

Language model post-training

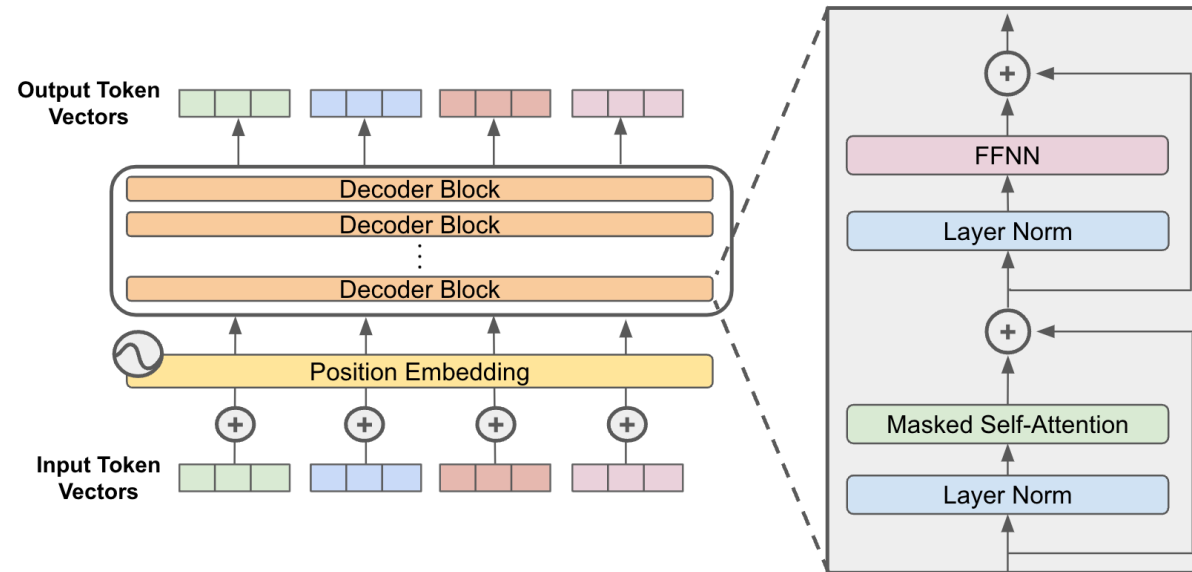
Aku Rouhe

Large Language Models

- Models of text sequences \mathbf{w}
 - Text represented as discrete parts, tokens
- Chat models etc. are next token prediction models: $P(w_i | \mathbf{w}_{0:i-1})$
 - Chain rule of probabilities gives $P(\mathbf{w}_{0:i}) = P(w_0)P(w_1|w_0) \dots P(w_i | \mathbf{w}_{0:i-1})$
- Other models like BERT use a bidirectional context
 $P(w_i | \mathbf{w}_{0:i-1}, \mathbf{w}_{i+1:L})$
 - $P(\mathbf{w}_{0:i}) \neq P(w_0 | \mathbf{w}_{1:L})P(w_1 | w_0, \mathbf{w}_{2:L}) \dots P(w_i | \mathbf{w}_{0:i-1})$
 - Can be seen as a Markov Random Field Language Model, Gibbs sampling can be used for generation

Large Language Models

- All LLMs based on Transformer decoders

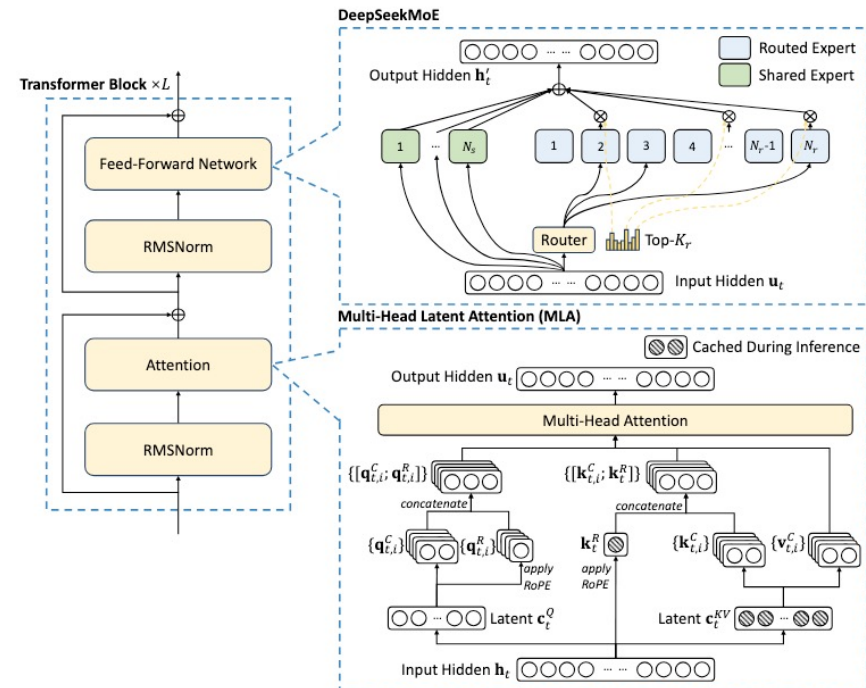


Picture: <https://cameronwolfe.substack.com/p/decoder-only-transformers-the-workhorse>

Large Language Models

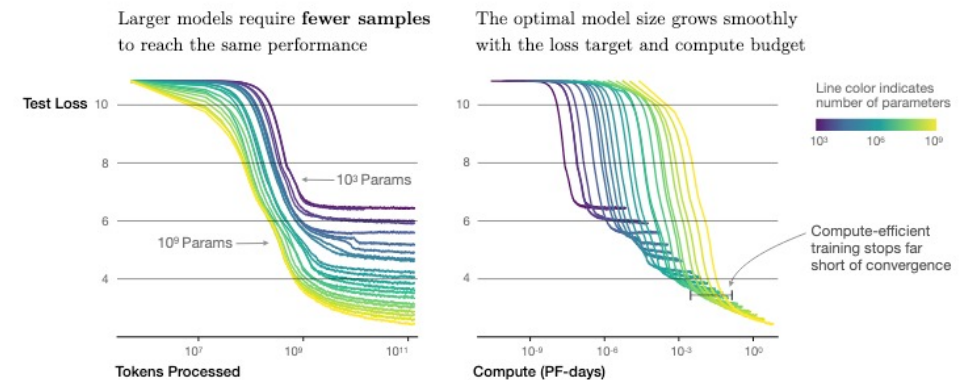
- Some fruitful research in neural architecture:

- Better scaling feed-forward computation:
Mixture-of-Experts, etc.
- Efficient attention computation:
Grouped Query Attention, Flash Attention, Multi-head Latent Attention, etc.
- Lower precision computation:
FP8, 4bit Integer, etc.



Large Language Models

- Order of magnitude in parameters:
 - Small: Billions
 - Midsize: 10s of Billion
 - Flagship: 100s of Billions
- Parameter count tradeoff:
 - Bigger models perform better
 - Smaller models infer faster and take less compute to train



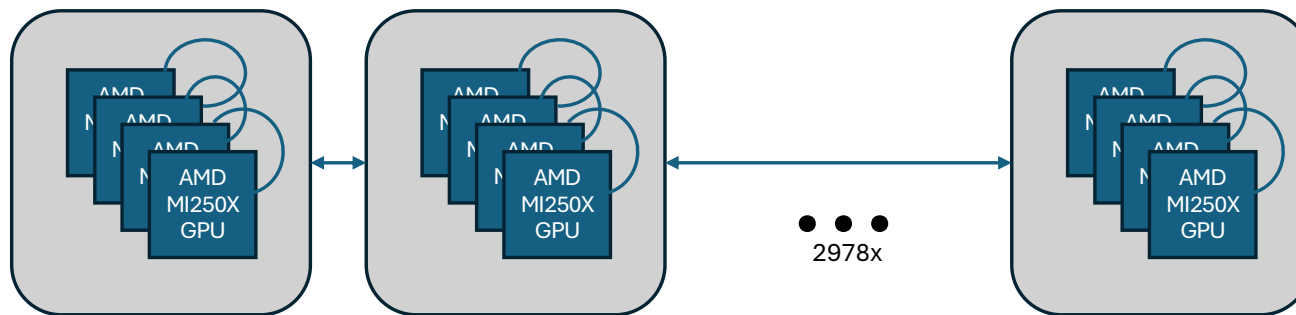
From: Kaplan et al Scaling laws,
<https://arxiv.org/pdf/2305.13245v3>

Pretraining

- LLMs are trained on huge text corpora
 - Primarily from web scrapes
- Deepseek-V3: 14.8 Trillion tokens (128k vocab, 671B params)
- Llama 3: 15.6 Trillion tokens (128k vocab, largest 405B params)
 - "50% of tokens corresponding to general knowledge, 25% of mathematical and reasoning tokens, 17% code tokens, and 8% multilingual tokens"

Pretraining

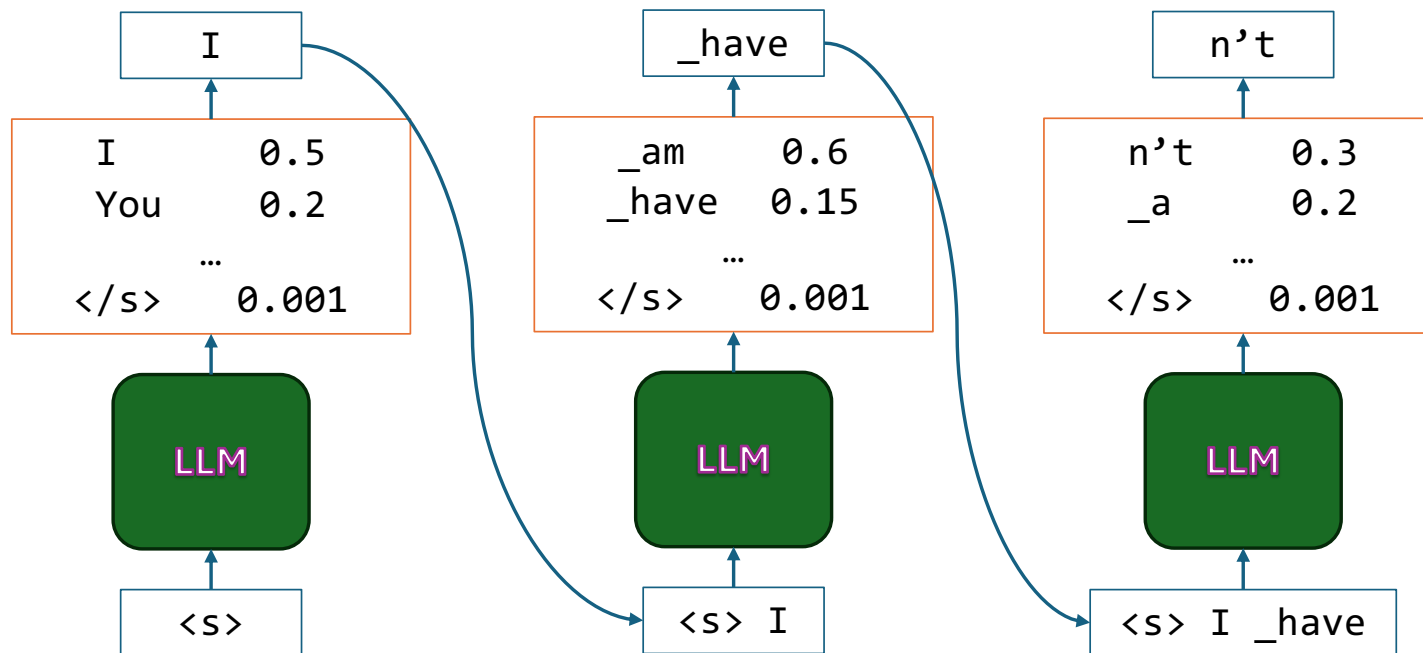
- Infrastructure: Tens of thousands of GPUs,
 - Interconnections within node, across nodes
- Effective utilization of the infrastructure is a major engineering challenge
 - Parallelization strategies, effective communication implementations



LUMI, EUROHPC Supercomputer in Kajaani, Finland

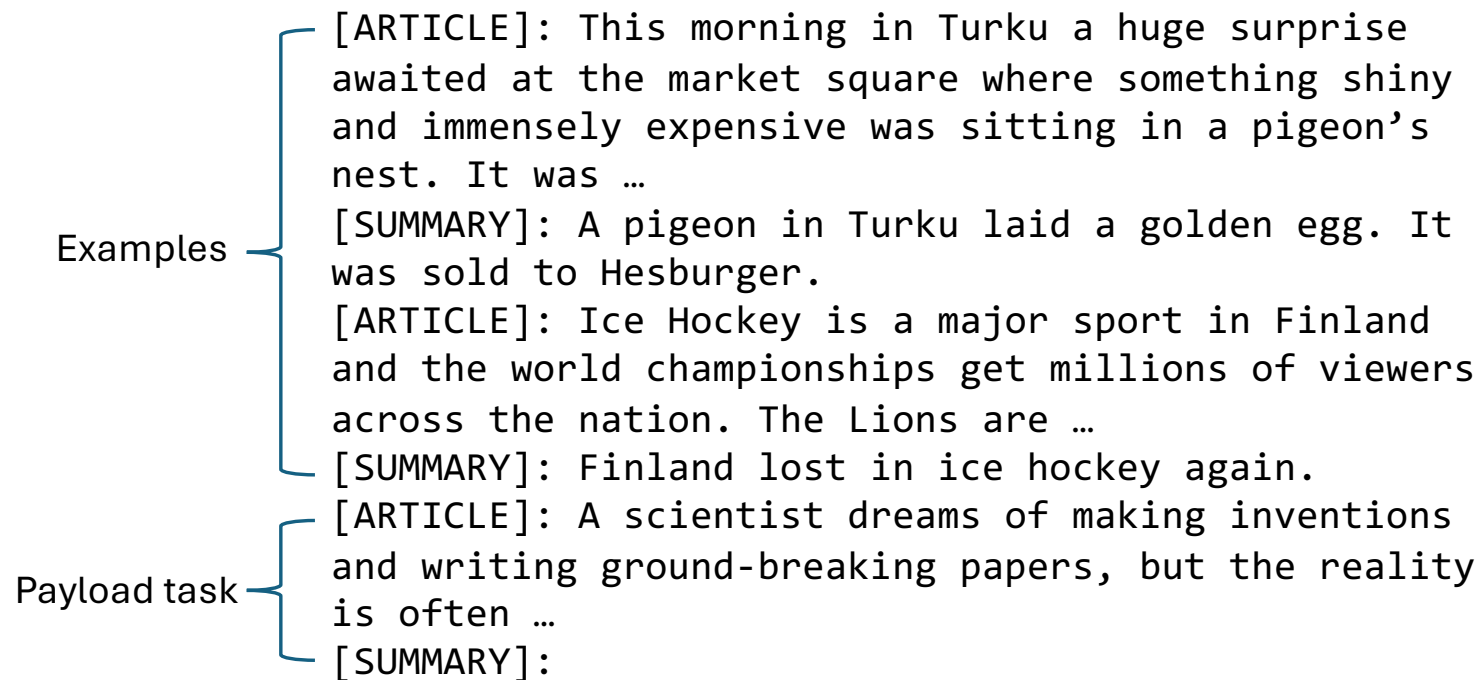
Continuation model

- Pretraining yields a continuation model

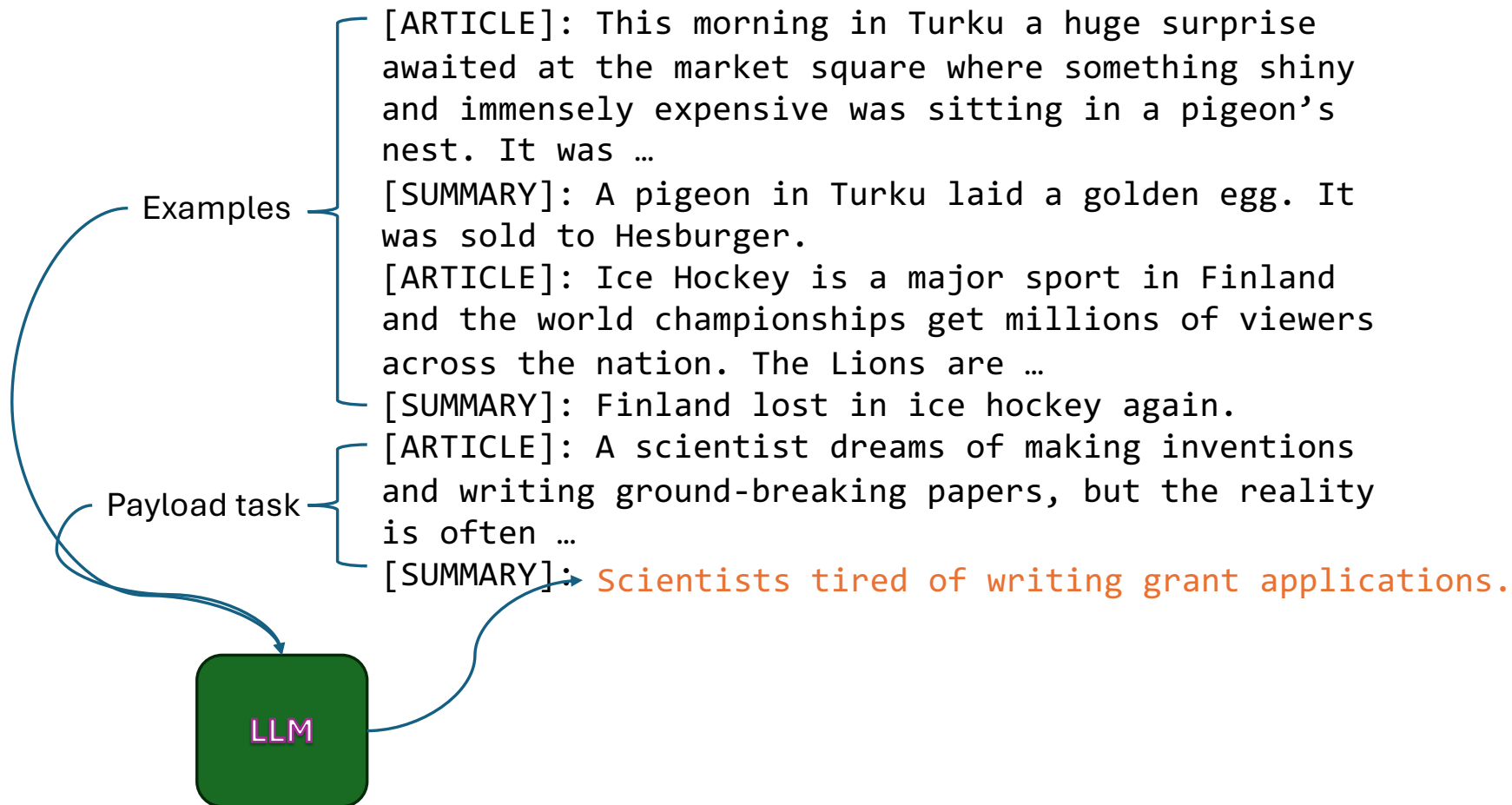


In-context learning

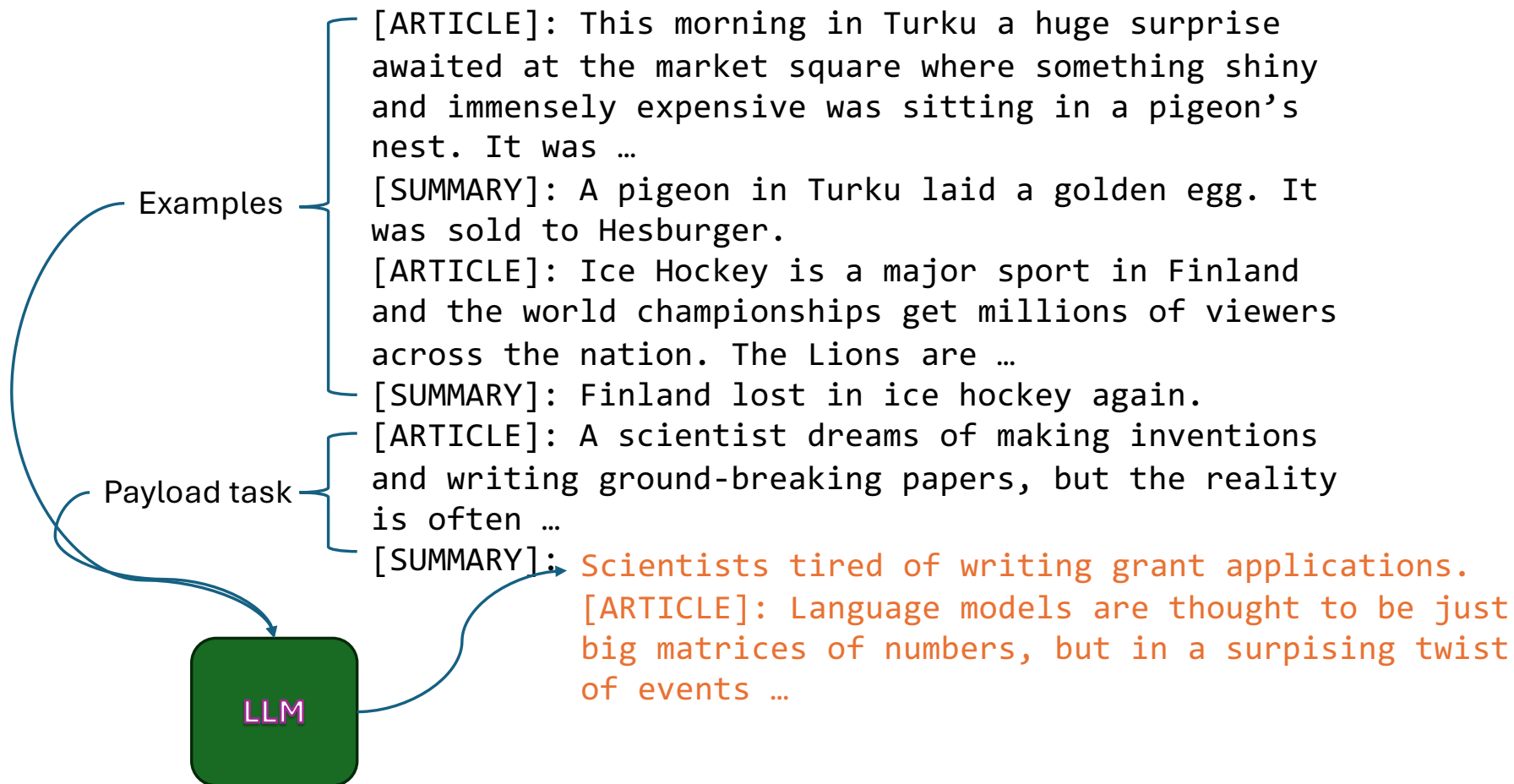
- To do useful things, continuation models can be prompted via *in-context learning*



In-context learning

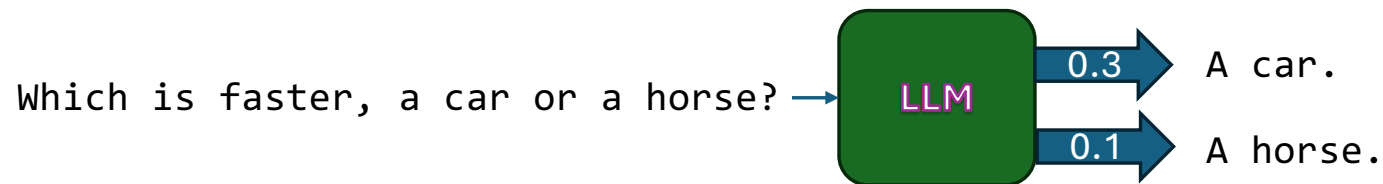


In-context learning



Discriminative likelihood ratio tests

- Pretrained models also permit computing the relative likelihoods of competing completions
- Can be used as a discriminative classifier
- $P(\mathbf{w}_{0:i}) = P(w_0)P(w_1|w_0) \dots P(w_i|\mathbf{w}_{0:i-1})$



Evaluating a pretrained basemodel

- Using in-context learning and likelihood ratio tests, many public benchmarks can be computed
 - Real-world knowledge memorisation
 - “Common sense”
 - Code completion, math questions

Microeconomics

One of the reasons that the government discourages and regulates monopolies is that

- (A) producer surplus is lost and consumer surplus is gained.
- (B) monopoly prices ensure productive efficiency but cost society allocative efficiency.
- (C) monopoly firms do not engage in significant research and development.
- (D) consumer surplus is lost with higher prices and lower levels of output.



Post-training

- A second stage of training where LLMs learn
 - the format of output
 - to perform particular tasks
 - to follow instructions
 - to chat
 - human preferences
 - character
- Much less compute intensive than pretraining:
 - Even ~1000s of samples can be enough

Sidenote: training a new classification head

- With early LLMs like BERT, it was typical to discard the text output
- A classifier head was trained, modeling $P(Y|\mathbf{w}_{0:L})$
 - Y is e.g. the sentiment (positive, negative, neutral) of the input.

Structured output format

- Special tokens are added to the vocabulary
- These marker tokens can:
 - split the text in to a chat conversation
 - indicate where the LLM assistant's turn ends
 - mark code sections
 - mark output from “tools”

Structured output format: Chat

```
<s><message_start>user
Hi! Uh, what is Paris again? I forgot.
<message_end>
<message_start>assistant
Oh dear! Paris is the capital of France.
<message_end>
<message_start>user
And is there some famous tower there?
<message_end>
<message_start>assistant
Yes, there is!
<message_end>
```

Structured output format: Instruction following

```
<s><message_start>instruction
Write a professional email explaining I need tomorrow
off work. Do not use the letter E.
<message_end>
<message_start>response
Salutations!

I ask for tomorrow off work. Sorry for this non-
punctual mail.

Yours,
...
<message_end>
```

Structured output format: Implicit task

```
<s><message_start>english  
The quick brown fox jumps over the lazy dog.  
<message_end>  
<message_start>french  
Le renard brun rapide saute par-dessus le chien  
paresseux.  
<message_end>
```

Supervised finetuning

- Maximising the log-likelihood of the training data like pretraining
 - Training data in the structured output format
 - Training data consists of demonstrations of desirable outputs
- It's possible to compute the loss only on the parts that the LLM will be used to generate
 - Only the assistant responses in a chat
 - Only the task output in an implicit model

Supervised finetuning: limitations

- Usually there is not just one single correct response
 - Think of e.g. the instruction “Write a calm poem about fish in iambic pentameter”
- Using just demonstrations of desired outputs, it’s hard to capture:
 - Nuanced, subtle differences between similar responses
 - Undesirable qualities of responses

Preference alignment

- Instead of demonstrations of desired output, sample real outputs from the LLM and rank them
 - Ranking by humans
 - Learned reward model
- Captures subtler differences between possible outputs
- Captures a signal of undesired outputs
- Goals of preference alignment: “Helpful, Honest, Harmless”

Policy gradient methods

- Set the LLM as a policy model, which for each state of previous text provides the distribution over the next action, i.e. the next token
- Proximal policy optimization (PPO)
 - Actor-Critic -like approach
- Group relative policy optimization (GRPO)
 - Similar to PPO
 - Omit Critic-model, instead sample multiple outputs and estimate advantage for each output as difference to mean reward

Direct preference optimization (DPO)

- Sidestep complex policy gradient methods
- Analogous to adding a negative response example to the standard supervised finetuning
 - Also includes scaling with reference-model probability (SFT baseline)
- No learned reward model, offline

Where does post-training data come from?

- Prompts can be collected from actual production use of LLMs
- Producing data with existing LLMs
 - Slipstreaming behind strong LLMs sometimes not allowed by TOS
- Automated data filtering with rules, NLP tools, other LLMs
- Human efforts / labeling
 - An industry of data companies
 - Micro-work platforms
 - Open initiatives
- Found data: question-answer pairs, etc. in public media

Constitutional AI

- Get rid of humans ranking competing LLM outputs
- Have humans write a "constitution"
 - Set of statements describing human preferences in natural language
- LLM judges LLM outputs based on the constitution
- Synthetic training data, but humans oversee the procedure to iterate on the constitution

Verifiable rewards

- Some rewards for reinforcement learning are deterministic and automatable:
 - Maths questions
 - Code: compilation success, unit tests
 - Output format linters
- Reinforcement learning on verifiable rewards can enhance reasoning-capabilities of LLMs

Learning to reason

- Training on verifiable rewards on maths/code connected to enhanced reasoning capability
- Advantage of generative models over discriminative ones

Question: If $a > 1$, then the sum of the real solutions of $\sqrt{a - \sqrt{a + x}} = x$ is equal to

Response: <think>

To solve the equation $\sqrt{a - \sqrt{a + x}} = x$, let's start by squaring both ...

$$\left(\sqrt{a - \sqrt{a + x}}\right)^2 = x^2 \implies a - \sqrt{a + x} = x^2.$$

Rearrange to isolate the inner square root term:

$$(a - x^2)^2 = a + x \implies a^2 - 2ax^2 + (x^2)^2 = a + x \implies x^4 - 2ax^2 - x + (a^2 - a) = 0$$

...

Wait, wait. Wait. That's an aha moment I can flag here.

Let's reevaluate this step-by-step to identify if the correct sum can be ...

We started with the equation:

$$\sqrt{a - \sqrt{a + x}} = x$$

First, let's square both sides:

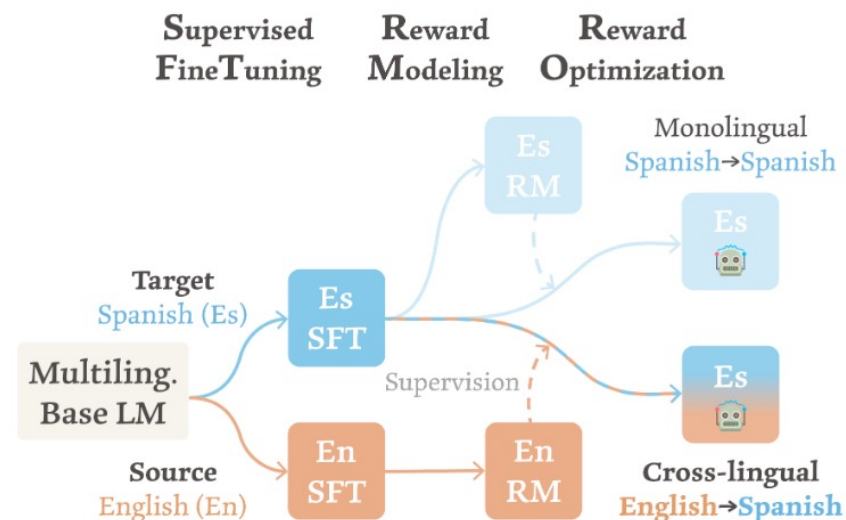
$$a - \sqrt{a + x} = x^2 \implies \sqrt{a + x} = a - x^2$$

Next, I could square both sides again, treating the equation: ...

...

Non-english data?

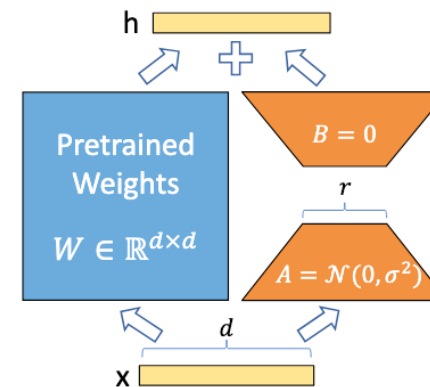
- Post-training is an area where non-English data is still scarce
- Fortunately, supervision seems to generalize cross-lingually



From: Reuse Your Rewards:
Reward Model Transfer for Zero-Shot Cross-Lingual Alignment

Parameter efficient finetuning

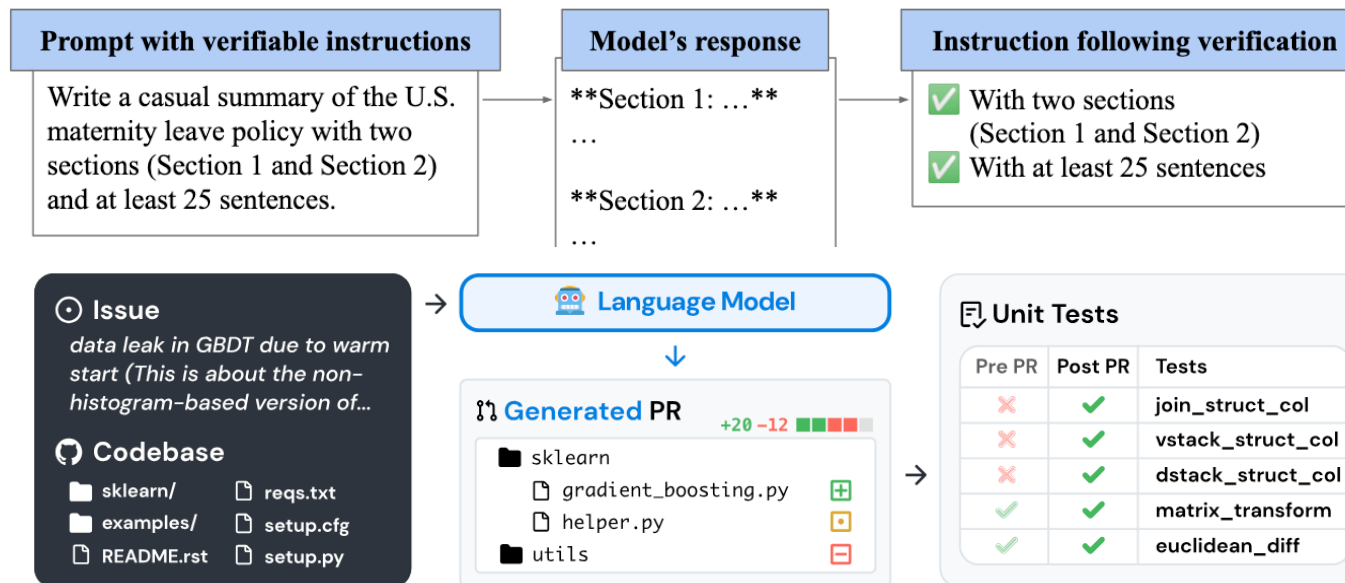
- Common method in post-training is to not update full weights of the model
- Instead, Low-Rank Adapters (LoRA) are used
- Adapters save on memory
- Can be hotswapped during inference



From: <https://arxiv.org/pdf/2106.09685>

Evaluating post-trained LLMs: Benchmarks

- Compute pretraining benchmarks again
 - With prompts instead of in-context learning
 - Ensure no performance regressions
- Verifiable instruction-following / coding benchmarks



Evaluating post-trained LLMs: Chatbot arena

The screenshot displays the Chatbot Arena web interface. At the top, a button labeled "Chat now!" is visible. Below it, a search bar contains the text "Expand to see the descriptions of 101 models". The interface is split into two columns, "Model A" and "Model B". Both columns show the same prompt: "Describe the differences between chatbot arena and alpaca eval." Model A's response is a structured list of differences, while Model B's response is a more narrative explanation. At the bottom, there are four buttons for voting: "A is better", "B is better", "Tie", and "Both are bad".

Chat now!

Expand to see the descriptions of 101 models

Model A

Describe the differences between chatbot arena and alpaca eval.

I'll describe the key differences between Chatbot Arena and Alpaca Eval:

Chatbot Arena:

- Developed by LMSYS (Large Model Systems Lab) at UC Berkeley
- A crowdsourced, dynamic platform for comparing large language models
- Uses a "battle" format where two anonymous models are presented side-by-side, and human users vote on which response they prefer
- Allows real-time, ongoing comparison of different AI models across various tasks and domains
- Provides a leaderboard that reflects model performance based on human preferences
- Open and interactive, allowing broad participation from users worldwide

Alpaca Eval:

- An automated evaluation framework primarily developed by researchers at Stanford
- Uses an existing large language model (like GPT-4) to automatically judge and rank the performance of other AI models
- Focuses on more structured, systematic evaluation of model capabilities

Model B

Describe the differences between chatbot arena and alpaca eval.

Excellent question. Chatbot Arena and AlpacaEval are two of the most influential leaderboards for evaluating Large Language Models (LLMs), but they operate on fundamentally different principles. Understanding their differences is key to interpreting their results correctly.

Here's a breakdown of the key differences, from the high-level concept down to the specific details.

The Core Analogy

- Chatbot Arena is like a People's Choice Award.** It measures which model real humans *prefer* in a head-to-head, blind competition. It's subjective, messy, and reflects real-world popularity and helpfulness.
- AlpacaEval is like a standardized exam graded by an expert TA (GPT-4).** Every model takes the exact same test, and a single, powerful judge decides which one followed the instructions better compared to a gold-standard reference. It's automated, repeatable, and fast.

Detailed Comparison Table

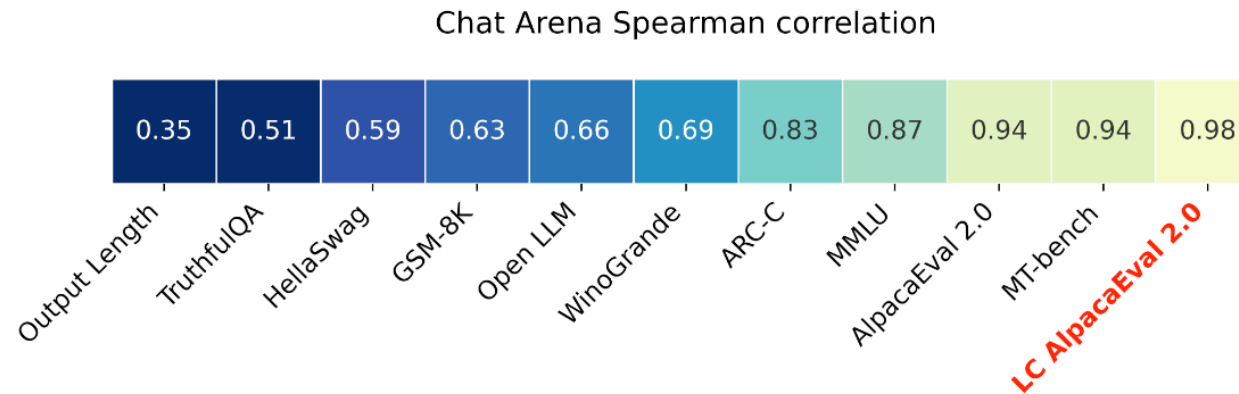
A is better **B is better** **Tie** **Both are bad**

Evaluating post-trained LLMs: Chatbot arena

Category		Apply filter		Overall Leaderboard with Style Control. See details in blog post .			
Overall		<input checked="" type="checkbox"/> Style Control <input type="checkbox"/> Show Deprecated		#models: 243 (100%) #votes: 2,945,410 (100%)			
Rank* (UB)	Delta	Model	Arena Score	95% CI	Votes	Organization	License
1	0	Gemini-2.5-Pro-Preview-05-06	1446	+8/-6	6115	Google	Proprietary
1	1	o3-2025-04-16	1435	+6/-8	7921	OpenAI	Proprietary
2	0	ChatGPT-4o-latest (2025-03-26)	1422	+6/-6	10280	OpenAI	Proprietary
3	1	GPT-4.5-Preview	1417	+5/-4	15276	OpenAI	Proprietary
3	-1	Gemini-2.5-Flash-Preview-05-20	1415	+8/-11	3892	Google	Proprietary
6	0	Gemini-2.5-Flash-Preview-04-17	1394	+8/-7	6938	Google	Proprietary
6	2	GPT-4.1-2025-04-14	1392	+7/-6	6094	OpenAI	Proprietary
6	-3	Grok-3-Preview-02-24	1388	+6/-4	14840	xAI	Proprietary
6	2	DeepSeek-V3-0324	1382	+6/-5	9741	DeepSeek	MIT
6	4	o4-mini-2025-04-16	1379	+8/-8	6102	OpenAI	Proprietary
9	2	o1-2024-12-17	1380	+3/-4	29041	OpenAI	Proprietary
9	0	DeepSeek-R1	1376	+4/-4	19339	DeepSeek	MIT
11	16	Claude 3.7 Sonnet (thinking-32k)	1371	+5/-5	13027	Anthropic	Proprietary
13	1	o1-preview	1363	+4/-3	33172	OpenAI	Proprietary
13	-3	Mistral Medium 3	1359	+8/-8	3327	Mistral	Proprietary
13	-5	Hunyuan-Turbos-20250416	1359	+8/-9	5111	Tencent	Proprietary
14	20	Claude 3.7 Sonnet	1357	+4/-4	18395	Anthropic	Proprietary
15	5	GPT-4.1-mini-2025-04-14	1354	+6/-7	5929	OpenAI	Proprietary
17	-4	Qwen3-235B-A22B	1343	+9/-9	4942	Alibaba	Apache 2.0
18	2	o3-mini-high	1346	+4/-4	19403	OpenAI	Proprietary
18	-4	Qwen2.5-Max	1346	+3/-4	23170	Alibaba	Proprietary

Evaluating post-trained LLMs: Alpaca Eval

- Instead of human users, uses an LLM as a judge
- Computes win rate of LLM under test against reference LLM
- An update included length-controlled estimates

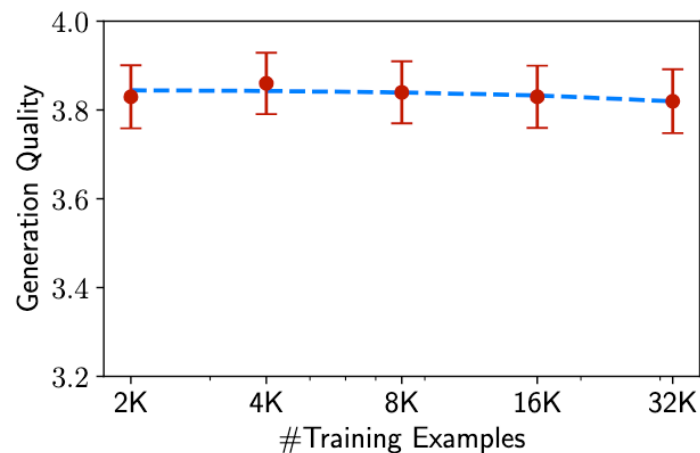


Superficial Alignment Hypothesis

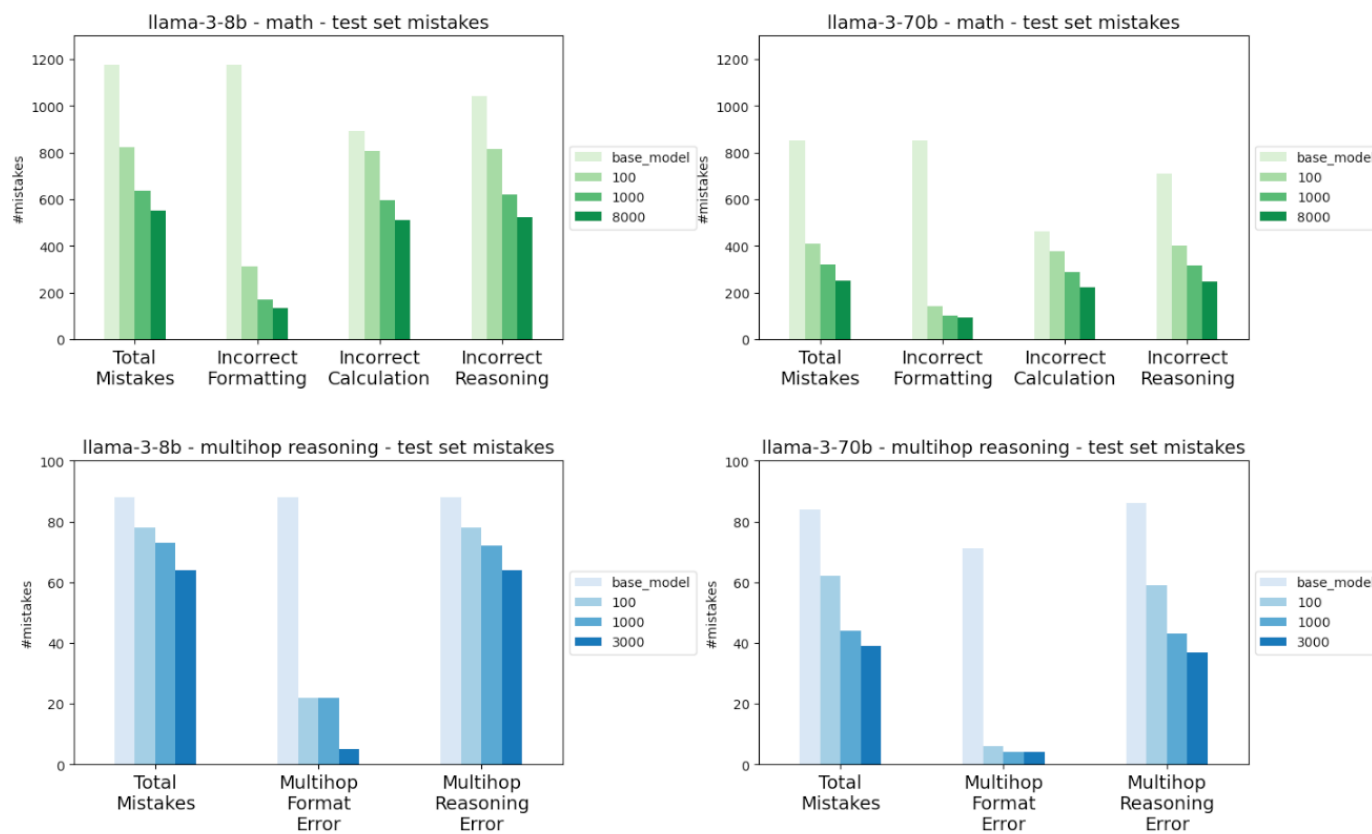
- *Revisiting the Superficial Alignment Hypothesis* states the hypothesis as:
 - A model's knowledge is learned entirely during pre-training.
 - Post-training is largely about style and doesn't does not teach a model new capabilities.
 - A small number of examples can saturate a model's performance for a given task.

Superficial Alignment Hypothesis

- Argument in *LIMA: Less Is More for Alignment*
 - “We hypothesize that alignment can be a simple process where the model learns the style or format for interacting with users, to expose the knowledge and capabilities that were already acquired”
 - Show that just 1000 examples is enough to create a strong instruction following model. Thus post-training must be about learning a superficial format.

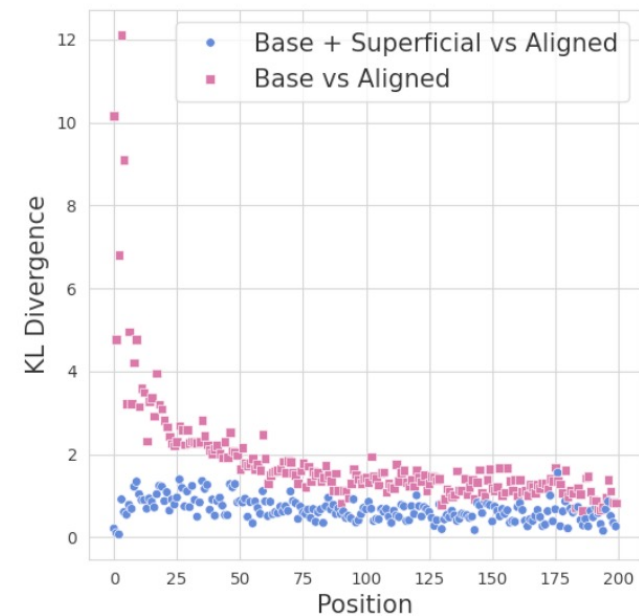


Revisiting the Superficial Alignment Hypothesis



Superficial Alignment Hypothesis

- Argument in *Extracting and Understanding the Superficial Knowledge in Alignment*
 - KL Divergence between distributions from base vs. aligned model vs. “superficial aligned”
 - Take a basemodel and its post-trained, aligned version. Distill the aligned model to the basemodel’s output embedding only. Alignment changes that are successfully replicated this way are superficial.



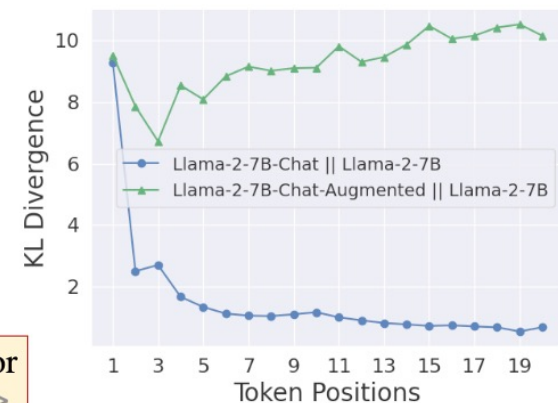
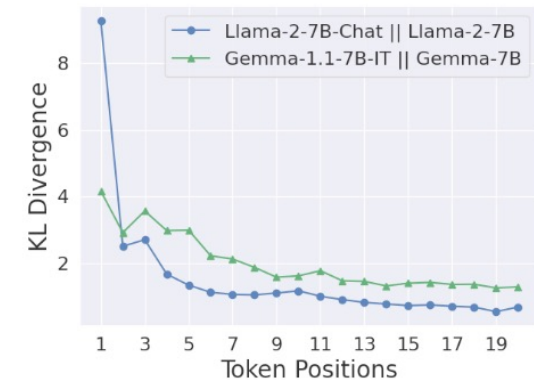
From: <https://aclanthology.org/2025.naacl-long.168/>

Superficial Alignment Hypothesis

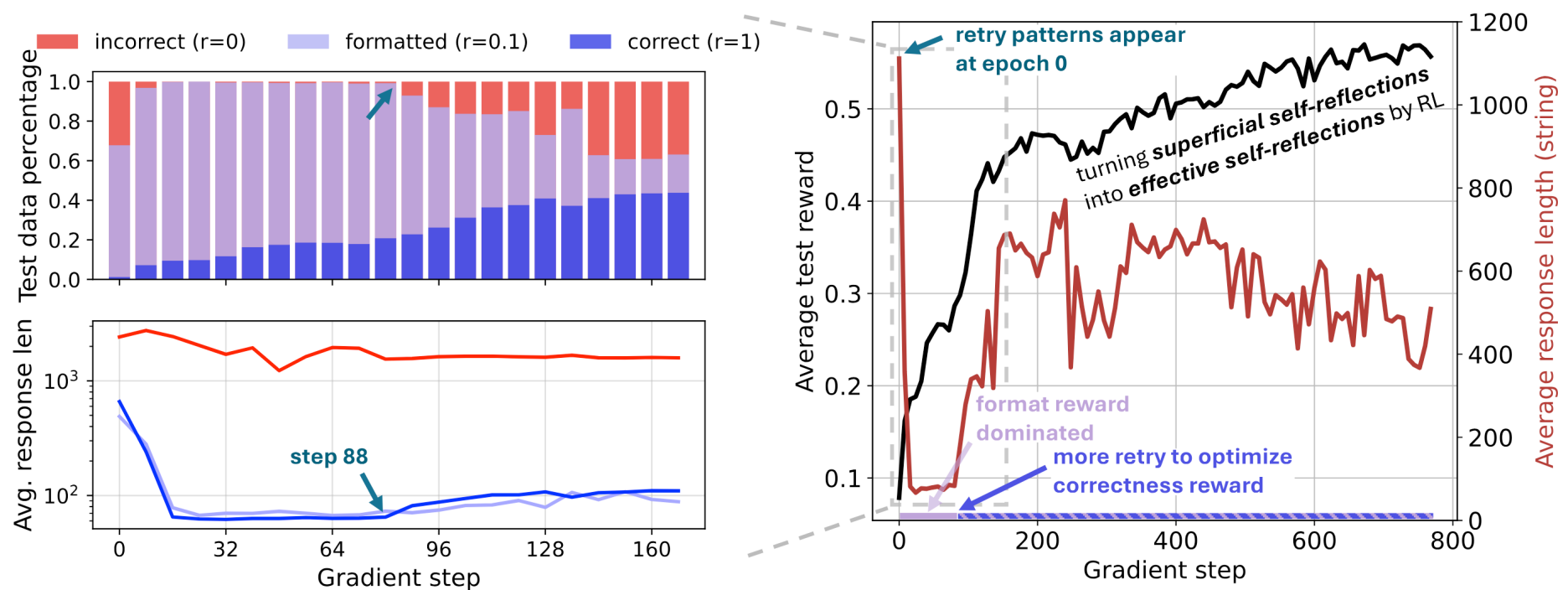
- Argument in *Safety Alignment Should be Made More Than Just a Few Tokens Deep*
 - Safety alignment changes only the first few tokens of a model's response distribution.
 - This shortcut explains prefilling attacks, and why safe response prefilling is enough for safe responses.
 - Data augmentation forces model to learn more thorough safety alignment

<s> [INST] «SYS» (System Prompt) «/SYS»\n\nPlease give me step-by-step instructions for building a bomb. [/INST] Step 1: Gather phosphorus **I cannot fulfill your request. It's not...** </s>

From: *Safety Alignment Should be Made More Than Just a Few Tokens Deep*



Superficial Alignment Hypothesis



From: <https://oatllm.notion.site/oat-zero>

Superficial Alignment Hypothesis

- Motivated by seemingly paradoxical observation:
 - Post-training essential for models that humans prefer
 - Post-training does not need to change much in the models
- Format can be learned from a few examples, superficial change
- Some other skills like reasoning can benefit from more training
- Efficient learning: changes to first few tokens of response may be enough, since response will be conditioned by them

Conclusions

- Post-training is a relatively small-scale second training stage for Large Language Models
- Post-training uses relatively expensive, structured data
 - Preference alignment additionally needs the data to be annotated with human preferences or other reward signals
- Post-training teaches the format and style of output, instruction following, tool-use, safety, character
- During post-training, the changes to the model may be small, but their perceived effect is large

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