

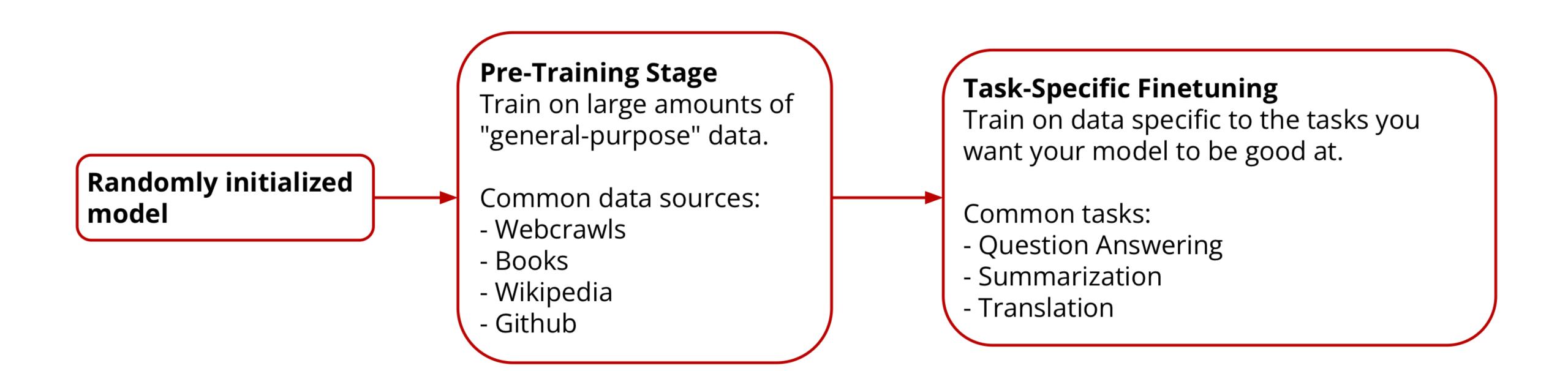
Parameter-Efficient Tuning and Evaluation

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Oct 3, 2025

Review: Pretraining -> Fine-Tuning

Paradigm shift around 2018



Review: GPT-1

- Pre-train a decoder-only LM with a language modelling objective.
- Finetune once per NLP task

Table 2: Experimental results on natural language inference tasks, comparing our model with current state-of-the-art methods. 5x indicates an ensemble of 5 models. All datasets use accuracy as the evaluation metric.

Method	MNLI-m	MNLI-mm	SNLI	SciTail	QNLI	RTE
ESIM + ELMo [44] (5x)	-	_	89.3	_	-	-
CAFE [58] (5x)	80.2	79.0	89.3	-	-	-
Stochastic Answer Network [35] (3x)	80.6	<u>80.1</u>	-	-	-	-
CAFE [58]	78.7	77.9	88.5	<u>83.3</u>		
GenSen [64]	71.4	71.3	_	-	82.3	59.2
Multi-task BiLSTM + Attn [64]	72.2	72.1	-		82.1	61.7
Finetuned Transformer LM (ours)	82.1	81.4	89.9	88.3	88.1	56.0

Review: Disadvantage of Fine-Tuning for Each Task

- One model per task is fine for small models, but not for today's big ones.
 - Training is expensive
 - Overfitting on small datasets
 - Storing one model for each task is expensive

Solutions

- Avoid fine-tuning entirely
 - In-context learning
- Parameter-efficient fine-tuning
- Multi-task fine-tuning -> instruction tuning

Language Models Are Few-Shot Learners

Zero-shot

The model predicts the answer given only a natural language description of the task. No gradient updates are performed.

Few-shot

In addition to the task description, the model sees a few examples of the task. No gradient updates are performed.

```
Translate English to French: 

sea otter => loutre de mer 

peppermint => menthe poivrée

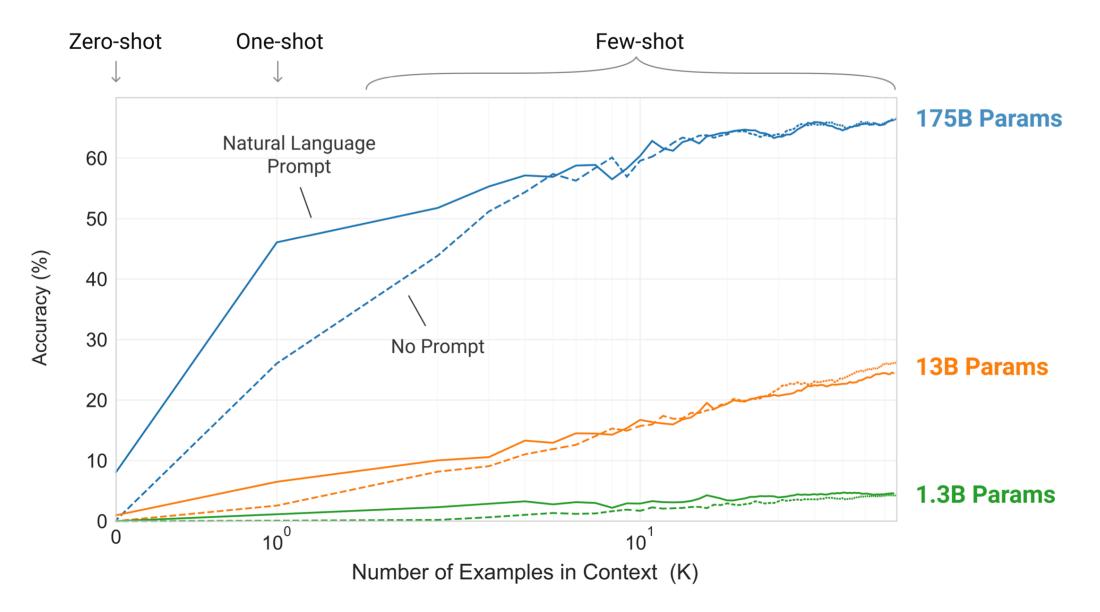
plush girafe => girafe peluche

cheese => 

prompt
```

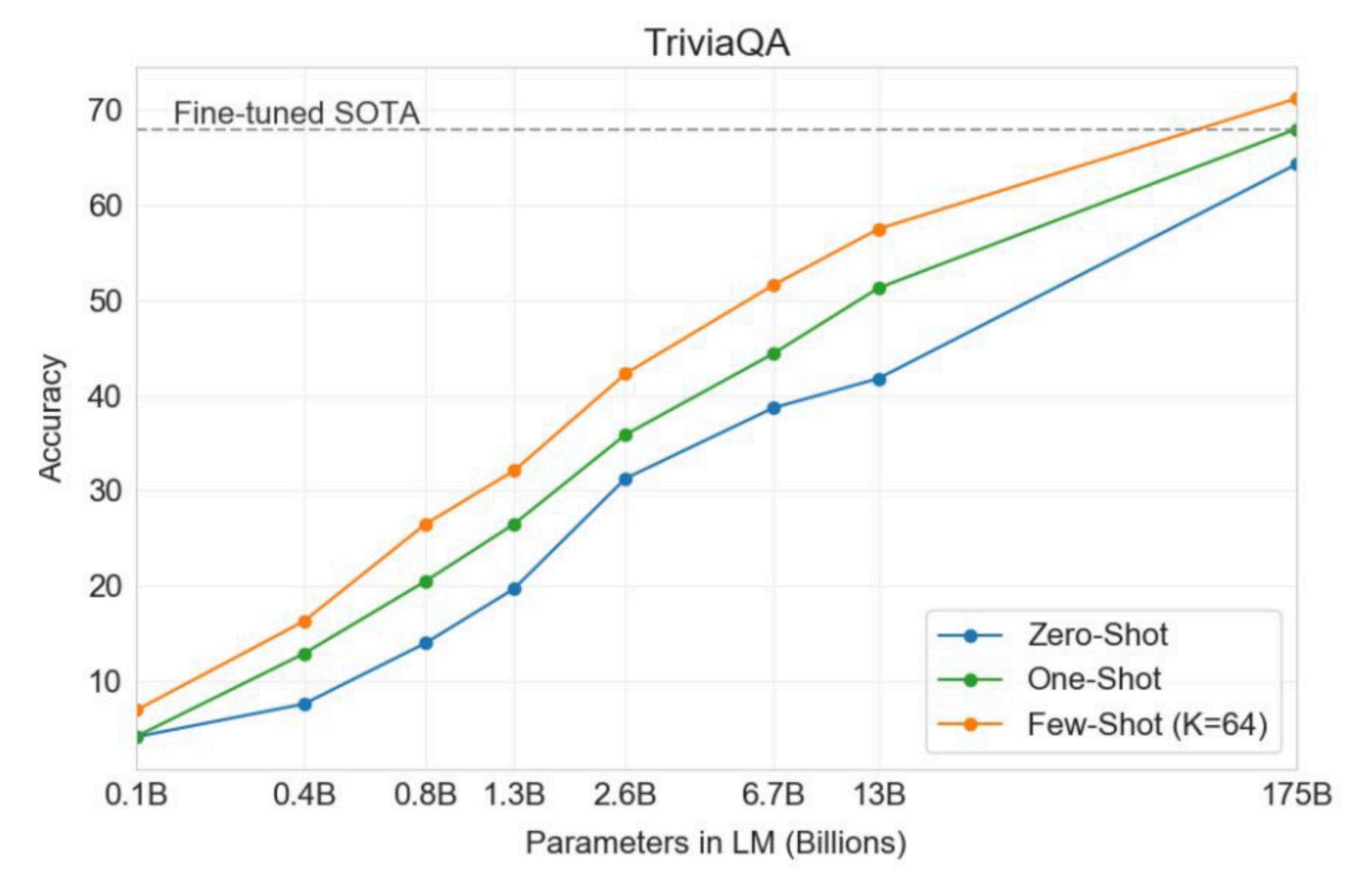
One-shot

In addition to the task description, the model sees a single example of the task. No gradient updates are performed.



In-Context Learning

Language Models Are Few-Shot Learners



Formally, In-Context Learning is...

- LLM zero-shot learning: a prompt that contains instructions for the task, but no actual examples of the task being performed.
- LLM few-shot learning: a prompt that contains both instructions as well as several examples of the task being performed.

Essentially, In-context Learning vs Fine-tuning?

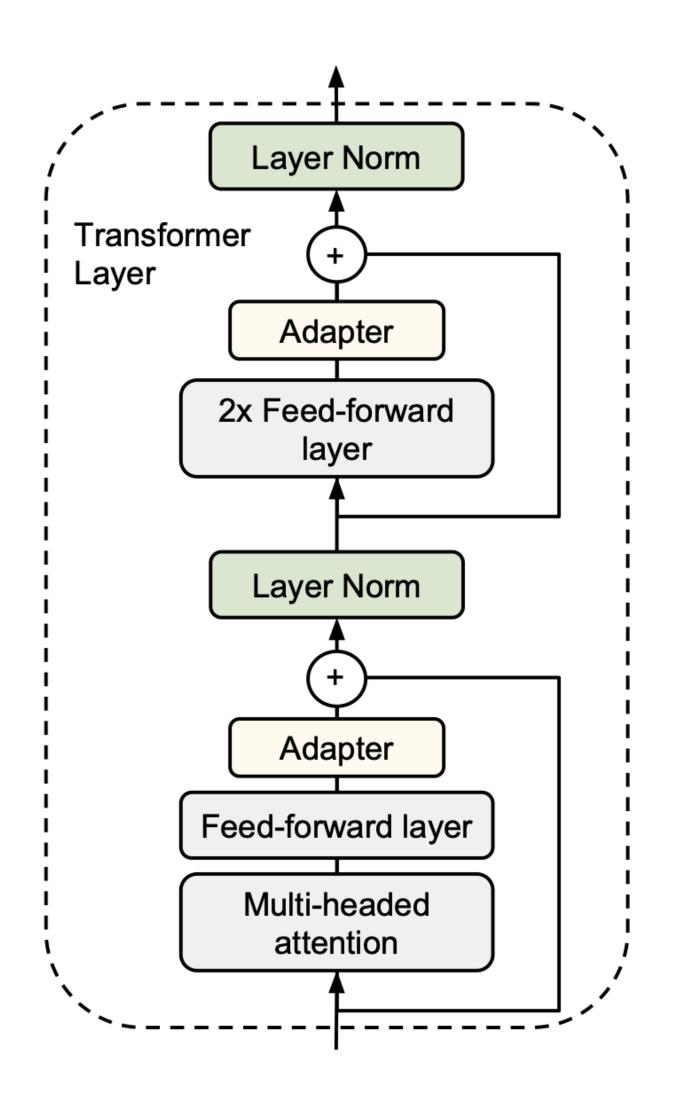
They are different ways of utilizing "annotated data"

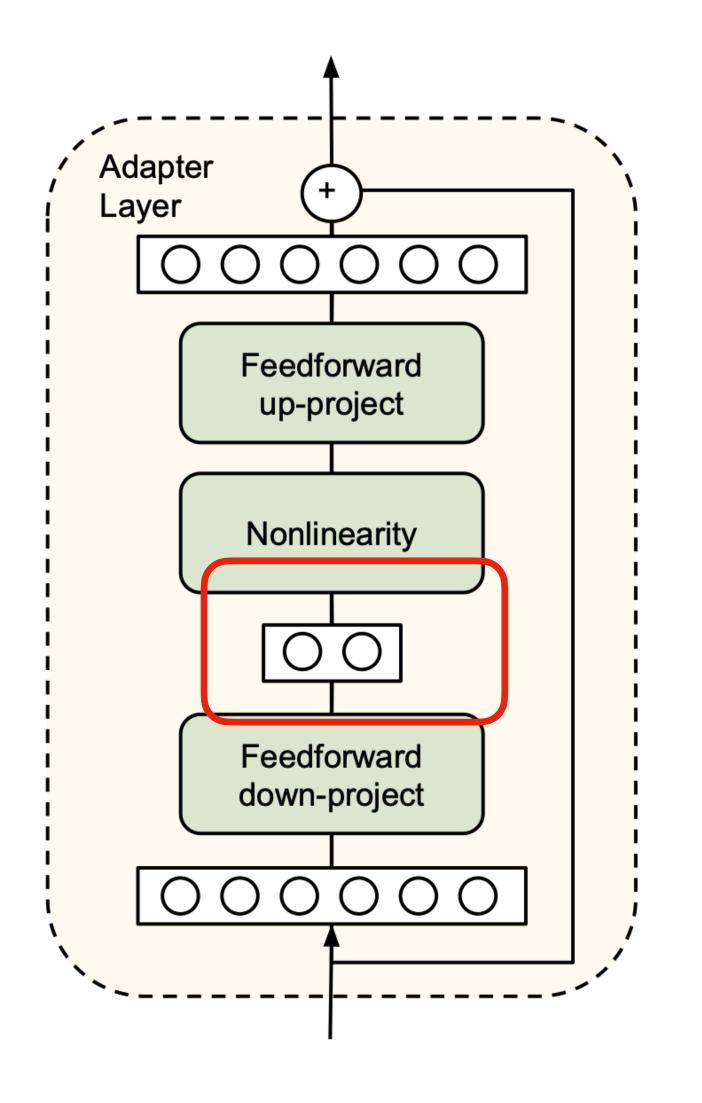
Parameter-Efficient Fine-Tuning

Instead of fine-tuning the entire model, we just fine-tune a small amount of parameters

Storage savings

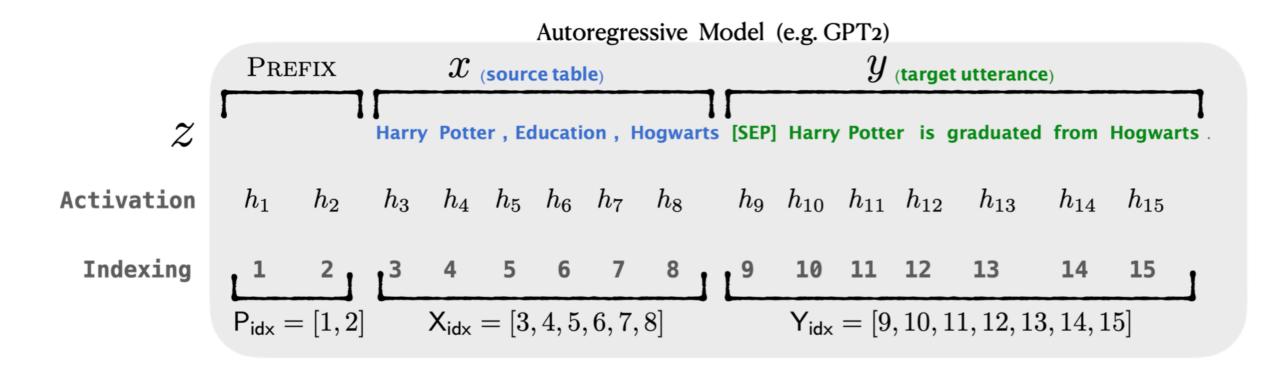
Adapter





Low-Rank

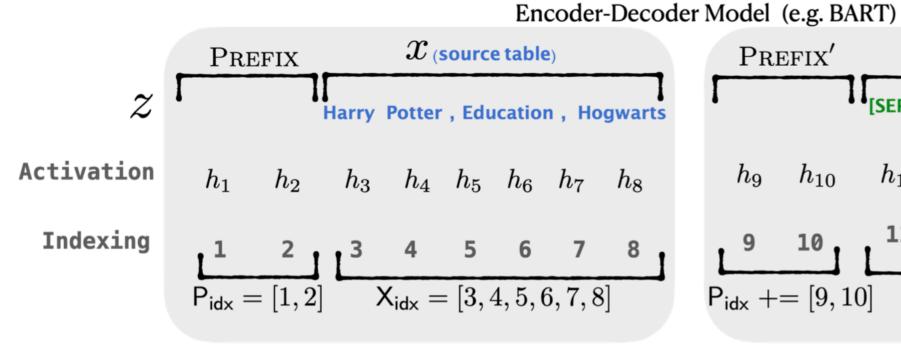
Prefix-Tuning

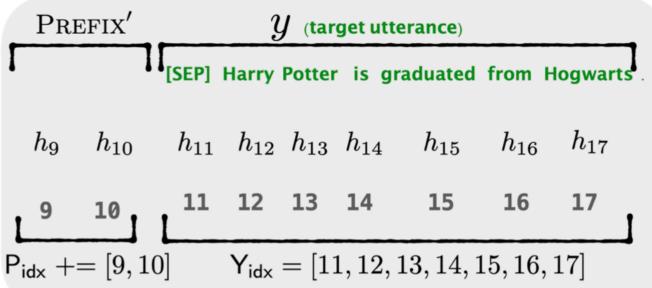


Summarization Example

Article: Scientists at University College London discovered people tend to think that their hands are wider and their fingers are shorter than they truly are. They say the confusion may lie in the way the brain receives information from different parts of the body. Distorted perception may dominate in some people, leading to body image problems ... [ignoring 308 words] could be very motivating for people with eating disorders to know that there was a biological explanation for their experiences, rather than feeling it was their fault."

Summary: The brain naturally distorts body image — a finding which could explain eating disorders like anorexia, say experts.





Prefix

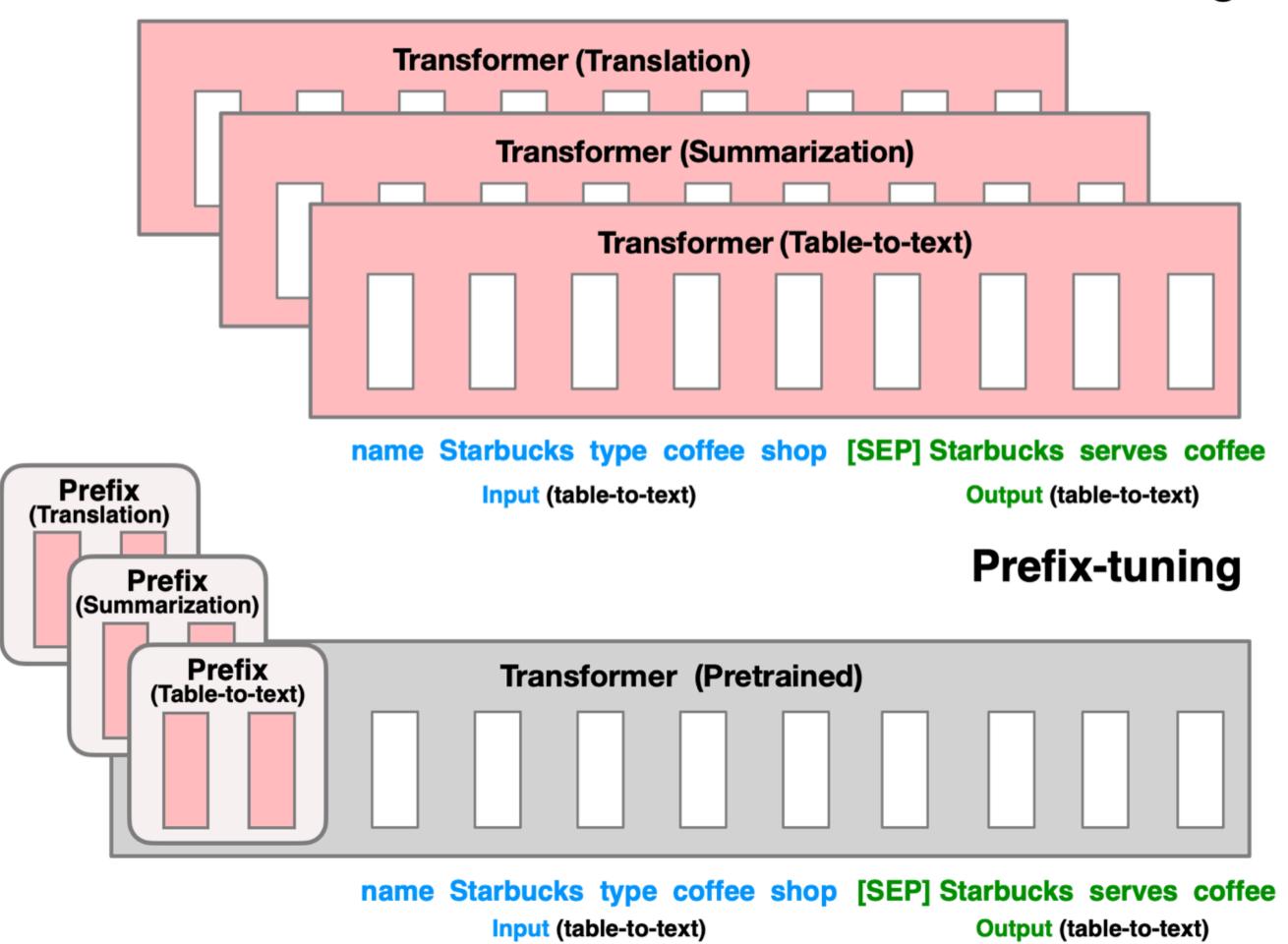
Table-to-text Example

Table: name[Clowns] customerrating[1 out of 5] eatType[coffee
shop] food[Chinese] area[riverside]
near[Clare Hall]

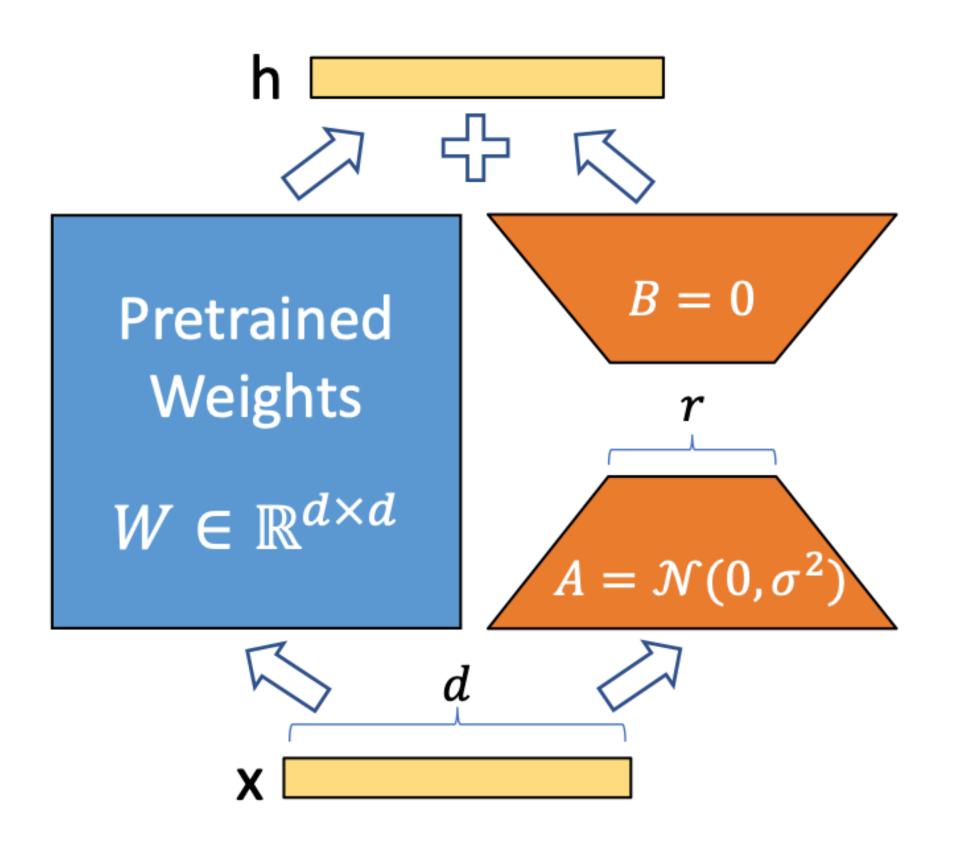
Textual Description: Clowns is a coffee shop in the riverside area near Clare Hall that has a rating 1 out of 5. They serve Chinese food.

Prefix-Tuning

Fine-tuning



LORA: LOW-RANK ADAPTATION

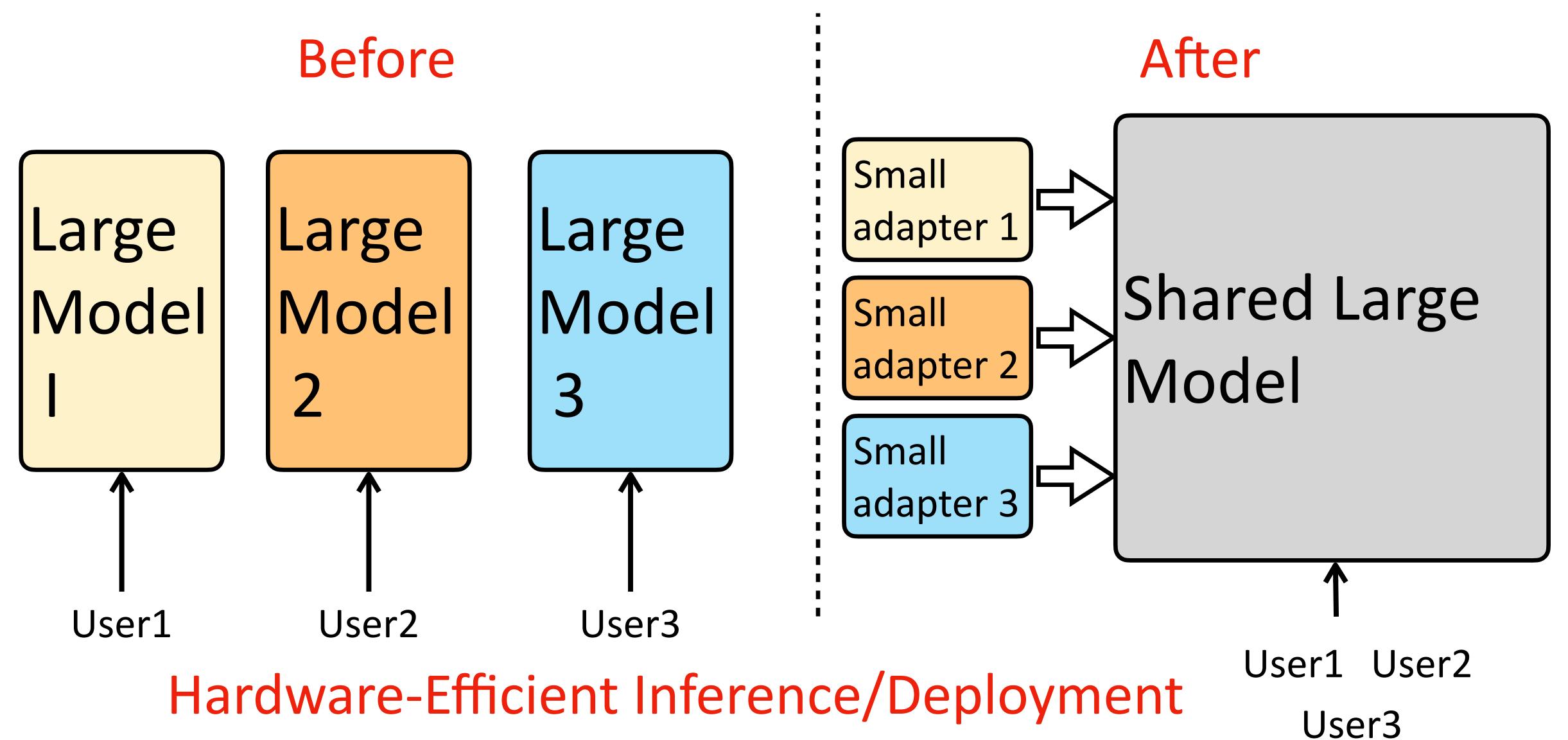


LORA: LOW-RANK ADAPTATION

Model & Method	# Trainable	E2E NLG Challenge				
	Parameters	BLEU	NIST	MET	ROUGE-L	CIDEr
GPT-2 M (FT)*	354.92M	68.2	8.62	46.2	71.0	2.47
GPT-2 M (Adapter ^L)*	0.37M	66.3	8.41	45.0	69.8	2.40
GPT-2 M (Adapter ^L)*	11.09M	68.9	8.71	46. 1	71.3	2.47
GPT-2 M (Adapter ^H)	11.09M	$67.3_{\pm .6}$	$8.50_{\pm.07}$	$46.0_{\pm.2}$	$70.7_{\pm.2}$	$2.44_{\pm.01}$
GPT-2 M (FT^{Top2})*	25.19M	68.1	8.59	46.0	70.8	2.41
GPT-2 M (PreLayer)*	0.35M	69.7	8.81	46.1	71.4	2.49
GPT-2 M (LoRA)	0.35M	$oxed{70.4}_{\pm.1}$	$\pmb{8.85}_{\pm .02}$	$\textbf{46.8}_{\pm .2}$	$\textbf{71.8}_{\pm.1}$	$\textbf{2.53}_{\pm .02}$
GPT-2 L (FT)*	774.03M	68.5	8.78	46.0	69.9	2.45
GPT-2 L (Adapter ^L)	0.88M	$69.1_{\pm.1}$	$8.68_{\pm.03}$	$46.3_{\pm.0}$	$71.4_{\pm.2}$	$\textbf{2.49}_{\pm.0}$
GPT-2 L (Adapter ^L)	23.00M	$68.9_{\pm .3}$	$8.70_{\pm.04}$	$46.1_{\pm .1}$	$71.3_{\pm.2}$	$2.45_{\pm.02}$
GPT-2 L (PreLayer)*	0.77M	70.3	8.85	46.2	71.7	2.47
GPT-2 L (LoRA)	0.77M	$oxed{70.4}_{\pm.1}$	$\pmb{8.89}_{\pm .02}$	$\textbf{46.8}_{\pm .2}$	$\textbf{72.0}_{\pm \textbf{.2}}$	$2.47_{\pm.02}$

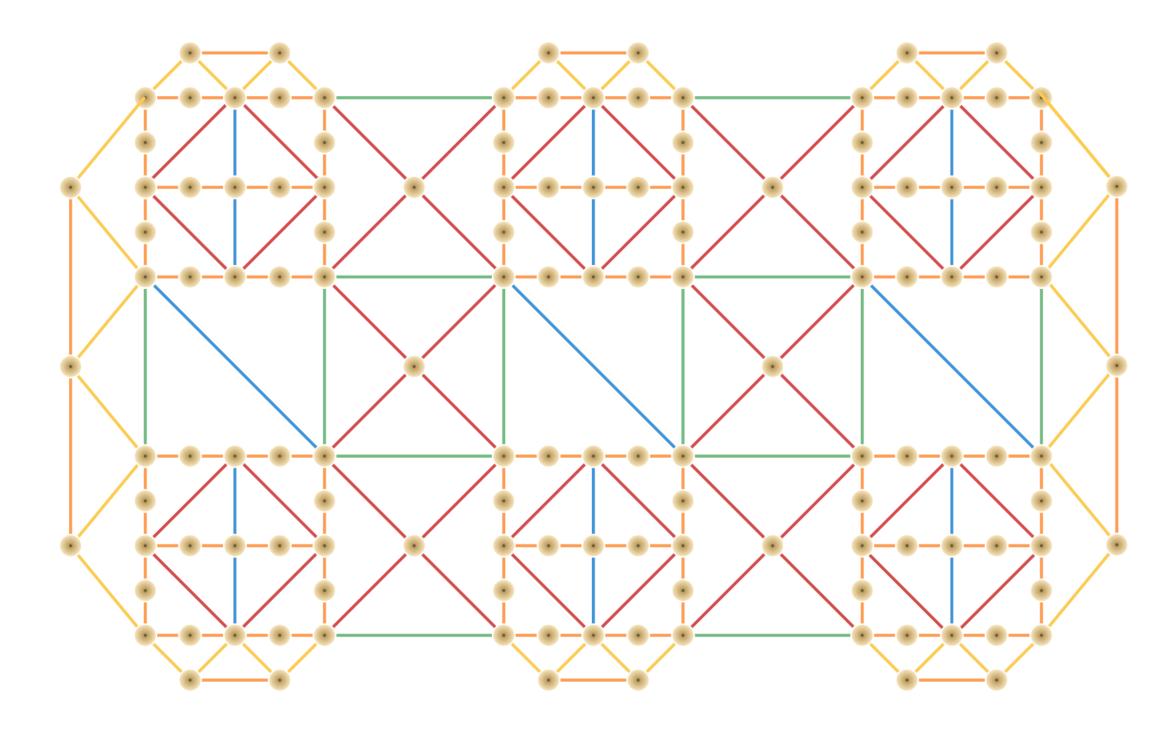
Table 3: GPT-2 medium (M) and large (L) with different adaptation methods on the E2E NLG Challenge. For all metrics, higher is better. LoRA outperforms several baselines with comparable or fewer trainable parameters. Confidence intervals are shown for experiments we ran. * indicates numbers published in prior works.

Why Parameter-Efficient Tuning



Announcing Tinker

Thinking Machines Lab Oct 1, 2025



TinkerToy Computer invented by Daniel Hillis and Brian Silverman

Today, we are launching <u>Tinker</u>, a flexible API for fine-tuning language models. It empowers researchers and hackers to experiment with models by giving them control over the algorithms and data while we handle the complexity of distributed training. Tinker advances our mission of enabling more people to do research on cutting-edge models and customize them to their needs.

Fine-Tuning as Service



Evaluation of LLMs

Evaluation needs to come first before development starts

How to Evaluate a Language Model

Loss on validation/test set

$$\log p(x)$$

Average over number of tokens

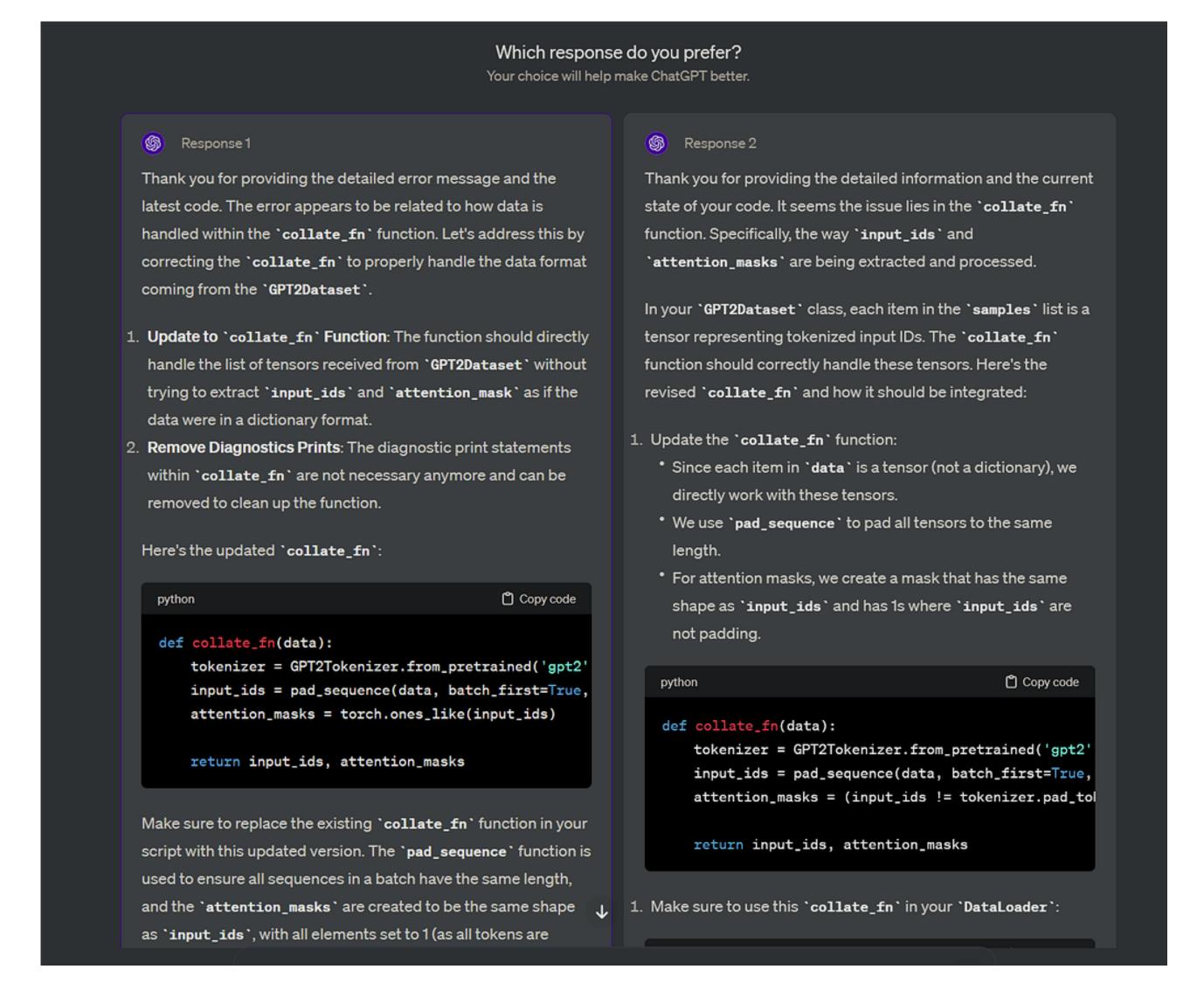
Perplexity

$$e^{-\log p(x)}$$

N: number of tokens

Evaluating for Downstream Tasks

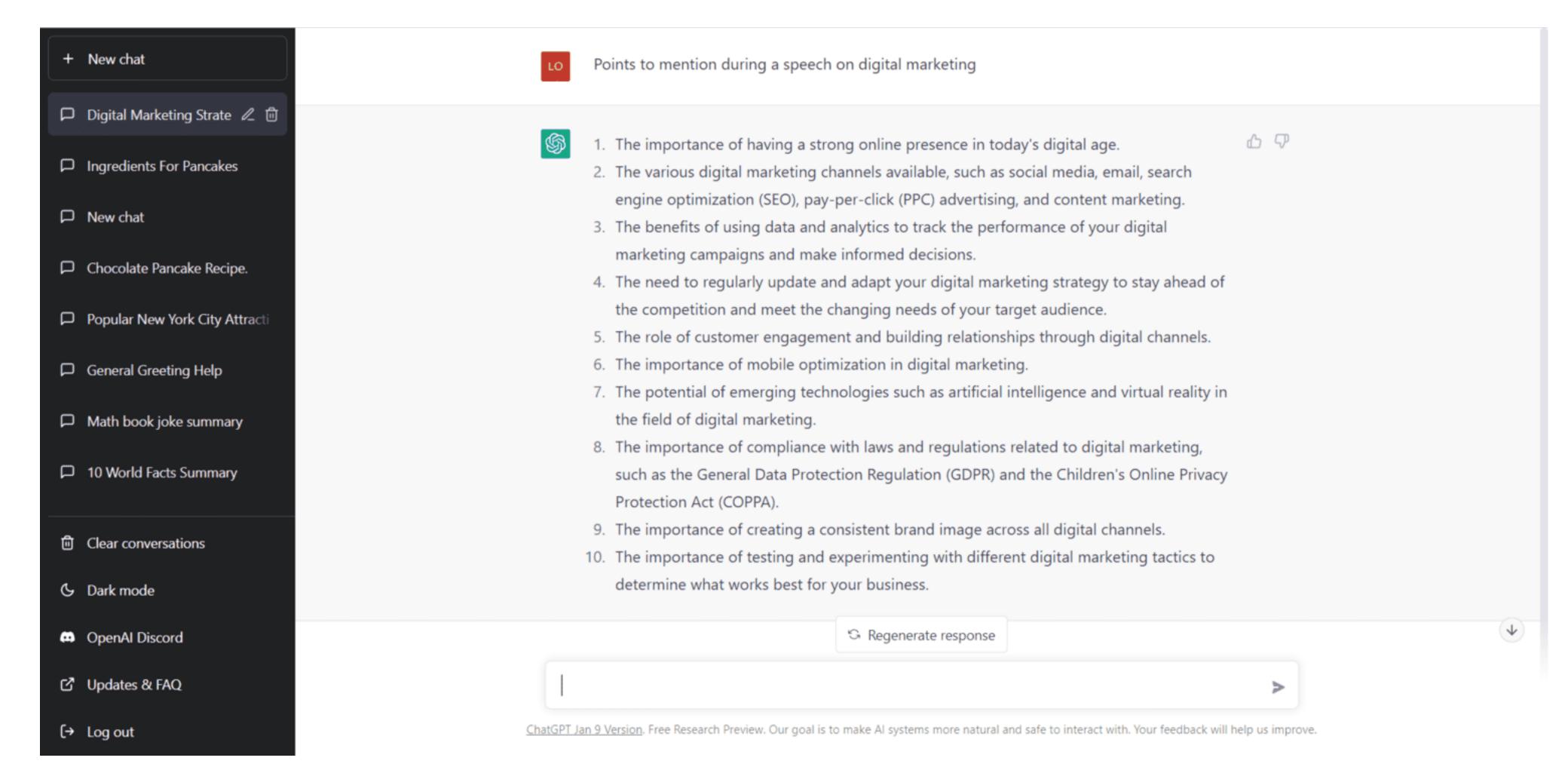
Chat:



Which one is better?

Evaluating for Downstream Tasks

Chat:

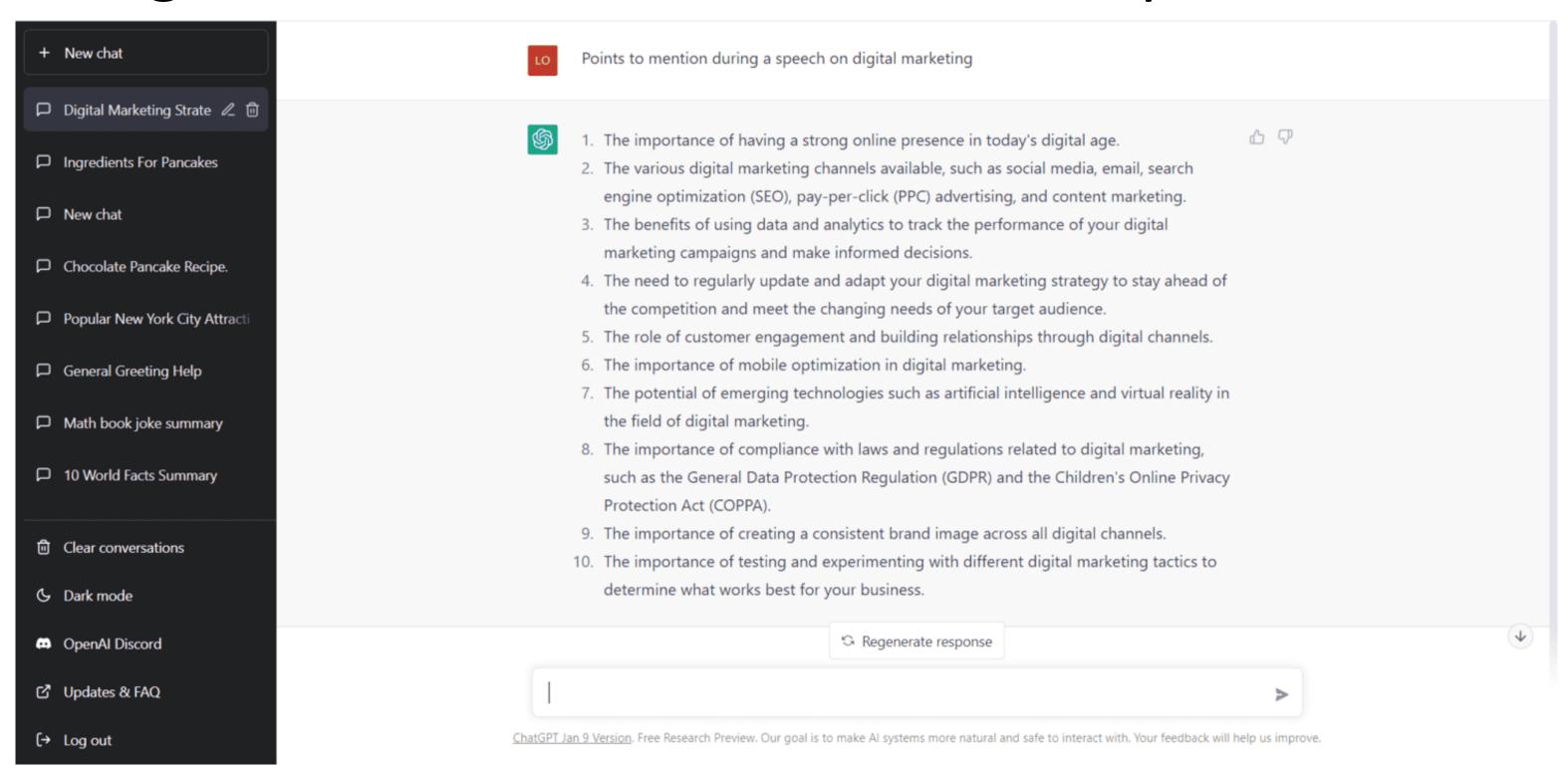


What is the quality of this response? It it helpful, factually correct, non-toxic?

Human Evaluation

Evaluating long-form generated text is hard and an old problem in NLP

for a long time



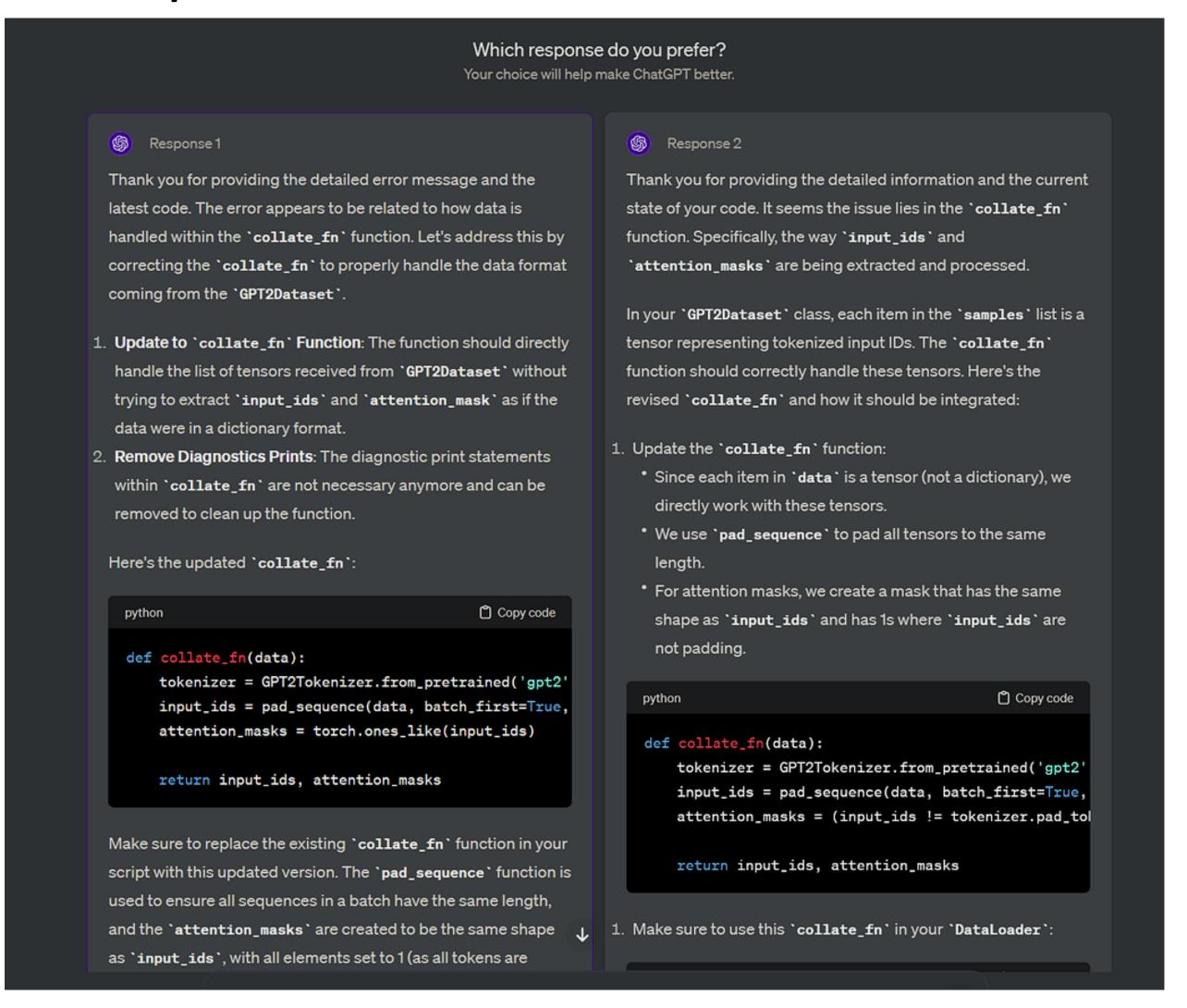
Q: Is this response helpful?

A. Very helpful; B. Helpful. C. Not useful at all

Why multi-choice questions?

Human Evaluation is Subjective

Comparative human evaluation is more reliable



Which one is better?



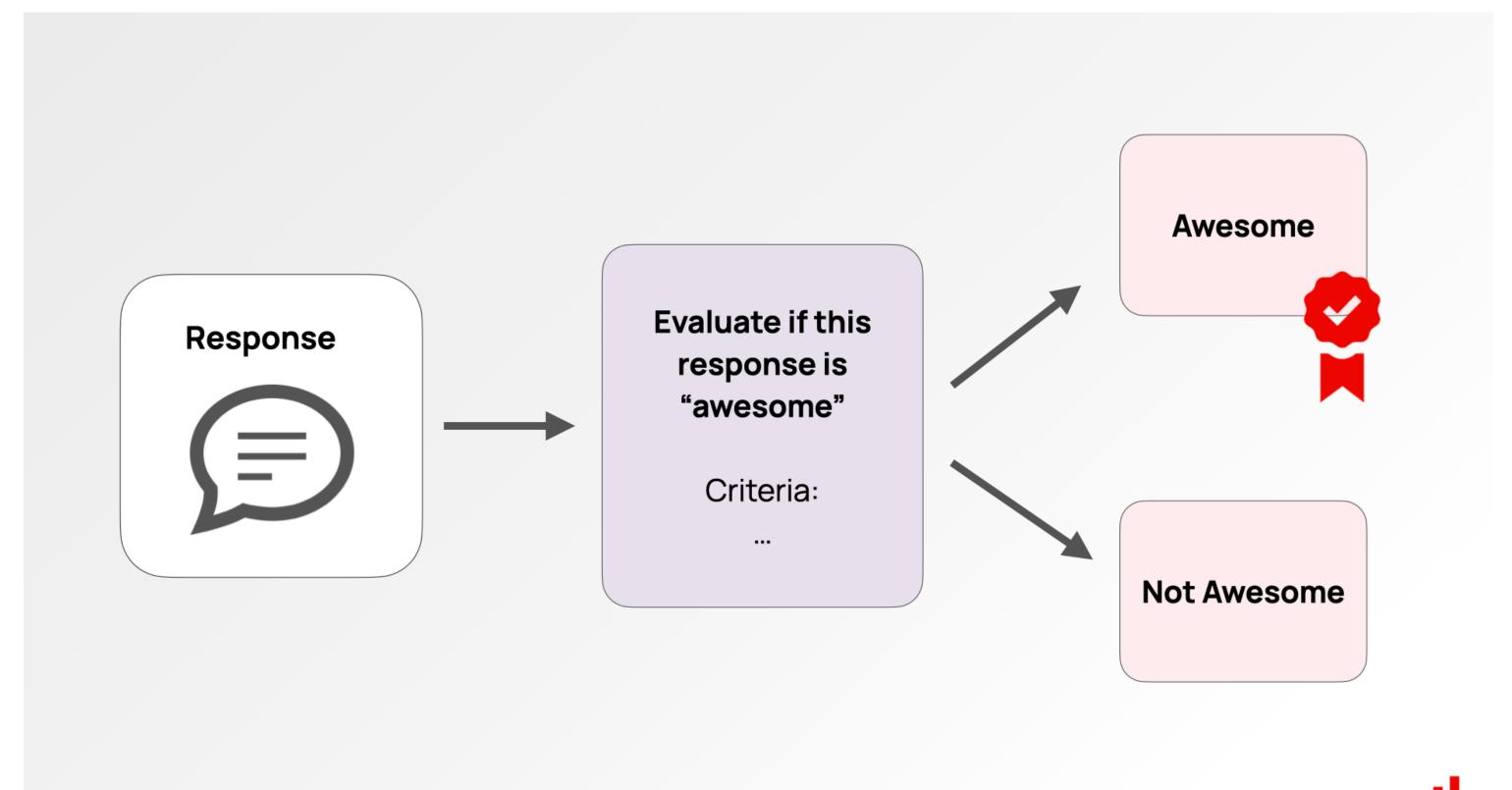
Sometimes Evaluation is Easier than Generation

Example: Humans can judge which essay is better from two model-written essays, but the humans may not generate such essays with similar quality

Humans can still judge AI in some tasks even though AI much stronger than humans

LLM as Judge

Human evaluation is slow, expensive, and not scalable



- Sometimes people just prompt models for judgement
- 2. Sometimes people train specific judgement model

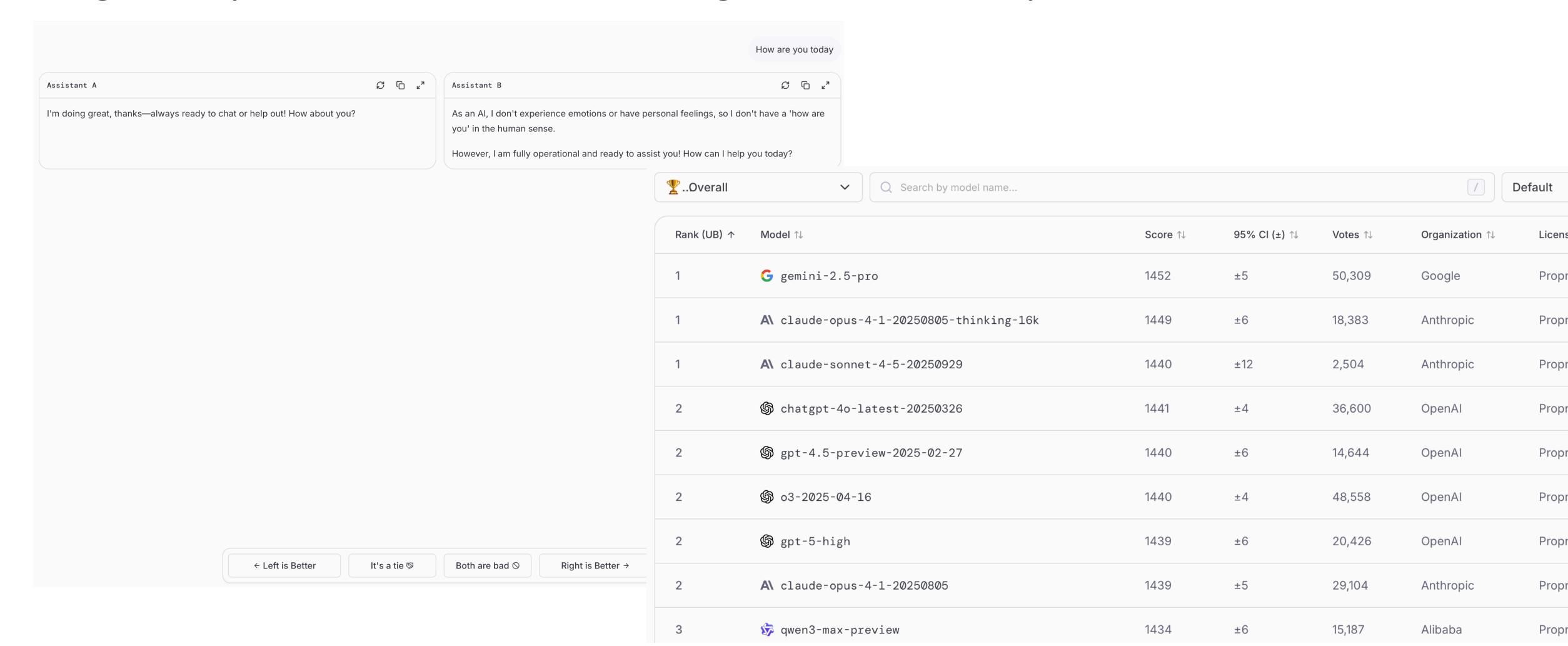
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LLM as judge may be inaccurate and uninterpretable.

Crowd-Sourcing Human Evaluation

https://lmarena.ai/

Imagine any two models can battle a game, whose response is better



Crowd-Sourcing Human Evaluation

✓ Overall ✓ Q Search by model name					/ Default	
Rank (UB) ↑	Model ↑↓	Score ↑↓	95% CI (±) ↑↓	Votes ↑↓	Organization ↑↓	License ↑↓
1	G gemini-2.5-pro	1452	±5	50,309	Google	Proprietary
1	A\ claude-opus-4-1-20250805-thinking-16k	1449	±6	18,383	Anthropic	Proprietary
1	A\ claude-sonnet-4-5-20250929	1440	±12	2,504	Anthropic	Proprietary
2	\$\text{\$\text{\$\text{\$chatgpt-40-latest-20250326}}\$	1441	±4	36,600	OpenAl	Proprietary
2	\$\text{\$\text{gpt-4.5-preview-2025-02-27}}\$	1440	±6	14,644	OpenAl	Proprietary
2		1440	±4	48,558	OpenAl	Proprietary
2		1439	±6	20,426	OpenAl	Proprietary
2	A\ claude-opus-4-1-20250805	1439	±5	29,104	Anthropic	Proprietary
3		1434	±6	15,187	Alibaba	Proprietary

Elo scores as in sports

Evaluate Language Model Knowledge

Automatic evaluations typically seek for objective metrics Example from MMLU:

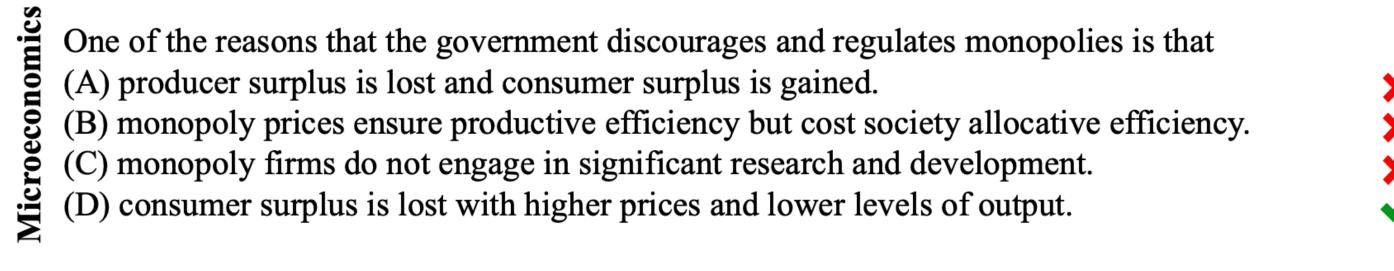


Figure 3: Examples from the Microeconomics task.

When you drop a ball from rest it accelerates downward at 9.8 m/s². If you instead throw it downward assuming no air resistance its acceleration immediately after leaving your hand is

(A) 9.8 m/s²

(B) more than 9.8 m/s²

(C) less than 9.8 m/s²

(D) Cannot say unless the speed of throw is given.

Multi-choice QA

Ranging from middle school to college level

Mathematical Reasoning

Example from GSM8K:

Problem: Beth bakes 4, 2 dozen batches of cookies in a week. If these cookies are shared amongst 16 people equally, how many cookies does each person consume?

Solution: Beth bakes 4 2 dozen batches of cookies for a total of 4*2 = <<4*2=8>>8 dozen cookies

There are 12 cookies in a dozen and she makes 8 dozen cookies for a total of 12*8 = <<12*8=96>>96 cookies

She splits the 96 cookies equally amongst 16 people so they each eat 96/16 = <<96/16=6>>6 cookies

Final Answer: 6

Problem: Mrs. Lim milks her cows twice a day. Yesterday morning, she got 68 gallons of milk and in the evening, she got 82 gallons. This morning, she got 18 gallons fewer than she had yesterday morning. After selling some gallons of milk in the afternoon, Mrs. Lim has only 24 gallons left. How much was her revenue for the milk if each gallon costs \$3.50?

Mrs. Lim got 68 gallons - 18 gallons = <<68-18=50>>50 gallons this morning.

So she was able to get a total of 68 gallons + 82 gallons + 50 gallons = <<68+82+50=200>>200 gallons.

She was able to sell 200 gallons - 24 gallons = <<200-24=176>>176 gallons.

Thus, her total revenue for the milk is 3.50/gallon x 176 gallons = <<3.50*176=616>>616.

Final Answer: 616

Problem: Tina buys 3 12-packs of soda for a party. Including Tina, 6 people are at the party. Half of the people at the party have 3 sodas each, 2 of the people have 4, and 1 person has 5. How many sodas are left over when the party is over?

Solution: Tina buys 3 12-packs of soda, for 3*12= <<3*12=36>>36 sodas

6 people attend the party, so half of them is 6/2= <<6/2=3>>3 people

Each of those people drinks 3 sodas, so they drink 3*3=<<3*3=9>>9 sodas

Two people drink 4 sodas, which means they drink 2*4=<<4*2=8>>8 sodas

With one person drinking 5, that brings the total drank to 5+9+8+3= <<5+9+8+3=25>>25 sodas

As Tina started off with 36 sodas, that means there are 36-25=<<36-25=11>>11 sodas left

Final Answer: 11

Short-answer

Mathematical Reasoning

Example from AIME (American Invitational Mathematics Examination):

Problem

Let the sequence of rationals x_1, x_2, \ldots be defined such that $x_1 = \frac{25}{11}$ and

$$x_{k+1} = \frac{1}{3} \left(x_k + \frac{1}{x_k} - 1 \right).$$

 x_{2025} can be expressed as $\frac{m}{n}$ for relatively prime positive integers m and n. Find the remainder when m+n is divided by 1000.

Solution 1 (complete)

This problem can be split into three parts, listed below:

Part 1: Analyzing Fractions

Let $x_k = \frac{a_k}{b_k}$, where a_k, b_k are relatively prime positive integers. First, we analyze the moduli of the problem. Plugging in for x_2 yields $x_2 = \frac{157}{275}$. Notice that in both x_1 and x_2 , the numerator is equivalent to 1 and the denominator is equivalent to 2 modulus 3. We see that $x_2 = \frac{1}{2} \cdot \frac{(a_1 - b_1)^2 + a_1b_1}{a_2b_2}$. Specifically, we know that

$$(a_1 - b_1)^2 + a_1 b_1 \equiv (1 - 2)^2 + 1 \cdot 2 \equiv 0 \pmod{3}$$

Then this is always divisible by 3 for all x_k (it can be shown that for all x_k , we have $a_k \equiv 1 \pmod 3$ and $b_k \equiv 2 \pmod 3$ by using $\mod 9$).

Thus, $x_2 = \frac{\frac{1}{3}((a_1 - b_1)^2 + a_1b_1)}{a_1b_1}$, and the numerator and denominator of the right-hand side (RHS) correspond to the numerator and

denominator of x_2 in simplest form. (To further prove that the top and bottom are relatively prime, consider that a_k and b_k are by definition relatively prime, so $(a_k - b_k)^2$ and $a_k b_k$ share no factors.)

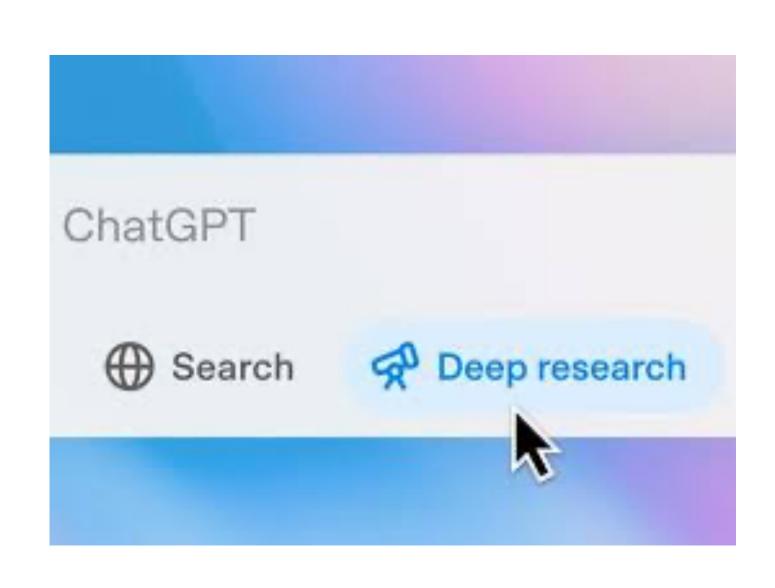
Notice that the above do not just apply to x_1 ; we did not use any specific properties of x_1 . Then we may generalize the above, finding that:

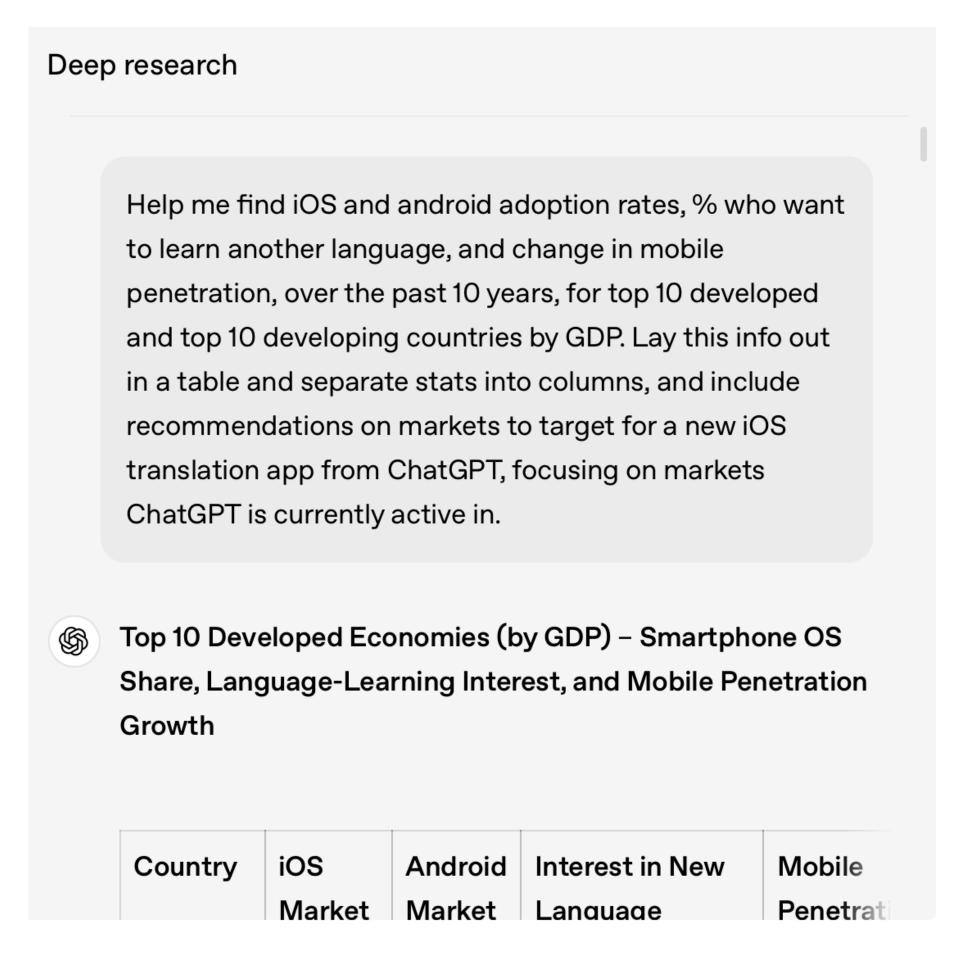
$$a_k = \frac{1}{3}((a_{k-1} - b_{k-1})^2 + a_{k-1}b_{k-1})$$

$$b_k = a_{k-1}b_{k-1}$$

Deep Research

https://openai.com/index/introducing-deep-research/





Hard to Evaluate

Evaluating Deep Research

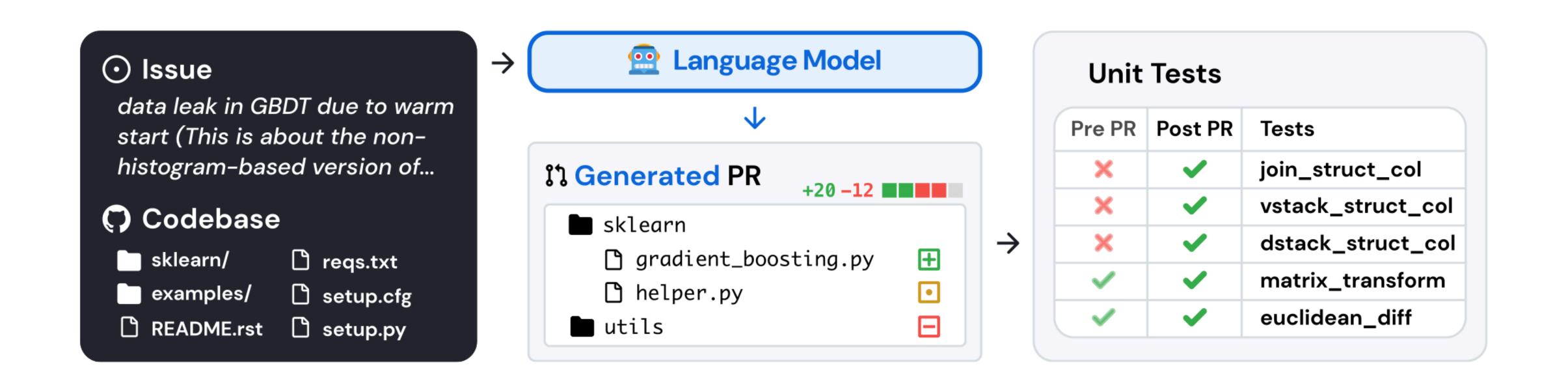
https://openai.com/index/browsecomp/

Please identify the fictional character who occasionally breaks the fourth wall with the audience, has a backstory involving help from selfless ascetics, is known for his humor, and had a TV show that aired between the 1960s and 1980s with fewer than 50 episodes.



Answer: Plastic Man

Software Engineering



Benchmarking code generation by running tests

Thank You!