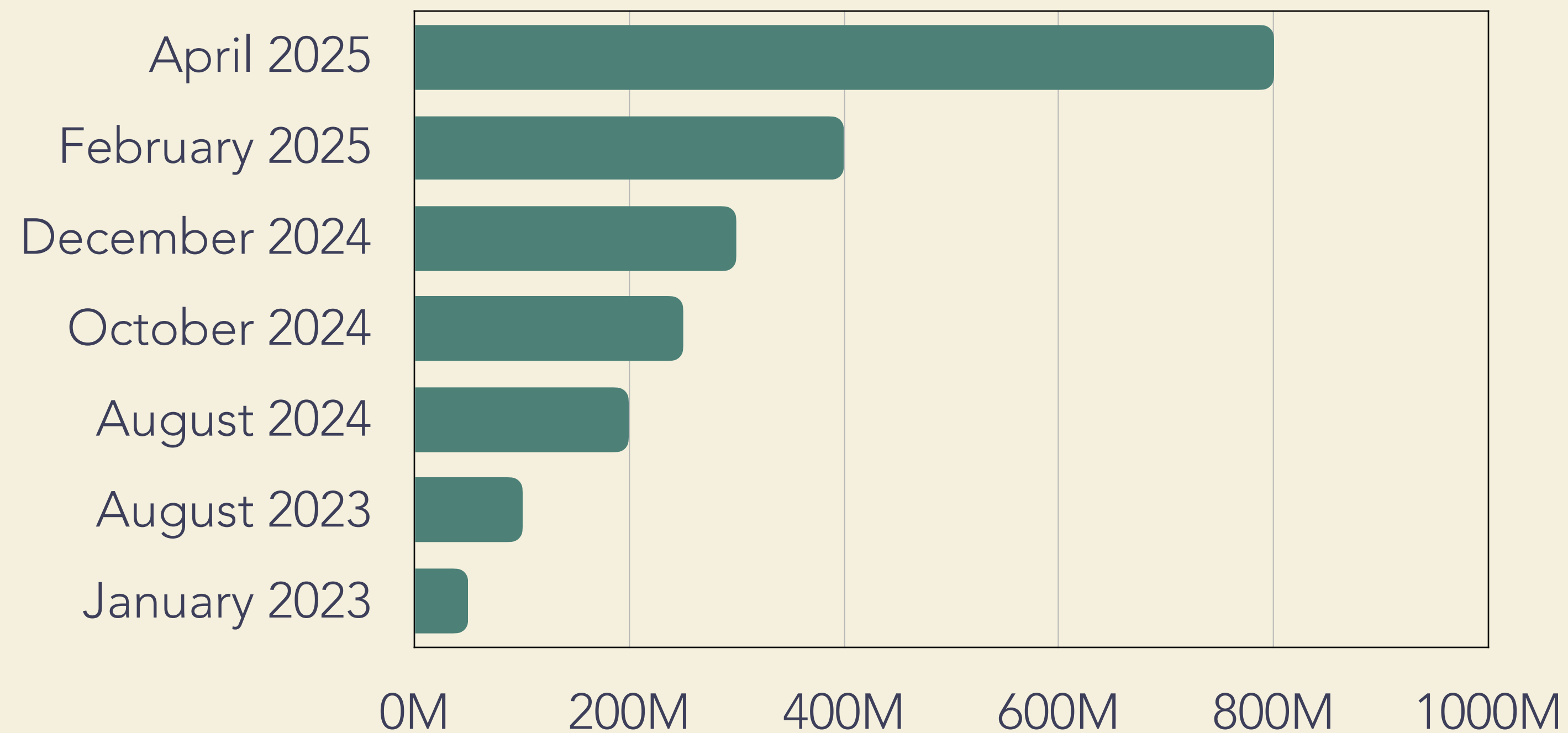
Going back to ChatGPT



But what is really behind ChatGPT?

Going back to ChatGPT

ChatGPT Weekly Active Users



But what is really
behind ChatGPT?

We don't know...

Why Open Models?

Democratization

Models should be widely available

Research

Investigation requires full knowledge of the model

Transparency

Openness enables auditing and fosters user trust

Collaboration

Inventions are built upon collective work

Privacy

Sensitive data requires on-site deployments

Customization

Access to weights enables fine-grained customization

Where do we start?

A tale of two worlds

Pre-training Knowledge

- ▶ Self-supervised training on documents from many sources;
- ▶ Acquire general knowledge about many domains;

Post-training Skills & Capabilities

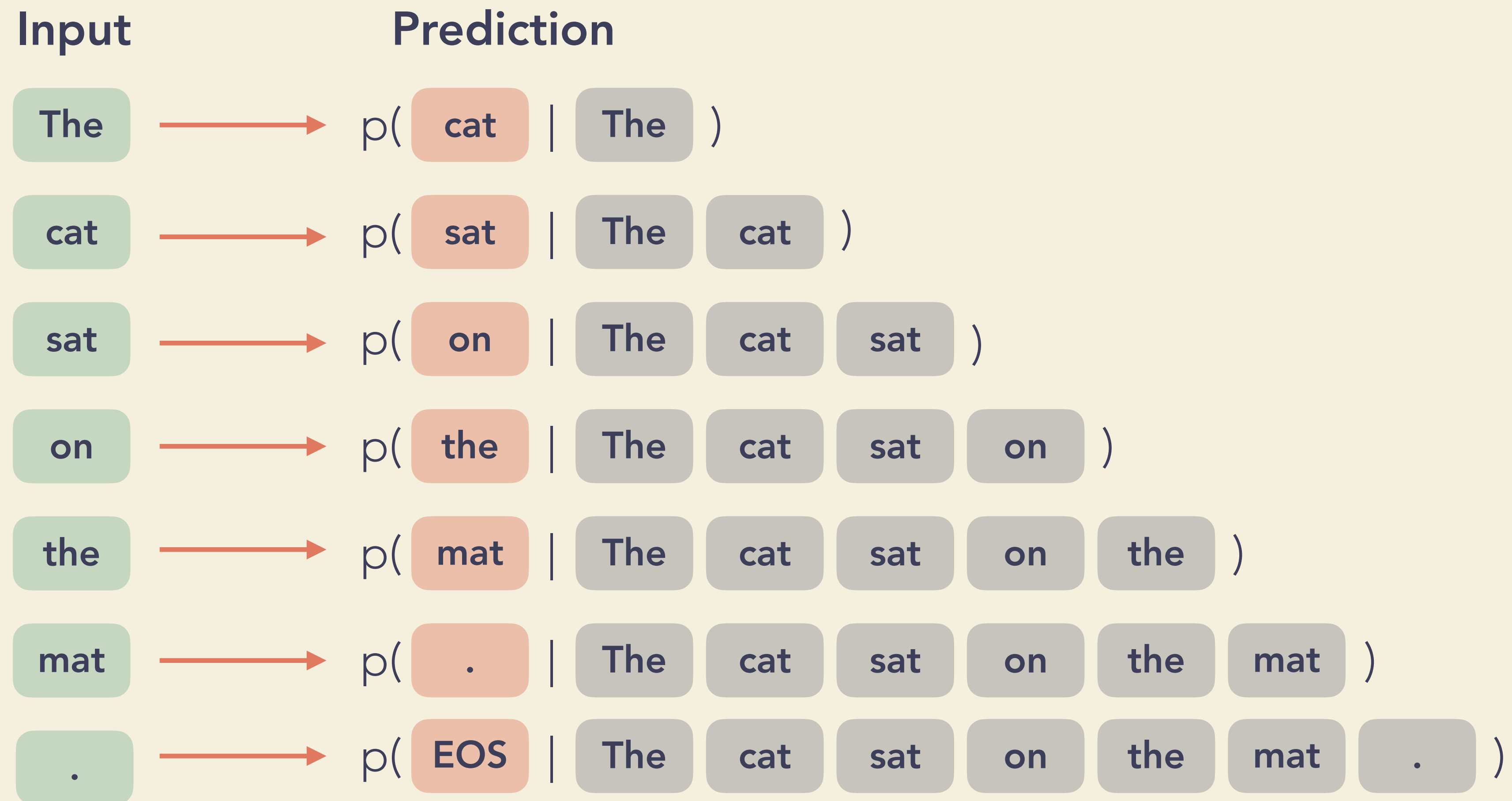
- ▶ Supervised fine-tuning and reinforcement learning on user instructions;
- ▶ Tune capabilities like instruction following, tool usage, or thinking effort.

Pre-training

What do we optimize?

Causal Language Modeling

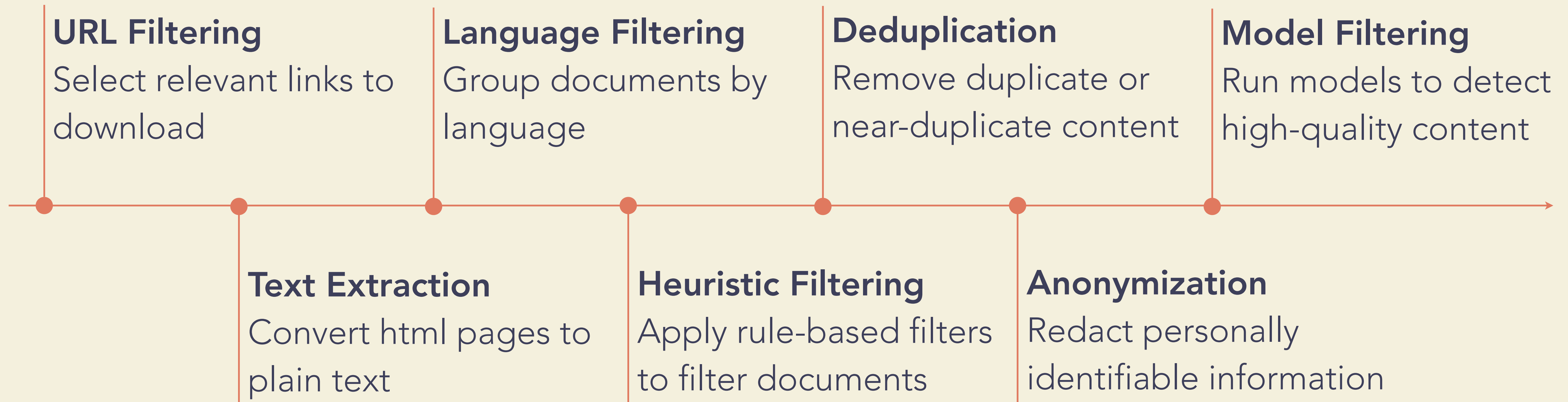
Causal Language Modeling



Predict the next token given the previous context

How do we collect the data?

Collecting web data at scale



Heuristic vs Model-based Filters

Heuristic

Fast rules

- ▶ Transparent and easy to explain;
- ▶ Cheap to run at scale;
- ▶ Hard to capture “fuzzy” concepts like quality.

Model-based

Learned filters

- ▶ Capture more subtle signals (style, coherence, etc);
- ▶ Reduce manual engineering;
- ▶ Hard to inspect, and expensive to run at scale.

What if we need more data?

Generating Synthetic Data at Scale

Seed Corpus

Diverse collection of documents.

Rephrasing

Rewrite the document, possibly improving it.

Question-Answer

Add question-answer pairs to the document.

Summarize

Extract the relevant knowledge in the text.

- ▶ Overcome the finite nature of the web;
- ▶ Repurpose low-quality data as high-quality documents;
- ▶ More control over the data distribution;
- ▶ Improves coverage of *rare* phenomena.

Data Curriculums

“We made (...) adjustments to the pre-training data mix during training to improve model performance (...)”

“on the final 40M tokens, (...) we also adjusted the data mix to upsample data sources of very high quality”

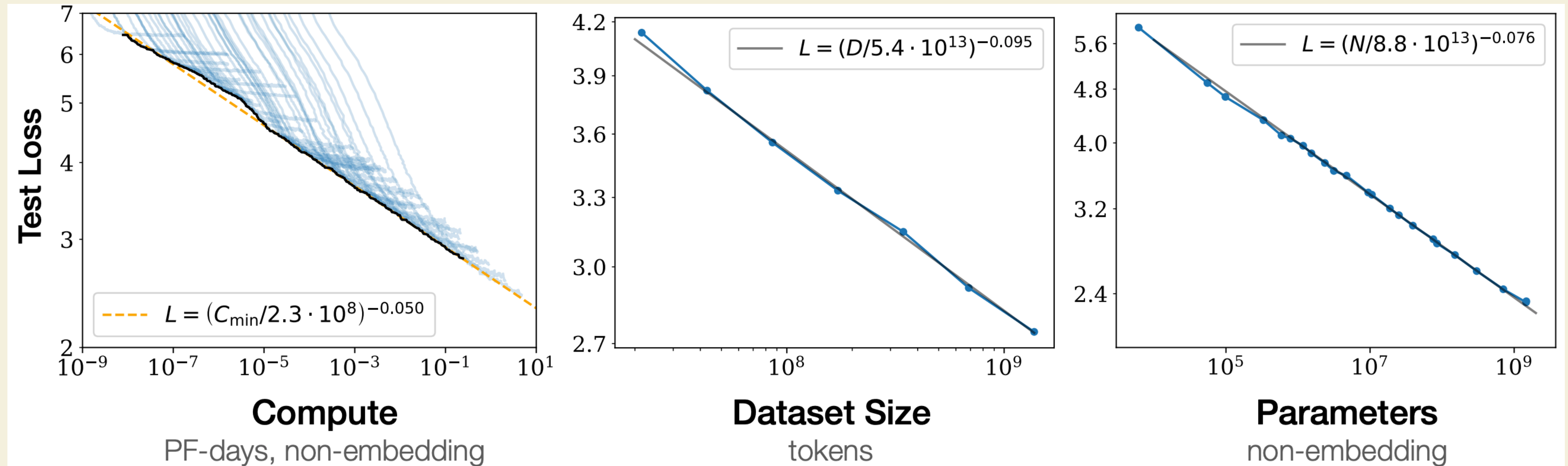
A Versatile Learning Rate Scheduler



- ▶ Pre-training at a constant learning rate;
- ▶ Annealing on high quality data;
- ▶ Doesn't require knowing the number of tokens a-priori;
- ▶ You can resume/extend/change pre-training at any point.

How can we experiment?

Scaling laws



Language models follow scaling laws on the compute budget, dataset size and model size

You can predict the loss of larger models from smaller ones

Compute-optimal models

For a given compute budget, what is the optimal dataset and model size you should use?

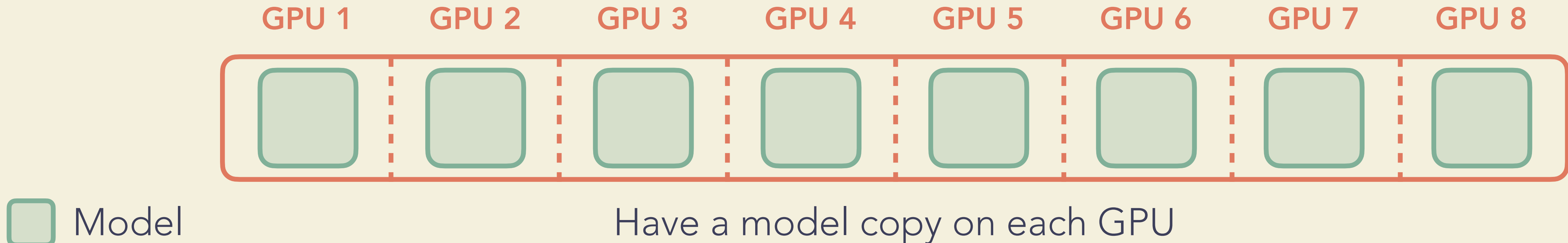
Chinchilla optimal: dataset size should be around 20x model size

In practice: overtrain models to facilitate inference

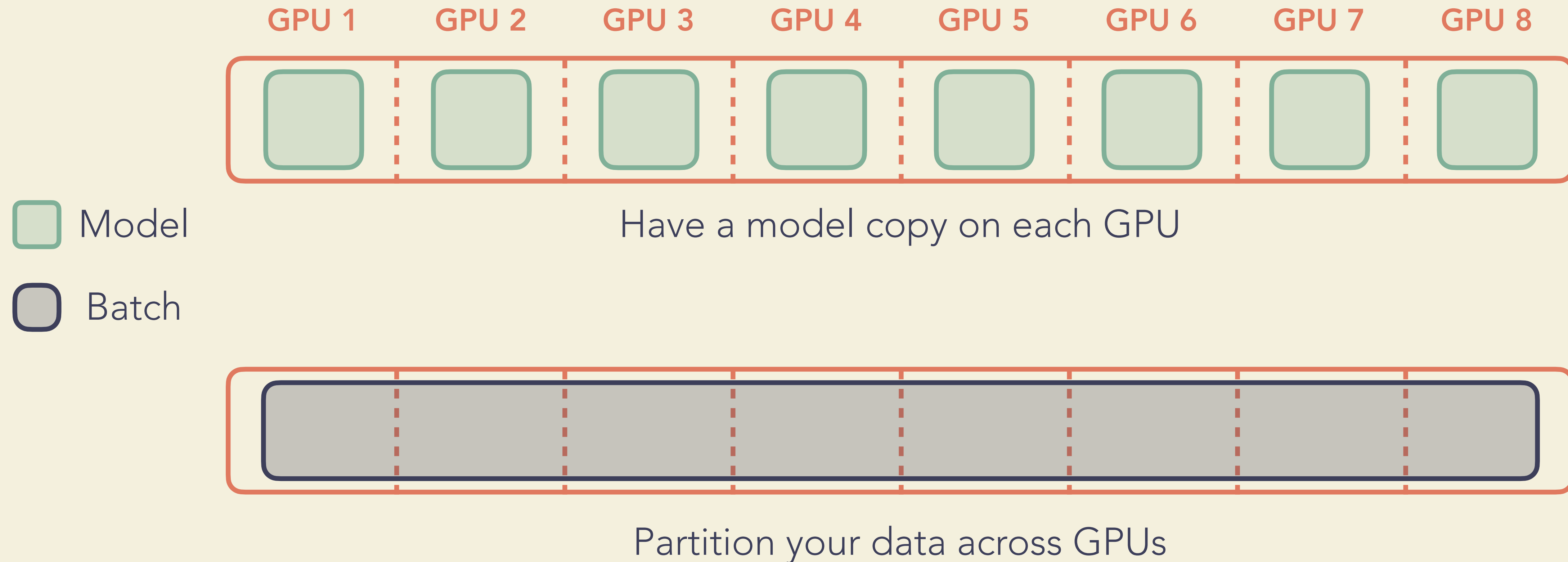
How to train at large scale?

Data Parallelism: Replicating your model

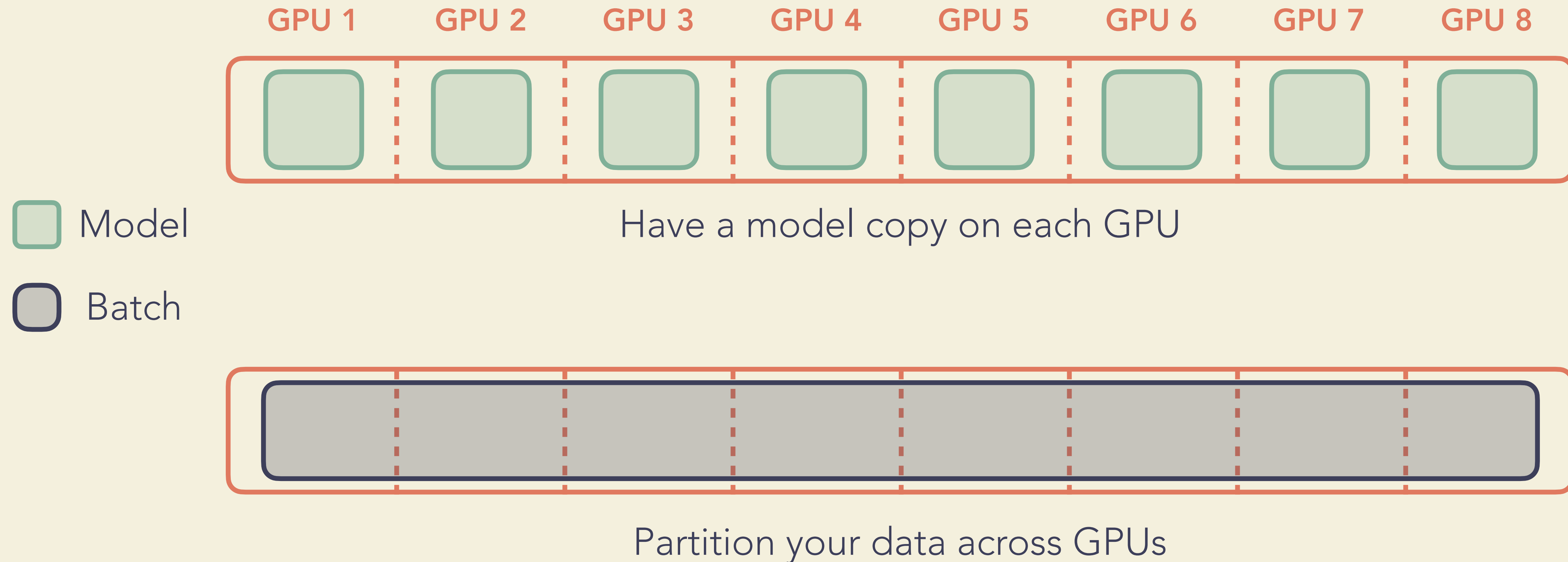
Data Parallelism: Replicating your model



Data Parallelism: Replicating your model



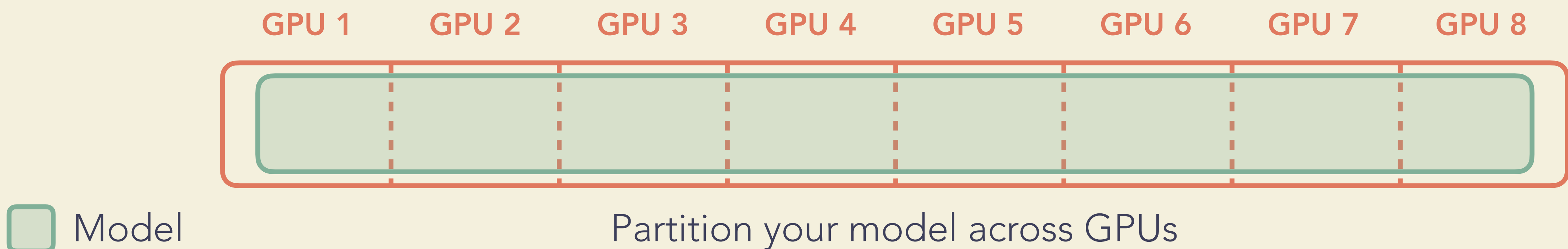
Data Parallelism: Replicating your model



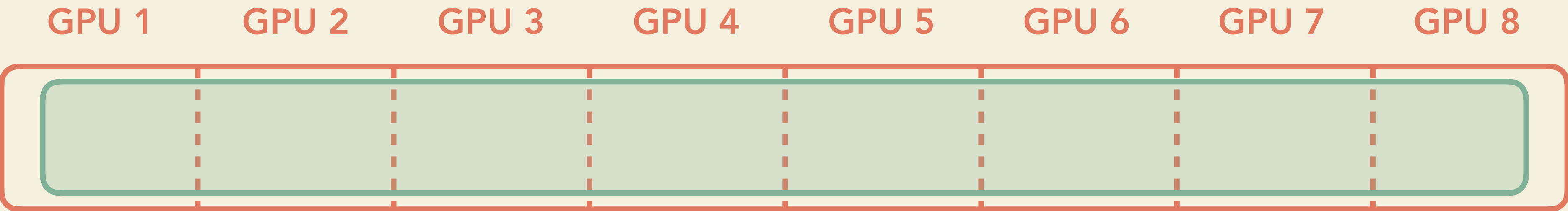
You can train on much larger batch sizes



Model Parallelism: Sharding your model

Model Parallelism: Sharding your model

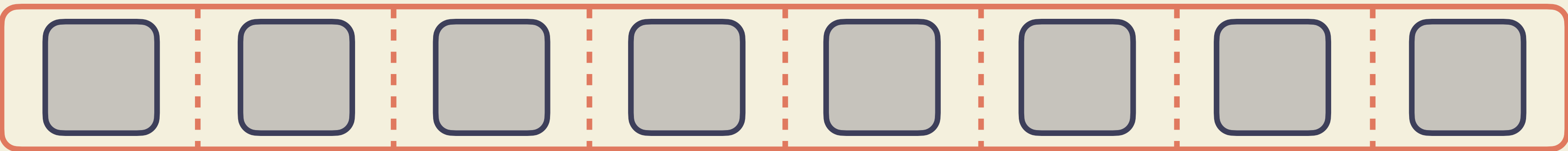


Model Parallelism: Sharding your model



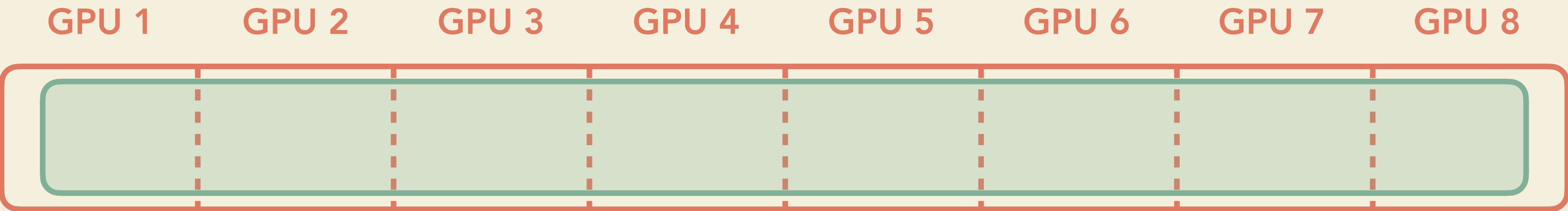
-  Model
-  Batch



Partition your model across GPUs



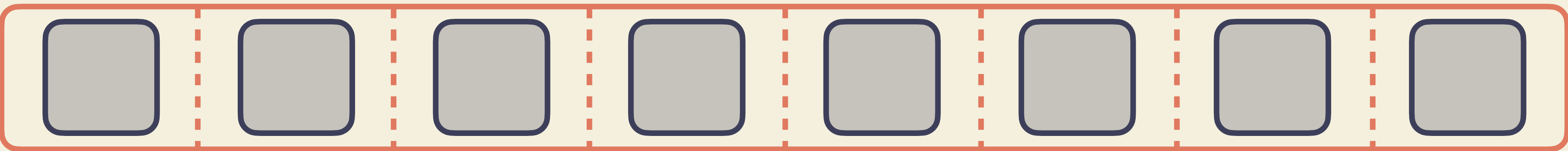
Replicate your data on all GPUs

Model Parallelism: Sharding your model



-  Model
-  Batch

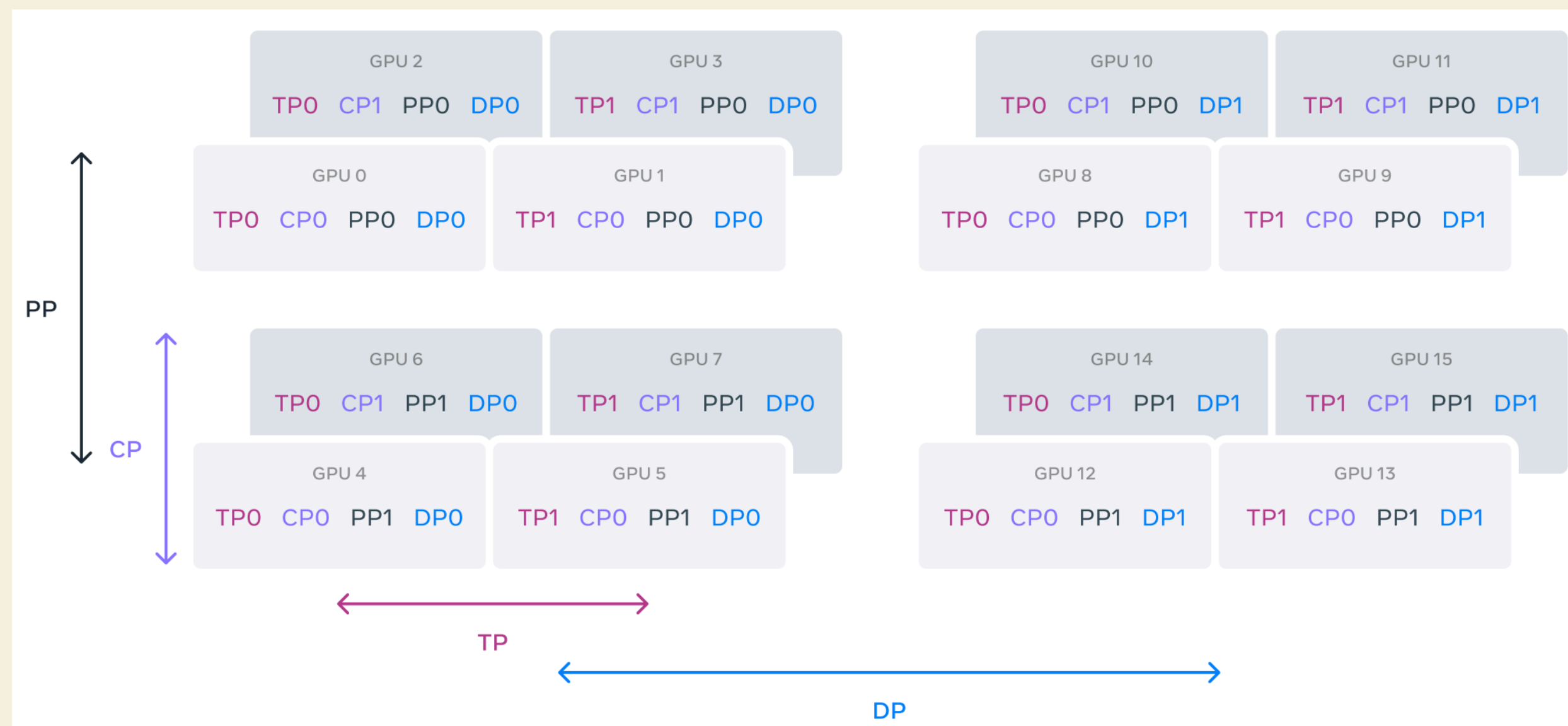
Partition your model across GPUs



Replicate your data on all GPUs

You can train much larger models

4D Parallelism: Combining everything



- **Data Parallel:** Split your batch across GPUs.
- **Tensor Parallel:** Split individual layers of the model.
- **Pipeline Parallel:** Split across layers of the model.
- **Context Parallel:** Split training sequences (for long context).

The hardware lottery

“we find **great unreliability** when it comes to GPU nodes which often fail due to **hardware errors** or **connection issues**.”

- ▶ At large scales, having a gpu failure becomes very common;
- ▶ Having good checkpoint logic is essential to resume training;
- ▶ Automatic monitoring and resuming from failures is becoming very relevant.

How is the model after
pre-training?

How is the model after pre-training?

The sky cracked open just as the first train arrived. *The pressure from the back of the train, the building with its massive windows, and the cabin walls were all falling open. Inside the cabin was a table, with a huge sign, and a table cloth. Some of the walls had been covered with sharp edges, and the railing was partly covered with hair. (...)*

Pre-trained models are powerful for auto-completion tasks

How is the model after pre-training?

Instruction: Sort the following list of numbers in ascending order and answer **ONLY** with the sorted list.

List: 5, 2, 9, 1

Answer: 9, 2, 9, 1

Number of strings to make: 1

Number of numbers to count: 9

(...)

They are not necessarily good at following user instructions

How is the model after pre-training?

Review: 'I loved this movie, it was fantastic!' Sentiment: POSITIVE

Review: 'This was the worst film I have ever seen.' Sentiment: NEGATIVE

Review: 'The plot was boring and the acting was terrible.' Sentiment: NEGATIVE

Review: 'A good ending.' Sentiment: NEGATIVE

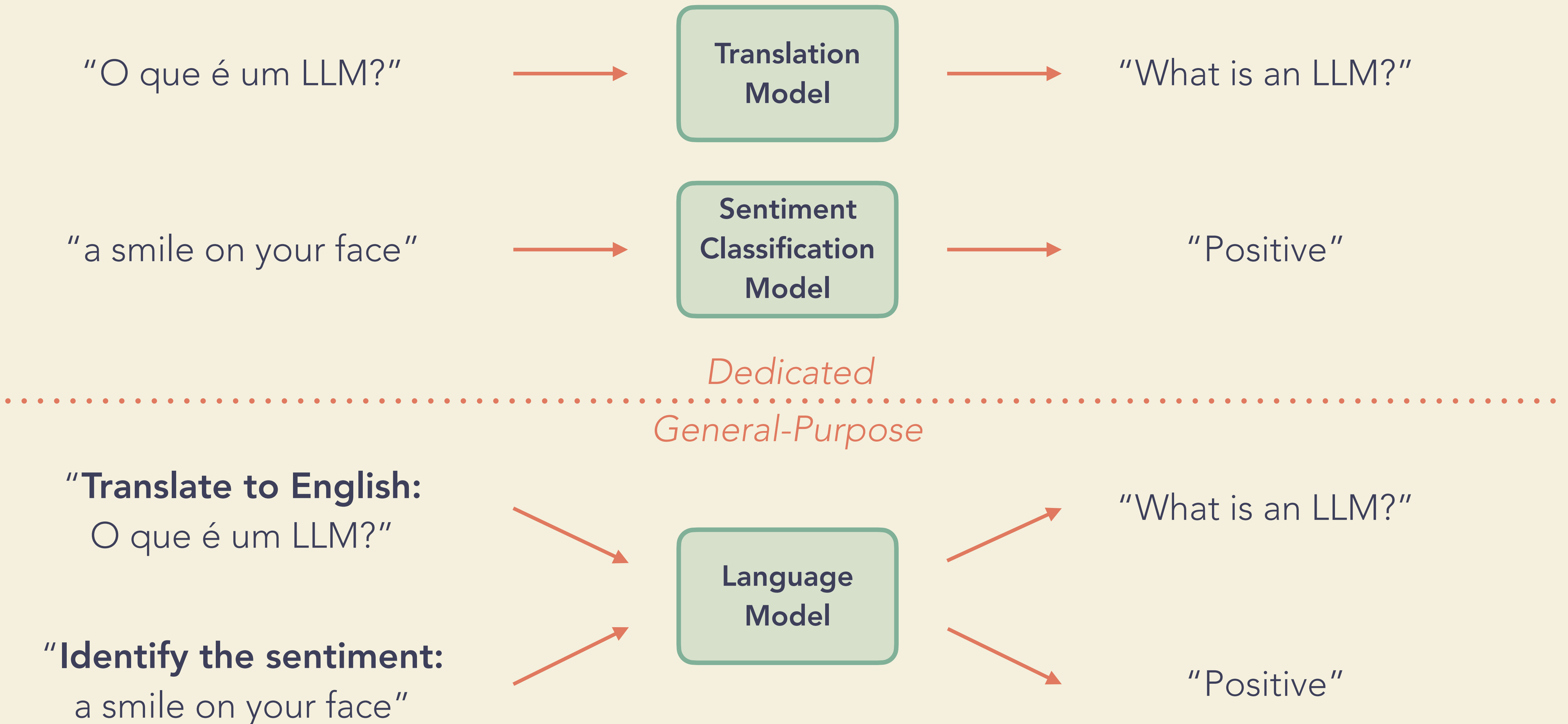
(...)

But they can solve tasks through in-context learning!

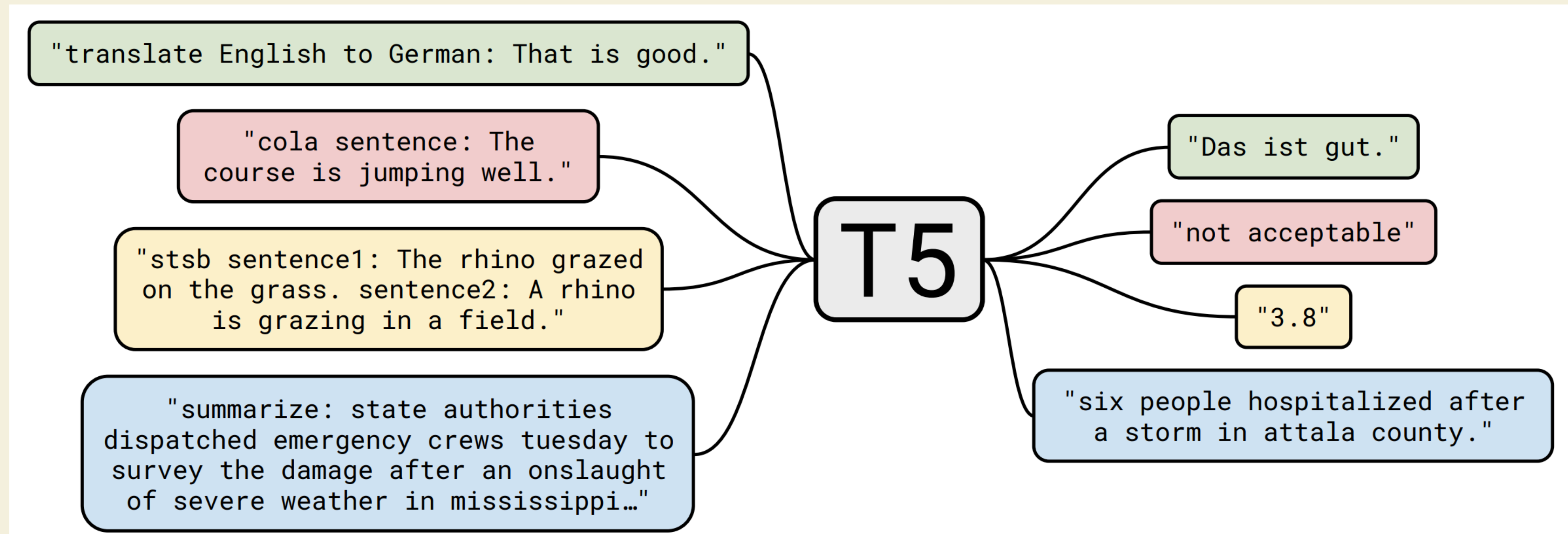
Post-training

How can a model perform many
tasks?

Framing tasks as text problems

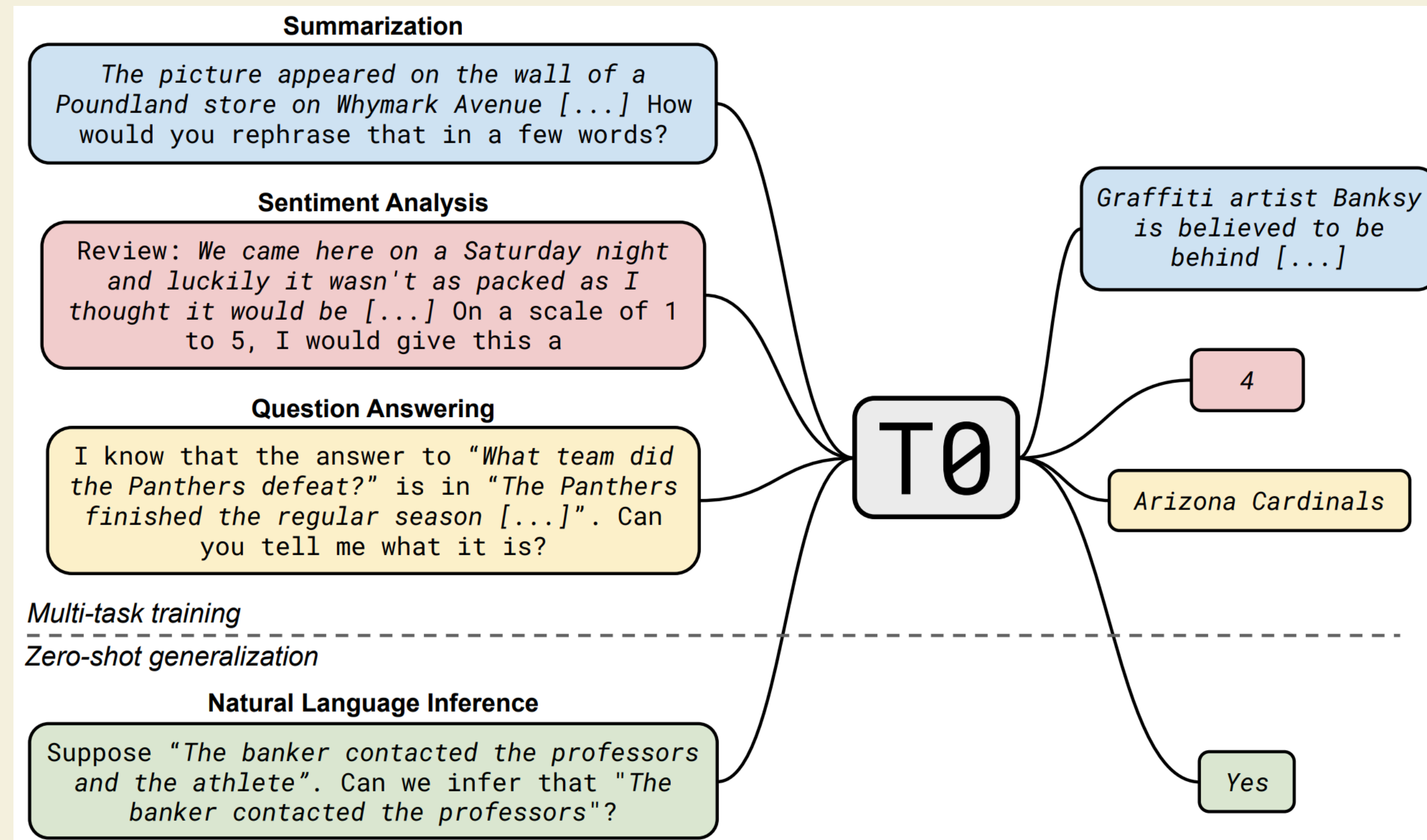


Framing tasks as text problems



Fine-tuned languages models can solve multiple tasks by **describing the task in the input**.

Framing tasks as text problems



Training on multiple tasks enables solving **previously unseen tasks**.

Aligning with human feedback

More than solving many tasks,
we want models that **follow user intent**

How to format a conversation?

Formatting a conversation as a text

Formatting a conversation as a text

User

What is a pastel de nata?

Assistant

A pastel de nata is a Portuguese ...

User

Where can I try them?

Assistant

You can find them throughout ...

Formatting a conversation as a text

User

What is a pastel de nata?

Assistant

A pastel de nata is a Portuguese ...

User

Where can I try them?

Assistant

You can find them throughout ...



<|im_start|>user

What is a pastel de nata?<|im_end|>

<|im_start|>assistant

A pastel de nata is a Portuguese...<|im_end|>

<|im_start|>user

Where can I try them?<|im_end|>

<|im_start|>assistant

You can find them throughout...<|im_end|>

Formatting a conversation as a text

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Roles

`<|im_start|>user`
What is a pastel de nata?`<|im_end|>`
`<|im_start|>assistant`
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`<|im_start|>user`
Where can I try them?`<|im_end|>`
`<|im_start|>assistant`
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`<|im_start|>assistant`
You can find them throughout...`<|im_end|>`

Special delimiter tokens

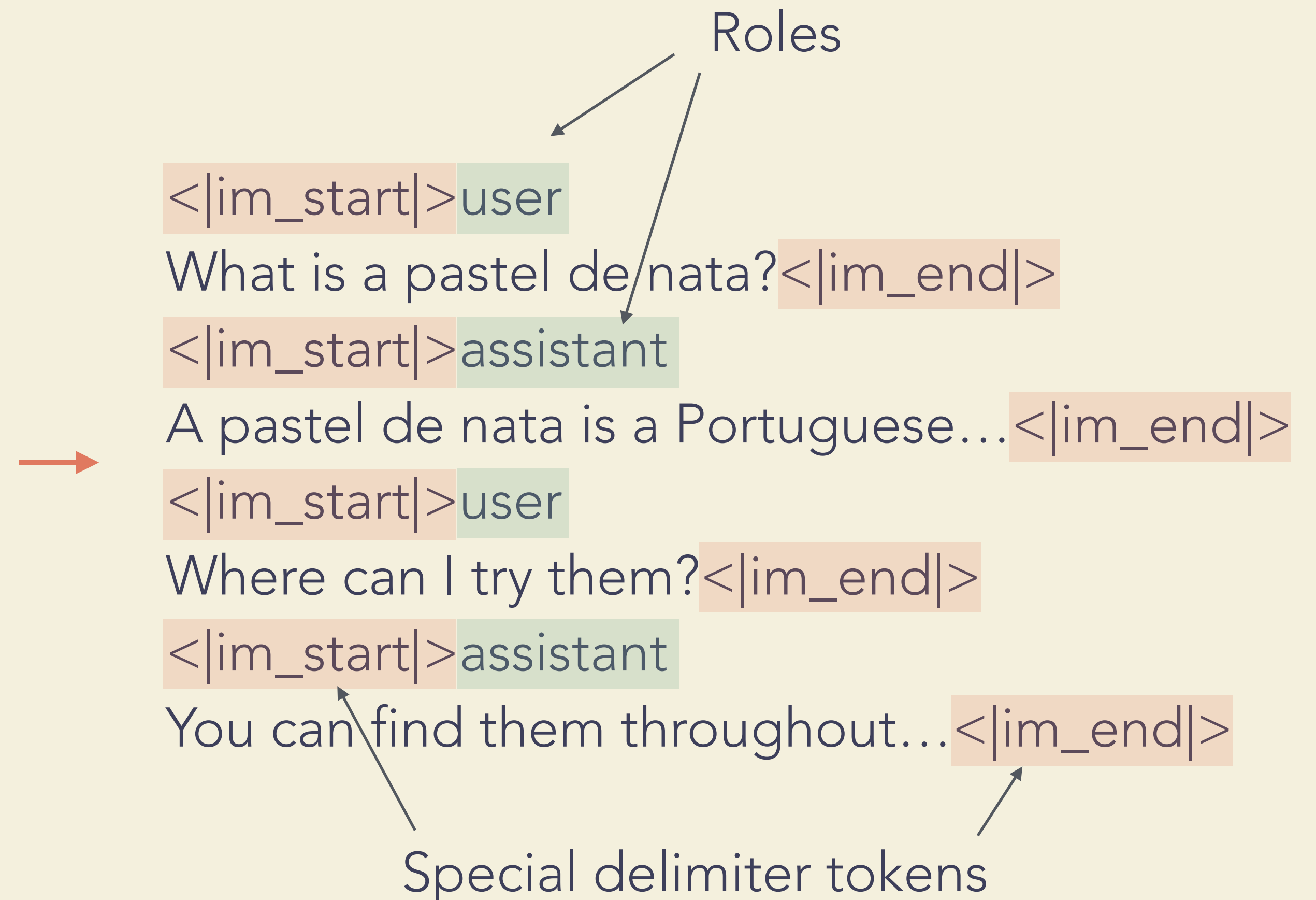
Formatting a conversation as a text

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What is a pastel de nata?

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Where can I try them?

Assistant
You can find them throughout ...



The chat template is the model "interface," you can specify special directives, tools, etc.

How to go about post-training?

A three step process

Step 1: Supervised fine-tuning

Collect demonstration data and train a supervised policy

Step 3: Optimize your policy

Optimize a policy against the reward model using reinforcement learning.

Step 2: Train a reward model

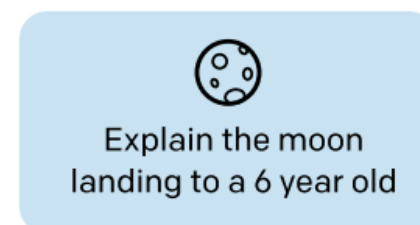
Collect comparison data, and train a reward model.

Step 1: Supervised fine-tuning

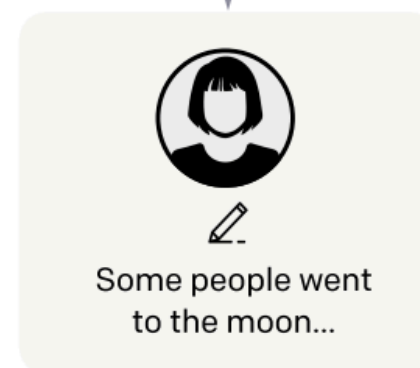
Step 1

Collect demonstration data, and train a supervised policy.

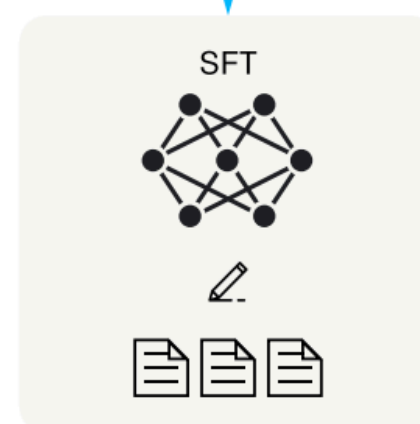
A prompt is sampled from our prompt dataset.



A labeler demonstrates the desired output behavior.



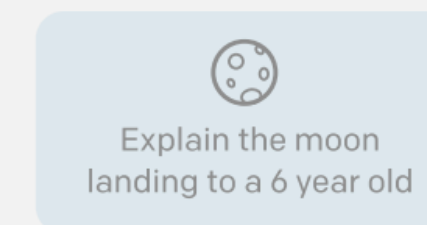
This data is used to fine-tune GPT-3 with supervised learning.



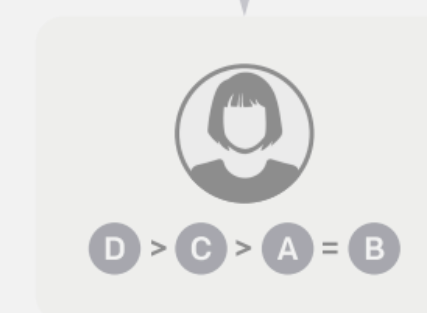
Step 2

Collect comparison data, and train a reward model.

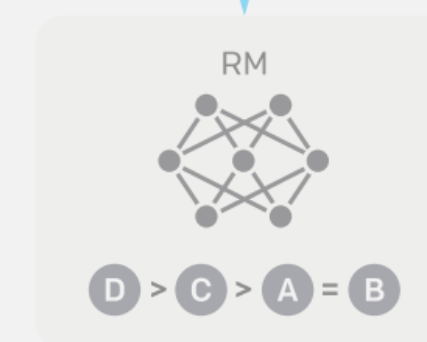
A prompt and several model outputs are sampled.



A labeler ranks the outputs from best to worst.



This data is used to train our reward model.



Step 3

Optimize a policy against the reward model using reinforcement learning.

A new prompt is sampled from the dataset.



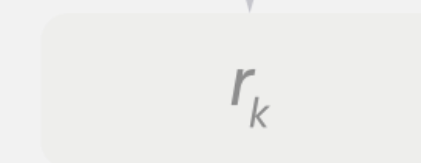
The policy generates an output.



The reward model calculates a reward for the output.



The reward is used to update the policy using PPO.



Quality and Diversity: The guiding principles

“We build TowerBlocks prioritizing data diversity and quality.”

TowerLLM Paper

“We construct a large-scale instruction-tuning dataset spanning diverse domains, guided by two core principles: maximizing prompt diversity and ensuring high response quality.”

Kimi K2 Technical Report

Alves et al. Tower: An Open Multilingual Large Language Model for Translation-Related Tasks. 2024

Kimi Team. Kimi K2: Open Agentic Intelligence. 2025

Collecting instructions

Human-written

Ask human annotators

- ▶ High quality;
- ▶ Closest to deployment scenarios;
- ▶ Expensive, in particular for specialized tasks

Templated tasks

Repurpose datasets

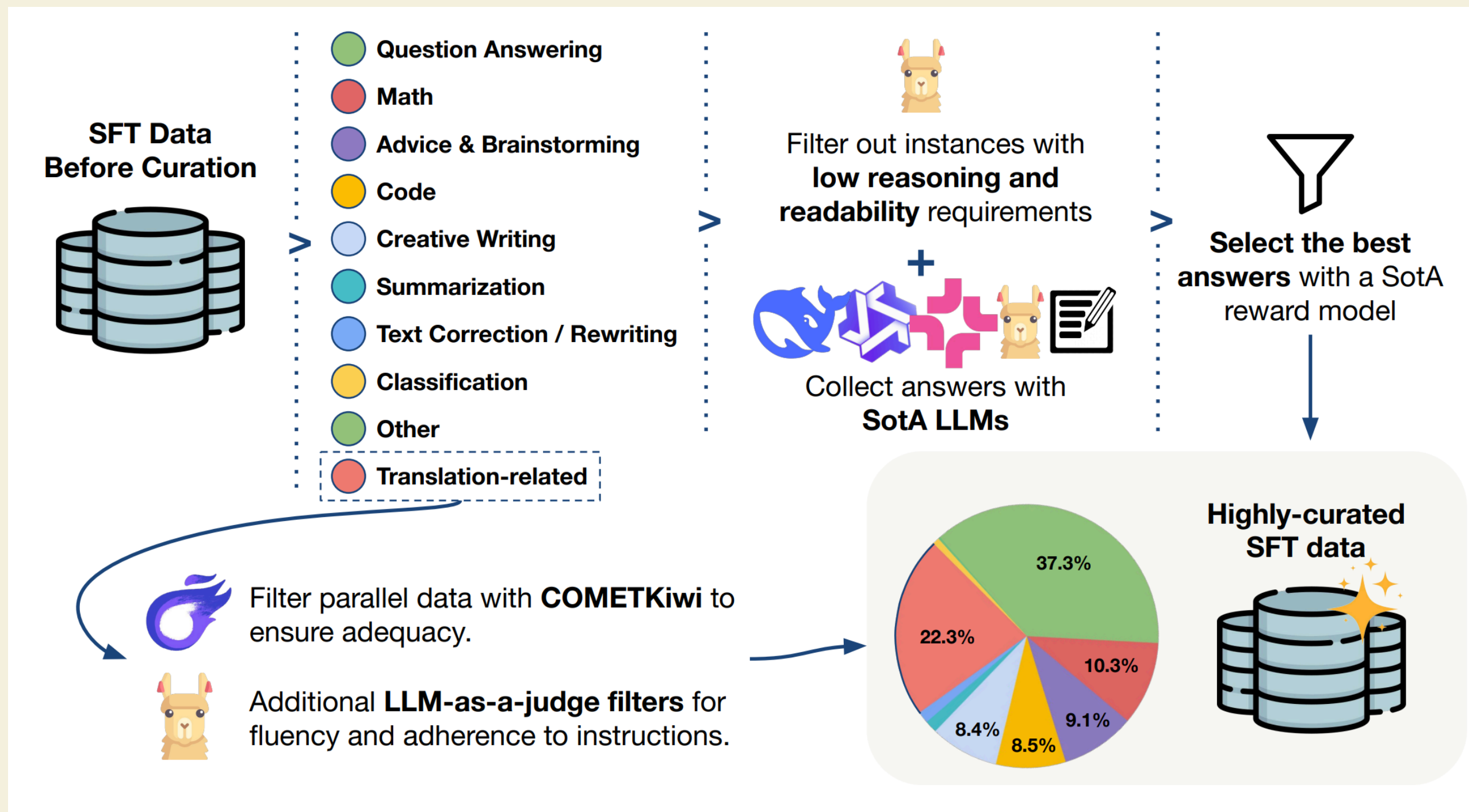
- ▶ Very cheap and easy;
- ▶ Best for targeting a particular task;
- ▶ Hard to scale to many tasks and templates.

Synthetic

Generate with models

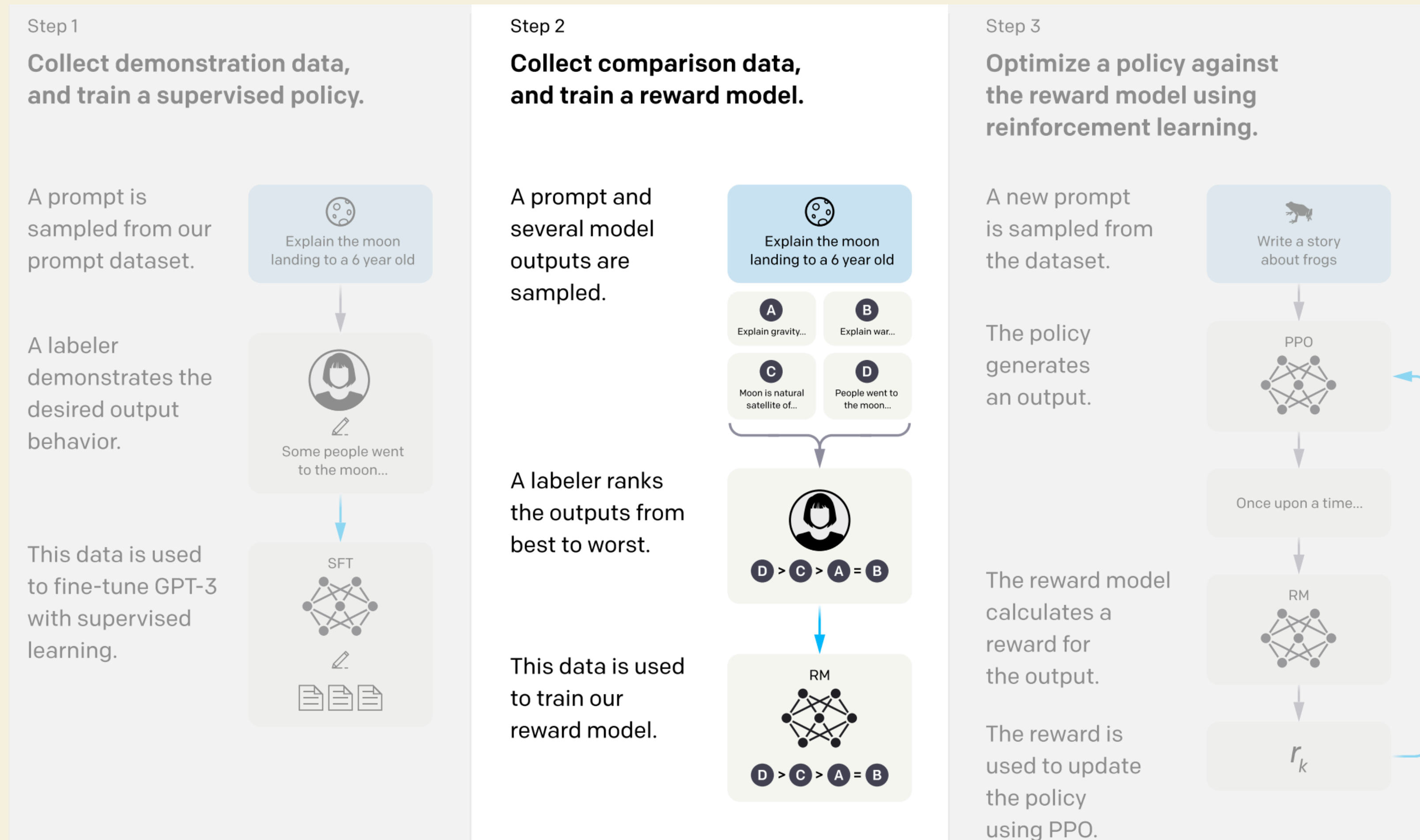
- ▶ Cheap and scalable;
- ▶ Easy to address specific scenarios;
- ▶ Models tend to not diversify much.

Generating responses for training

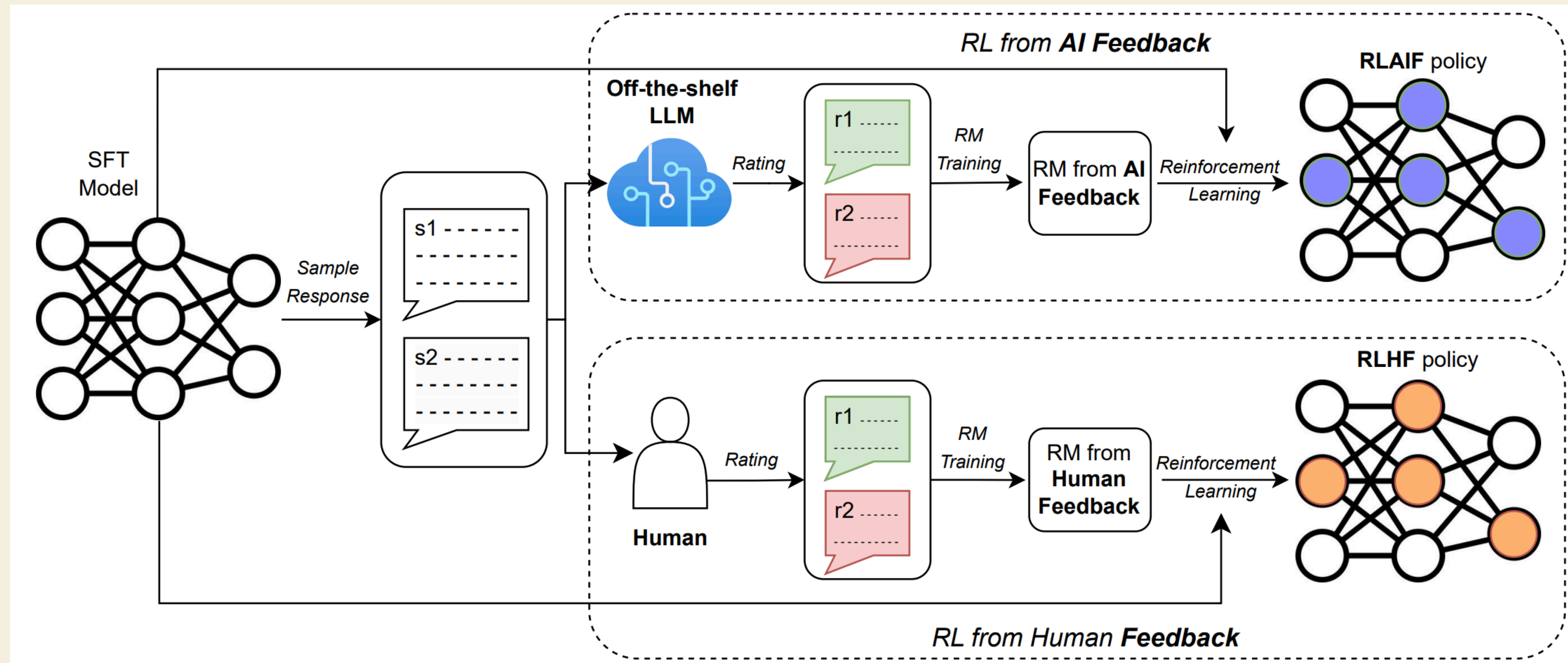


- ▶ Humans are usually lazy in their responses.
- ▶ We usually use models to create responses for fine-tuning.
- ▶ To improve quality, we usually generate with multiple models and select the best one.

Step 2: Training a reward-model

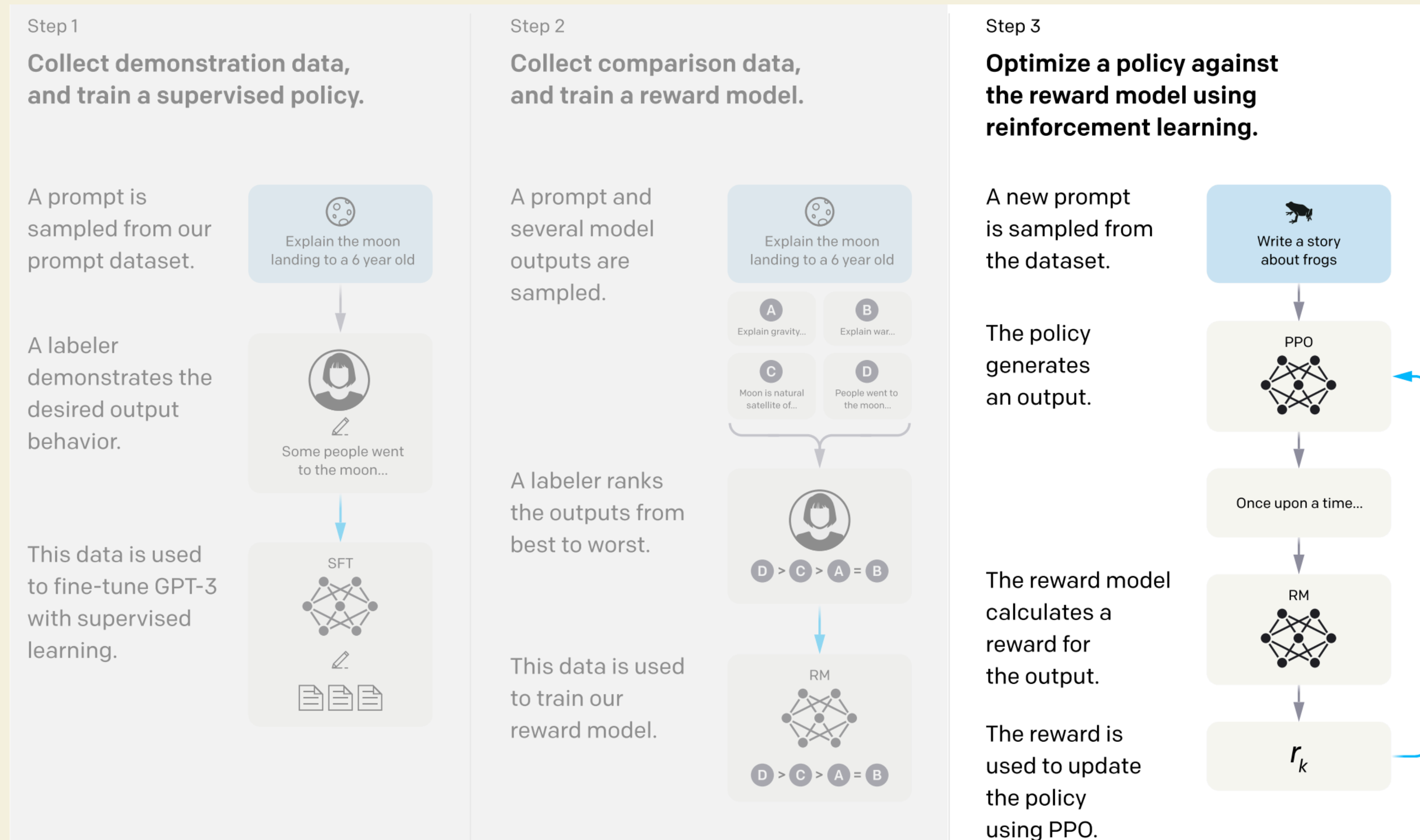


Collecting preference pairs



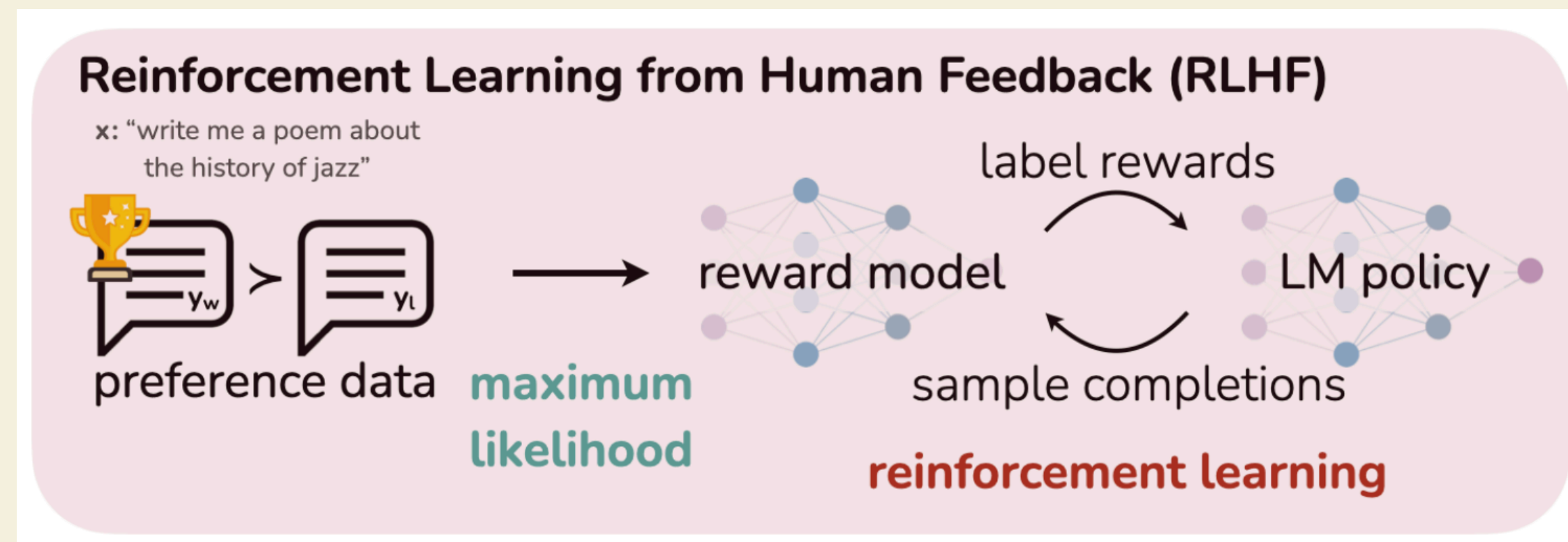
AI feedback is a relatively cheap way to obtain large scale feedback

Step 3: Optimizing your policy

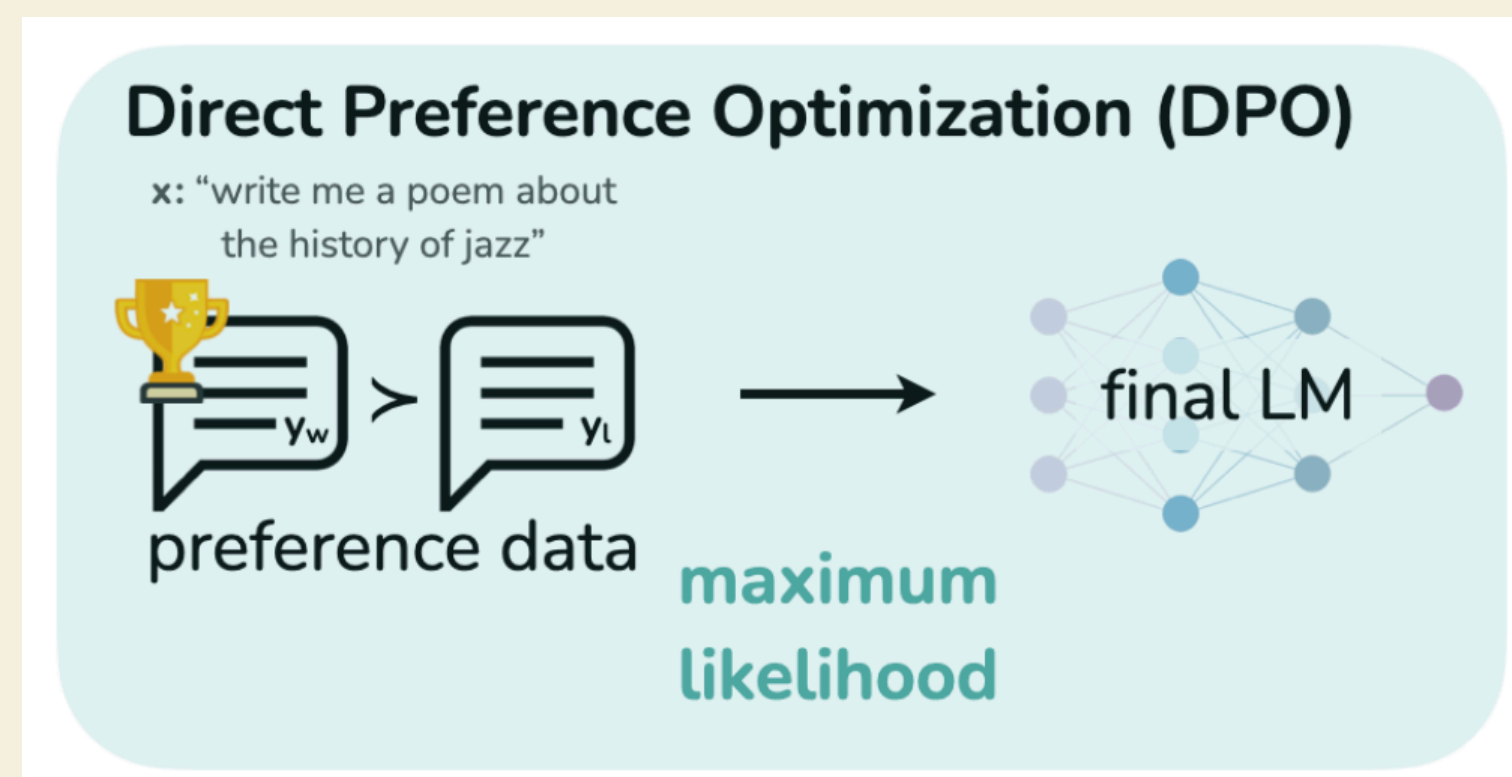


Implicit reward models (DPO)

Instead of:



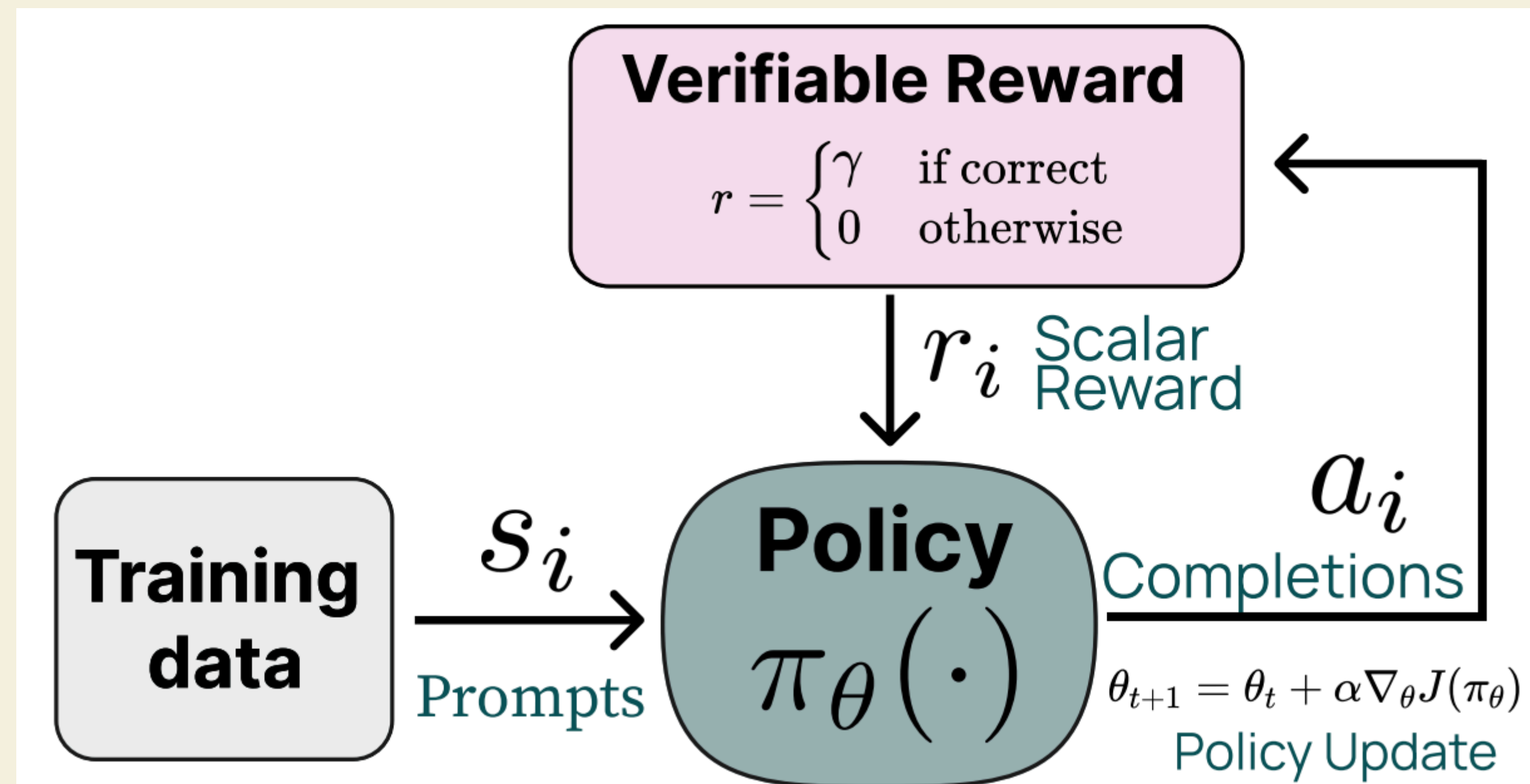
do



- ▶ Your language model functions as an (implicit) reward model;
- ▶ Only requires preference pairs:
- ▶ Avoids training a reward model;
- ▶ More stable than training a reward model and optimizing it with PPO.

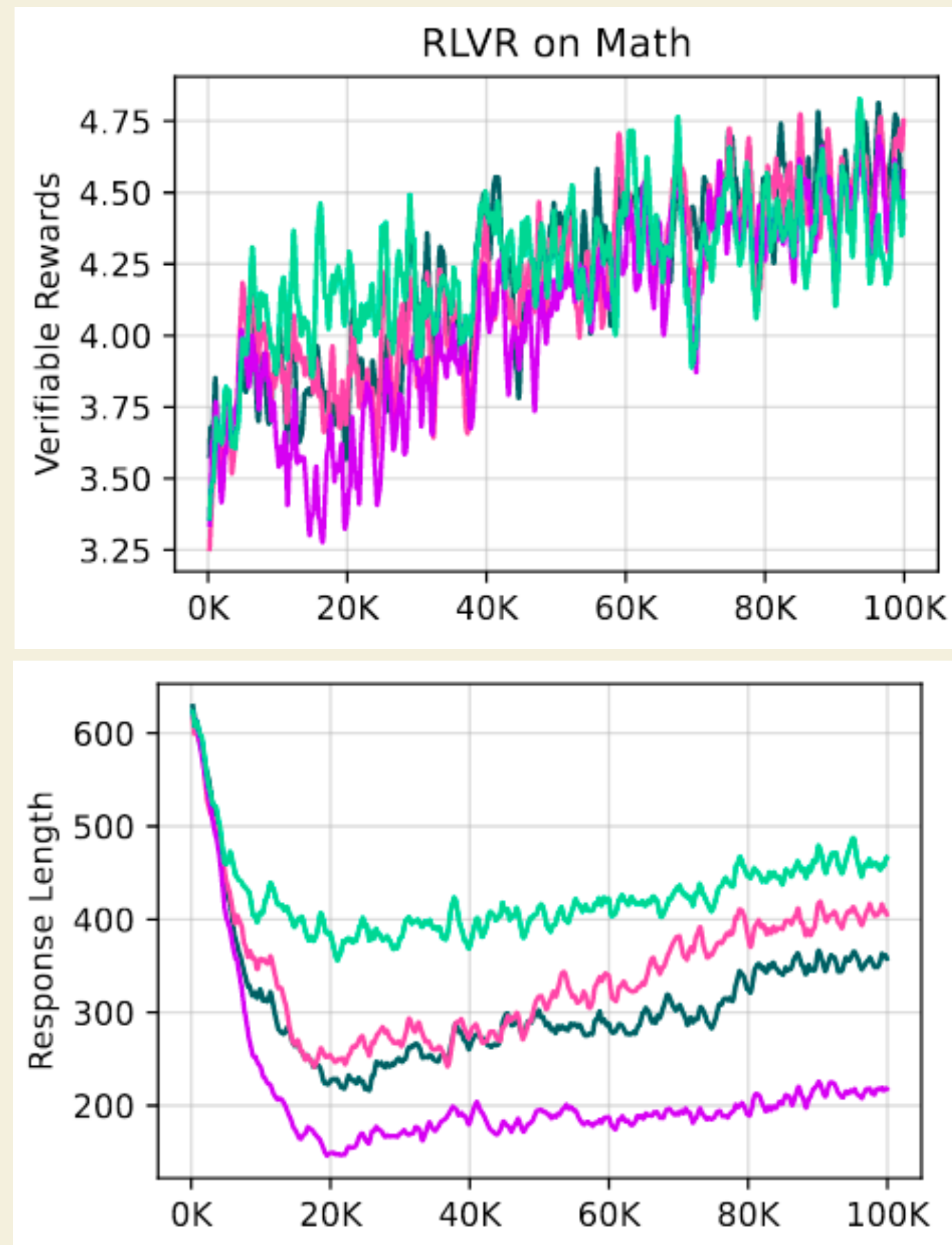
What about these recent
reasoning models?

Verifiable rewards



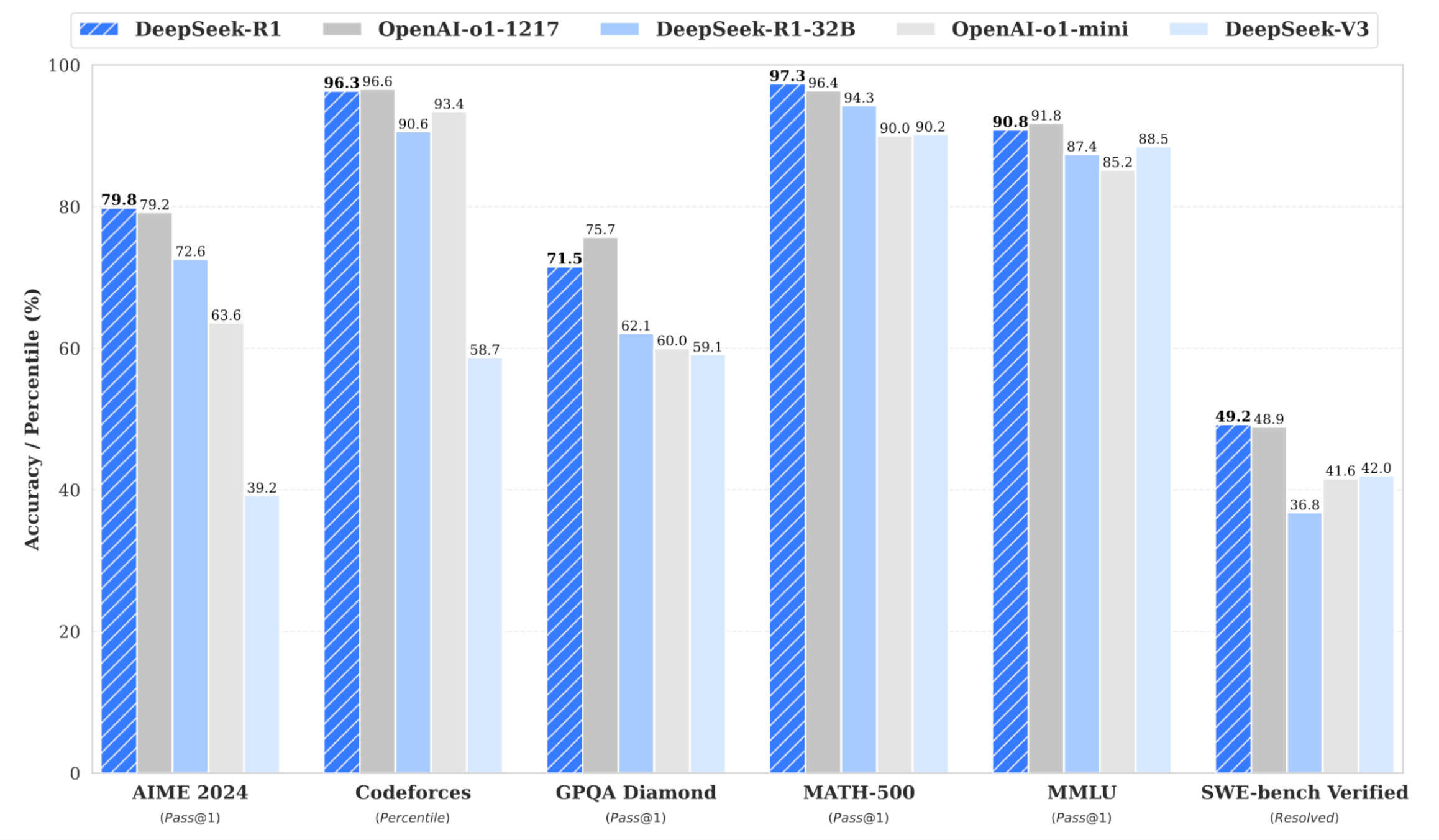
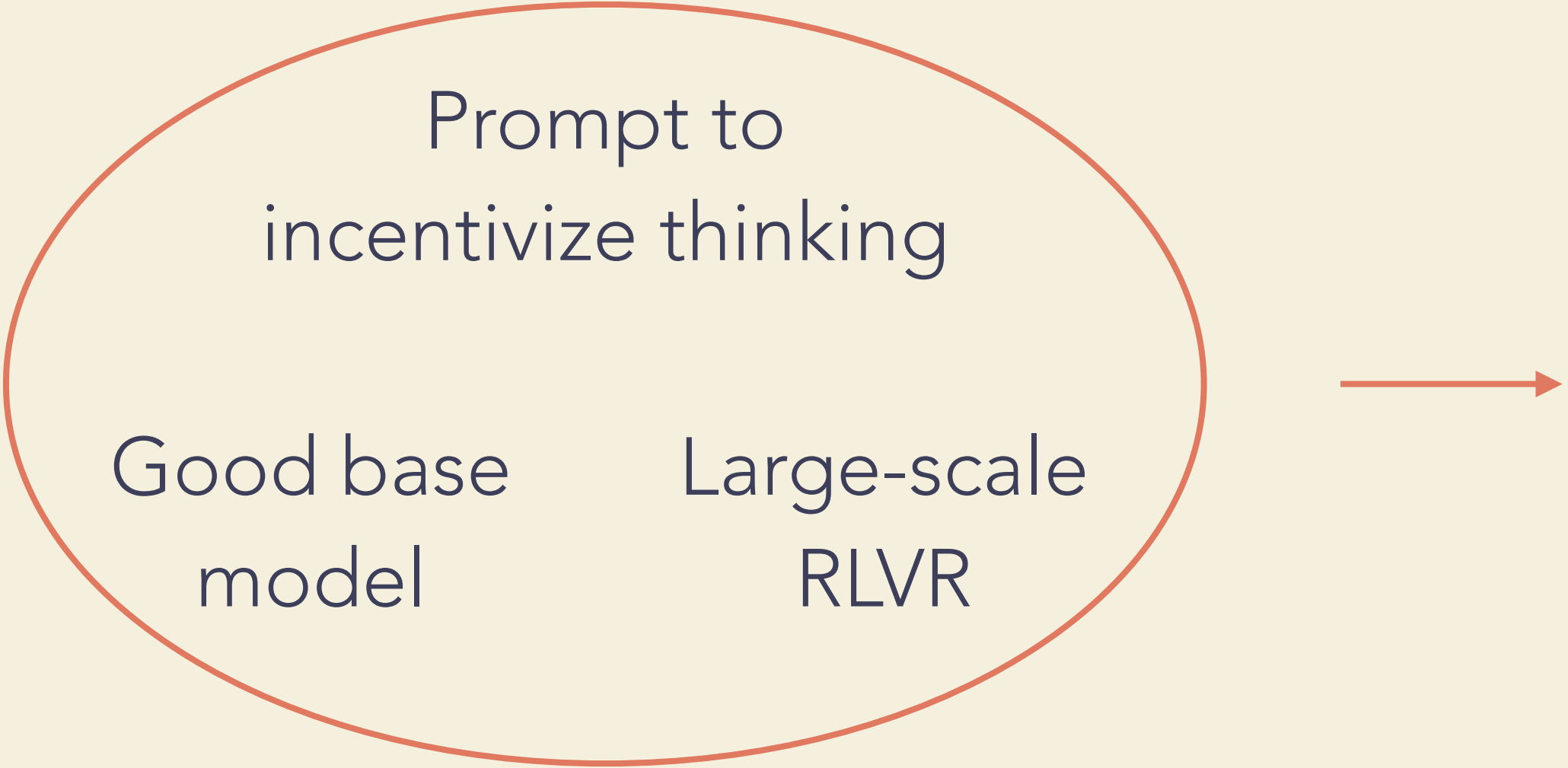
- For some domains (e.g. math or code) you can “easily” validate answers with a function;
- Instead of using a reward model, you can optimize that function.

Verifiable rewards

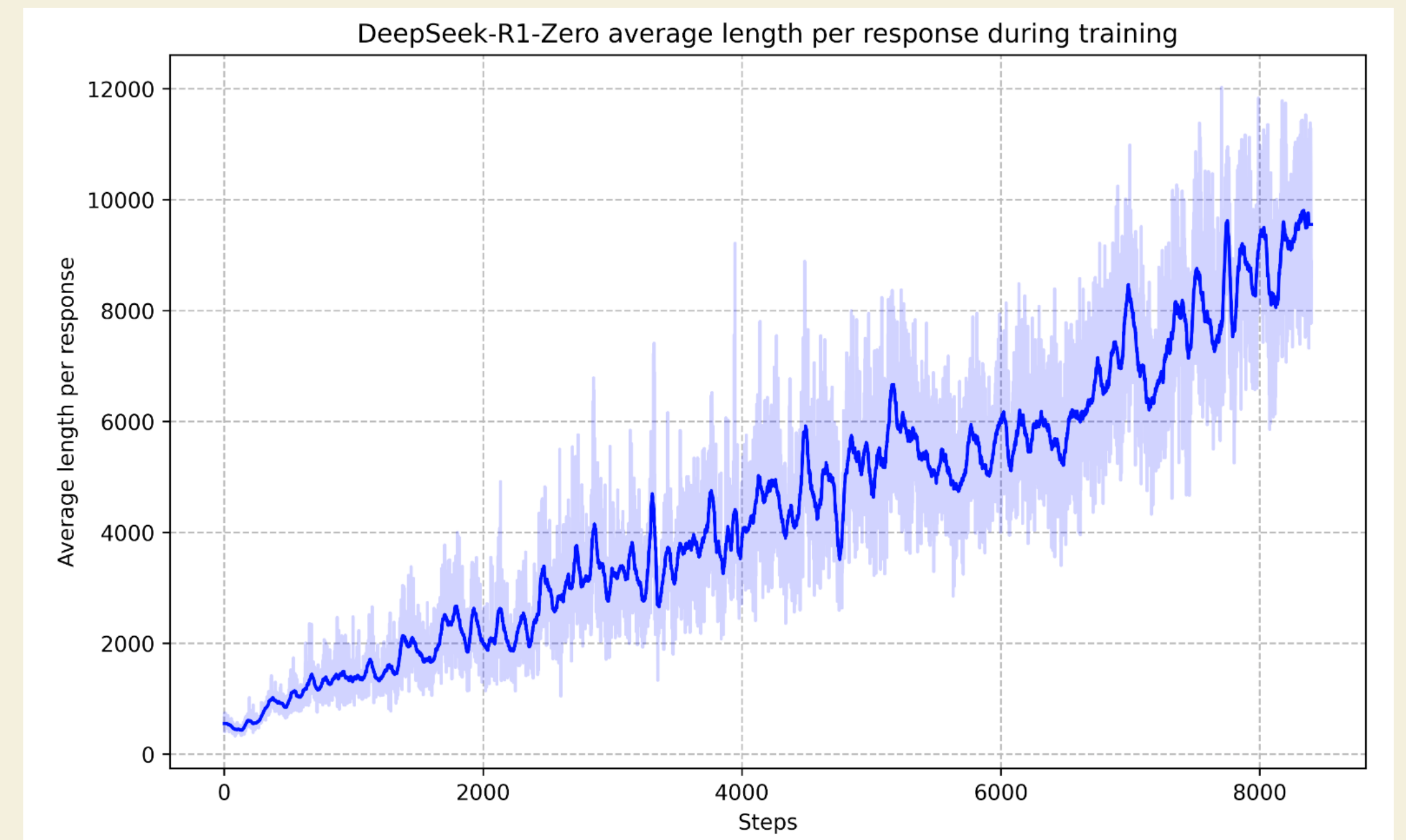
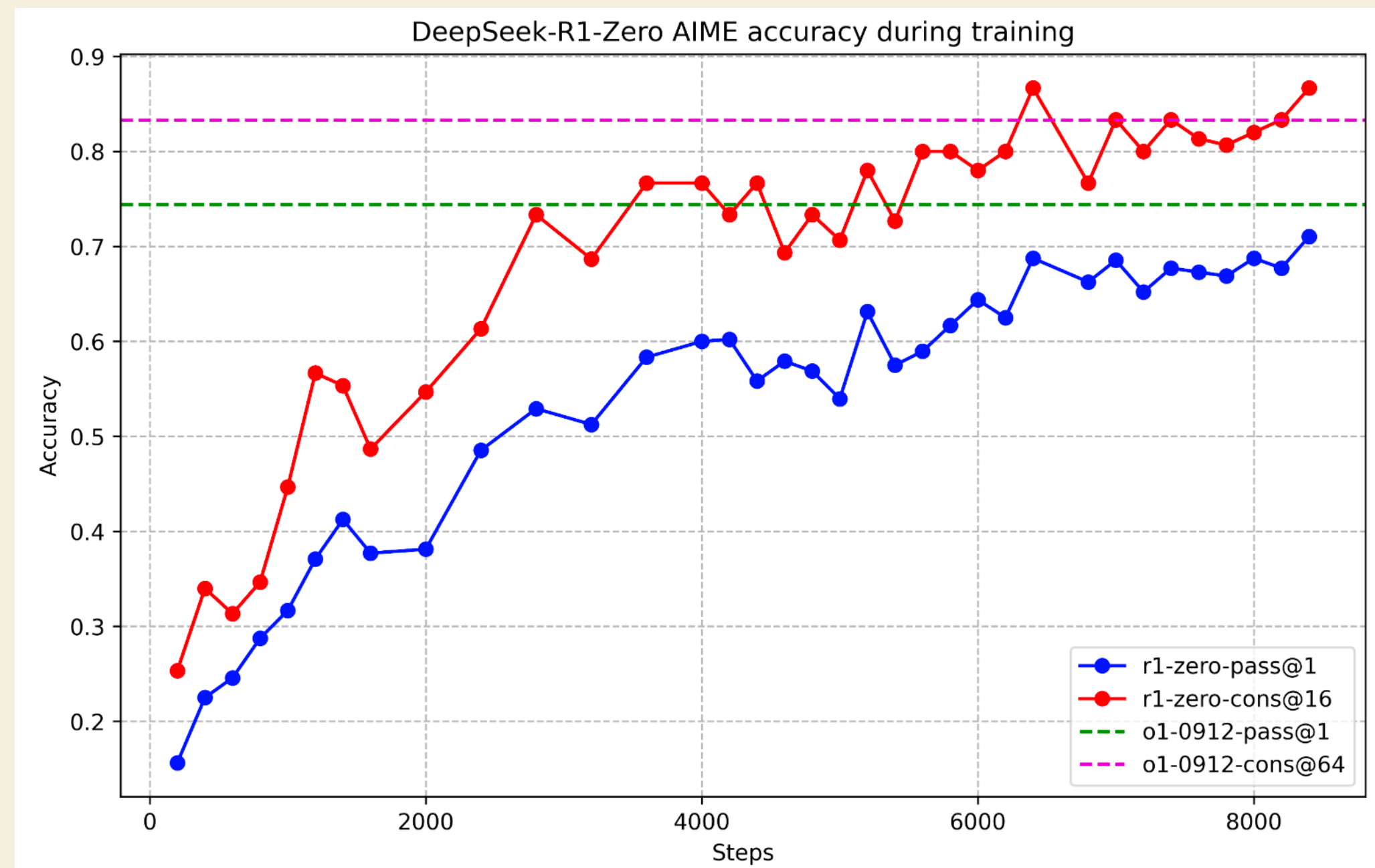


- ▶ RLVR improves capabilities such as math, code, instruction following;
- ▶ Models learn to think for a bit more.

Reasoning models



Reasoning models



As the model improves performance, it learns to “think” for longer

What about safety?

Helpful or harmful?

User

"I'm thinking of putting all my savings into Ethereum because a friend told me it will 5× next year. Should I do it?"

Assistant

Cryptocurrencies can yield high returns. If you want exposure, here's a typical strategy: put everything into ETH and stake it to maximize yield...

... and the user loses all their savings

Helpful or harmful?

User

"I'm thinking of putting all my savings into Ethereum because a friend told me it will 5× next year. Should I do it?"

Assistant

I cannot talk about financial decisions. I cannot provide investment information.

... and the user is left wondering what to do

Helpful or harmful?

User

"I'm thinking of putting all my savings into Ethereum because a friend told me it will 5× next year. Should I do it?"

Assistant

Investing in a single asset can be very risky. I can't tell you what to invest in, but I can explain concepts like diversification, risk tolerance,...

Provides information, but warns about the risks!

When designing a model, we need to balance between helpfulness and harmlessness

Evaluation

Capabilities

What does the model know?
Can it reason?

Alignment

How does the model behave?
Is it helpful? Is it safe?

Instruction-following

How well does the model
follow instructions?

Factuality

Does it hallucinate? Does it
know when it is wrong?

Multi-turn

How does the model handle
long conversations?

Dimensions of evals

And many more...

First... start with the vibes

*How does it feel to
talk to the model?*






- ▶ Similar to “look at your models’ outputs”
- ▶ You will catch a lot of errors;
- ▶ You will avoid expensive evals with strange results;

Disclaimer: Please don’t rely only on vibe-evals

Chatbot Arena: Scaling human evaluation

📄 Text

🕒 3 days ago

Rank ↑↓	Model ↑↓	Score ↓	Votes ↑↓
1	 gemini-3-pro	1495 ⓘ	5,471
2	 grok-4.1-thinking	1481 ⓘ	5,822
3	 grok-4.1	1462 ⓘ	5,825
4	 gpt-5.1-high	1454	4,980
5	 gemini-2.5-pro	1451	67,956

- ▶ Collect paired comparisons between models at scale.
- ▶ Create rankings based on gathered feedback.
- ▶ Subcategories to evaluate different capabilities.

LLM-as-a-Judge: Cheaper “human” evals

Given the query below, which of the following responses is better?

Query: ...

Response A: ...

Response B: ...

- ▶ LLM as a judge can be run easily at scale.
- ▶ LLMs have difficulty giving scores and exhibit several biases.
- ▶ Is advisable to rely on comparisons, or structured criteria.

To conclude

How to build an open LLM?

Pre-training Knowledge

- ▶ Self-supervised training on documents from many sources;
- ▶ Acquire general knowledge about many domains;

Post-training Skills & Capabilities

- ▶ Supervised fine-tuning and reinforcement learning on user instructions;
- ▶ Tune capabilities like instruction following, tool usage, or thinking effort.