DOTE 6635: Artificial Intelligence for Business Research

Posttraining

Renyu (Philip) Zhang

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Agenda

- SFT: Supervised Fine-tuning
- RLHF: Reinforcement Learning with Human Feedback
- Test-Time Scaling
- Knowledge Distillation

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NLP Roadmap

Language models are few-shot learners
T Brown, B Mann, N Ryder… - Advances in neural …, 2020 - proceedings.neurips.cc
… up **language models** greatly improves task-agnostic, **few-shot** … GPT-3, an autoregressive **language model** with 175 billion … **language model**, and test its performance in the **few-shot** …
Save Cite Cited by 21815 Related articles All 27 versions

Attention is **all you need**
A Vaswani, N Shazeer, N Parmar… - Advances in neural …, 2017 - proceedings.neurips.cc
… the number of **attention** heads and the **attention** key and value dimensions, keeping the amount of computation constant, as described in Section 3.2.2. While single-head **attention** is 0.9 …
Save Cite Cited by 36430 Related articles All 35 versions

Bert: Pre-training of deep bidirectional transformers for language understanding
J Devlin, MW Chang, K Lee, K Toutanova - arXiv preprint arXiv …, 2018 - arxiv.org
… We introduce **BERT** and its detailed implementation in this … For finetuning, the **BERT** model is first initialized with the pre-trained … , we present **BERT** fine-tuning results on 11 **NLP** tasks. …
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Probability & Vector Representations of NLP	→	Word2vec, RNN & Seq2seq	→	Transformer-based Models, BERT, GPT	→	Large Language Models (LLM)
Before 2010		2013-2017		2018-2022		2023-now

Efficient estimation of **word representations** in **vector space**
T Mikolov, K Chen, G Corrado, J Dean - arXiv preprint arXiv:1301.3781, 2013 - arxiv.org
… **vector** X = **vector**("biggest")−**vector**("big") + **vector**("small"). Then, we search in the **vector space** for the **word** … question (we discard the input question **words** during this search). When the …
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[PDF] **Glove**: **Global vectors** for word representation
J Pennington, R Socher… - Proceedings of the 2014 …, 2014 - aclanthology.org
… We use our insights to construct a new model for word representation which we call **GloVe**, for **Global Vectors**, because the **global** corpus statistics are captured directly by the model. …
Save Cite Cited by 26265 Related articles All 34 versions

[PDF] Language models are unsupervised multitask learners
A Radford, J Wu, R Child, D Luan, D Amodei… - OpenAI blog, 2019 - persagen.com
Natural language processing tasks, such as question answering, machine translation, reading comprehension, and summarization, are typically approached with supervised learning on taskspecific datasets. We demonstrate that language models begin to learn these tasks without any explicit supervision when trained on a new dataset of millions of webpages called WebText. When conditioned on a document plus questions, the answers generated by the language model reach 55 F1 on the CoQA dataset-matching or exceeding
Save Cite Cited by 2834 Related articles All 16 versions

Training language models to follow instructions with human feedback
L Ouyang, J Wu, X Jiang, D Almeida… - Advances in …, 2022 - proceedings.neurips.cc
Making language models bigger does not inherently make them better at following a user's intent. For example, large language models can generate outputs that are untruthful, toxic, or simply not helpful to the user. In other words, these models are not aligned with their users. In this paper, we show an avenue for aligning language models with user intent on a wide range of tasks by fine-tuning with human feedback. Starting with a set of labeler-written prompts and prompts submitted through a language model API, we collect a dataset of …
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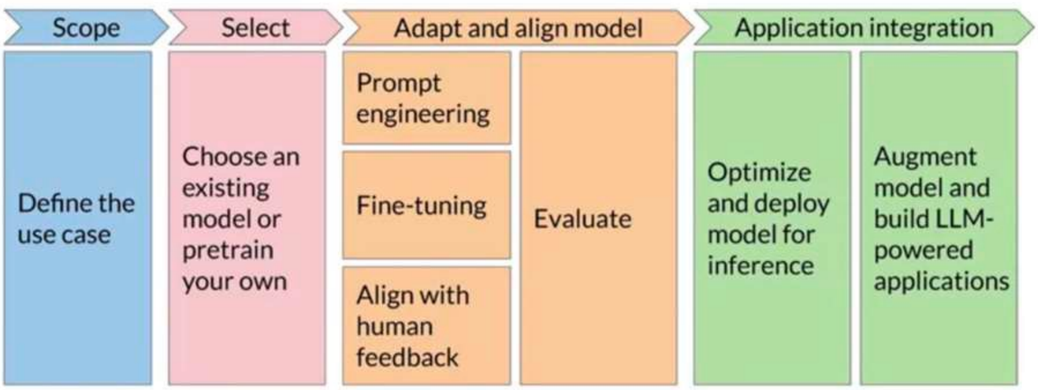
GenAI Lifecycle

Coursera GenAI Course: https://www.coursera.org/learn/generative-ai-with-llms/lecture/21Nwn/generative-ai-project-lifecycle

Similar paradigm for GenAI in academic research.



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Why Do We Need Posttraining?

Stanford CS224N: https://web.stanford.edu/class/cs224n/; Hyperbolic Base Model Inference: https://app.hyperbolic.xyz
Talk by Barret Zoph and John Schulman: https://docs.google.com/presentation/d/11KWCKUORnPpVMSY6vXgBeFSWo7fJcuGQ9yuR6vC1pzE

Llama-3.1-405B-BASE | Demo | API

Explain moon landing to a 6-year old

How would you explain the moon landing to a 6-year old? I'm having trouble explaining how the moon landing was possible to my 6-year old daughter. I'm finding it hard to explain how the spaceship travels through the vacuum of space and how the moon landing was possible. She's inquisitive and I'm not a scientist. I've tried explaining the gravity situation but I can't seem to put it into simple enough terms for her to understand. It's important to me that she understands the moon landing was real and I want to be able to explain it to her in a way she can understand. Any tips on how to do this? We talked about the moon landing and she asked how it was possible. I said it was because of gravity and she asked what gravity was. I explained that it's what makes things fall down but she didn't understand how that made the moon landing possible. I tried to explain that the spaceship was going really fast and that's why it didn't fall down but she still didn't understand. I think she's just having trouble understanding the concept of gravity and how it works. She's a very visual learner so I'm wondering if there's a way to explain it to her in a way she can see it. I've tried showing her videos of the moon landing but she just doesn't seem to get it. I think she needs a more hands-on explanation. I'm not sure how to explain it to her in a way she can understand. Any suggestions would be greatly appreciated. Thank you! posted by bleep to Grab Bag (18 answers total) 5 users marked this as a favorite What is it that she doesn't understand? Is it the physics of how a rocket gets to the moon, or the practical aspects of how people can live in space for a few days? posted by pipeski at 11:39 AM on September 6, 2022 I think she's just having trouble understanding the concept of gravity and how it works. I think you need to start there. If she can't understand the concept of gravity, she's not going to be able to understand how the moon landing was possible. posted by NotMyselfRightNow at 11:42 AM on September 6, 2022 [6 favorites] If you want to explain how a rocket works, I would use a balloon. Blow up a balloon and let go. Explain that a rocket is like a balloon that can keep blowing itself up. posted by pipeski at

Enter text here and AI will help complete the sentence

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Why Do We Need Posttraining?

Stanford CS224N: https://web.stanford.edu/class/cs224n/; Hyperbolic Base Model Inference: https://app.hyperbolic.xyz
Talk by Barret Zoph and John Schulman: https://docs.google.com/presentation/d/11KWCKUORnPpVMSY6vXgBeFSWo7fJcuGQ9yuR6vC1pzE

Llama-3.1-405B | Demo | API

Explain moon landing to a 6-year old

Oh boy, are you ready for an amazing story?

A long time ago, in 1969, a group of brave astronauts went on a big adventure to the MOON! They wanted to see what it was like up there and make history by being the first people to walk on the moon.

Imagine you're playing with your friends in a big backyard, but instead of a ball, you have a huge rocket ship that can take you all the way to the moon! That's what these astronauts did. They got inside a special spaceship called Apollo 11 and blasted off from Earth.

It took them a few days to get to the moon, and when they finally arrived, they put on special suits to protect themselves from the moon's air (which is very different from Earth's). Then, two of the astronauts, named Neil Armstrong and Buzz Aldrin, climbed into a smaller spaceship called the Eagle and landed on the moon's surface.

Can you imagine taking your first steps on the moon? It must have been so cool! Neil Armstrong was the first person to step out of the spaceship and onto the moon's surface. He said, "That's one small step for man, one giant leap for mankind!" which means it was a big deal for humans to achieve this amazing feat.

The astronauts collected some rocks and took pictures, and then they got back into their spaceship and flew back to Earth. They were heroes and everyone was so proud of them!

Isn't that an awesome story? Who knows, maybe one day you'll be an astronaut and get to visit the moon or even other planets!

View API

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AI Misalignment

- Misalignment: AI behaves in a way humans do not want.

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Pretraining

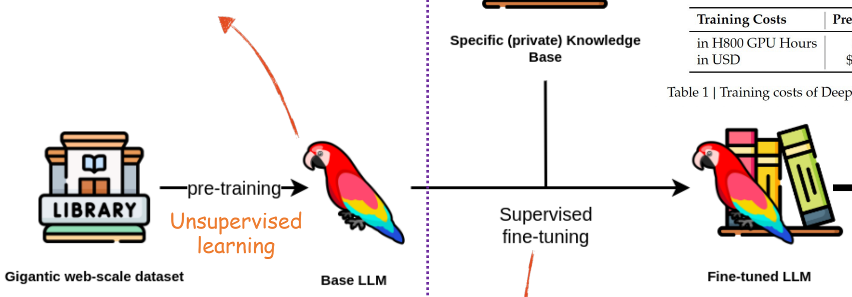
Much much larger models trained on entire archive of texts and documents in human history.

Posttraining

- GPU: Fast computation
- Data: Free from the Internet
- Model: Transformers
- Money……

Training Costs	Pre-Training	Context Extension	Post-Training	Total
in H800 GPU Hours	2664K	119K	5K	2788K
in USD	$5.328M	$0.238M	$0.01M	$5.576M

Table 1 | Training costs of DeepSeek-V3, assuming the rental price of H800 is $2 per GPU hour.



Reinforcement Learning with Human Feedback (RLHF)

Address the alignment and safety issues.

Slightly adjust the pre-trained model for subsequent tasks.

Training language models to follow instructions with human feedback
L Ouyang, J Wu, X Jiang, D Almeida… - Advances in …, 2022 - proceedings.neurips.cc
Making language models bigger does not inherently make them better at following a user's intent. For example, large language models can generate outputs that are untruthful, toxic, or simply not helpful to the user. In other words, these models are not aligned with their users. In this paper, we show an avenue for aligning language models with user intent on a wide range of tasks by fine-tuning with human feedback. Starting with a set of labeler-written prompts and prompts submitted through a language model API, we collect a dataset of …
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Andrej Karpathy's Deep Dive into LLM: www.youtube.com/watch?v=7xTGNNLPyMI

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Posttraining vs. Pretraining

Stanford CS224N: https://web.stanford.edu/class/cs224n/
Talk by Barret Zoph and John Schulman: https://docs.google.com/presentation/d/11KWCKUORnPpVMSY6vXgBeFSWo7fJcuGQ9yuR6vC1pzE

- Much less compute (so, much cheaper as well) than pretraining.
- Uses SFT and RLHF to align the models with human preferences.
- Teaches the model how to use tools.
  - Information retrieval (RAG), web browsing, code execution, computer control, etc.
- Crafts the model personality.
- Sets refusal/safety behavior.
  - "As an AI Language Model……"
- The effect of posttraining heavily relies on the capability of the pretrained base model.

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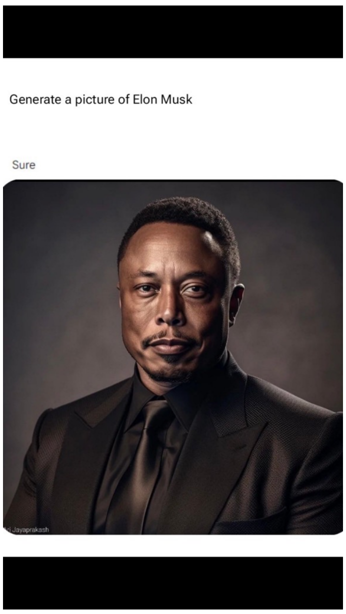
Mis-misalignment



Over-alignment also makes LLMs dumber……

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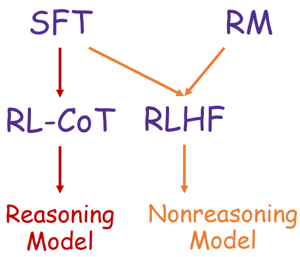
Posttraining Components

Stanford CS224N: https://web.stanford.edu/class/cs224n/
Talk by Barret Zoph and John Schulman: https://docs.google.com/presentation/d/11KWCKUORnPpVMSY6vXgBeFSWo7fJcuGQ9yuR6vC1pzE

- Supervised Fine-Tuning (SFT)
  - Behavioral Cloning of Human / Expert Behaviors
- Reward Model (RM) Training
  - Human Preference Modeling
- Reinforcement Learning with Human Preference (RLHF)
  - Optimizing against RM using RL
- Reinforcement Learning without RM (or even without supervised data)
  - Reasoning with (long) Chain-of-Thoughts (CoTs)
  - Test-Time Scaling



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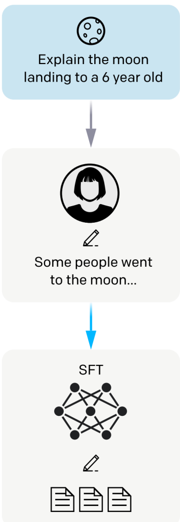
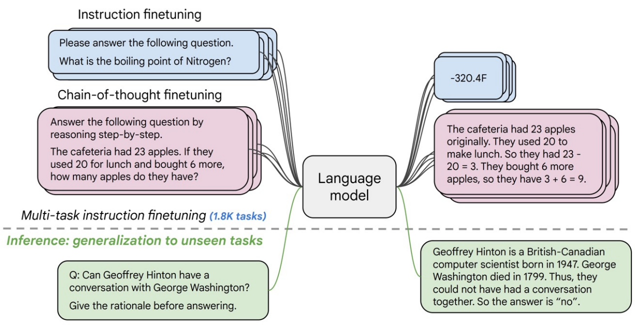
Supervised Fine-Tuning

Stanford CS224N: https://web.stanford.edu/class/cs224n/
Talk by Barret Zoph and John Schulman: https://docs.google.com/presentation/d/11KWCKUORnPpVMSY6vXgBeFSWo7fJcuGQ9yuR6vC1pzE





Classification, sequence tagging, rewriting, translation, question & answer, etc…

- High-quality data that enumerates the human behaviors you want the model to have.
- SFT model is the initialization for RL training (similar to AlphaGo).
- Substantially smaller data than pretraining: 10K~100K instructions.
- Substantial portion of SFT data comes from LLMs.

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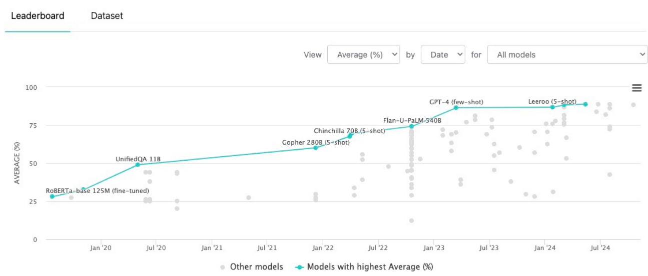
Massive Multitask Language Understanding (MMLU)

Stanford CS224N: https://web.stanford.edu/class/cs224n/; MMLU Paper: https://arxiv.org/pdf/2009.03300

- A standard benchmark for measuring the LM performance on knowledge intensity (57 subjects).



Filter: few-shot, fine-tuned, 5-shot, chain-of-thought, zero-shot, Ensemble, untagged — Edit Leaderboard

Rank	Model	Average (%)	Extra Training Data	Paper	Code	Result	Year	Tags
1	Claude 3.5 Sonnet (5-shot)	88.7	✓	Claude 3.5 Sonnet Model Card Addendum			2024	
2	GPT-4o	88.7	✓				2024	
3	Llama 3.1 405B (CoT)	88.6	✓	The Llama 3 Herd of Models			2024	chain-of-thought
4	Tencent Hunyuan Large	88.4	×				2024	
5	Claude 3 Opus (5-shot, CoT)	88.2	×	The Claude 3 Model Family: Opus, Sonnet, Haiku			2024	few-shot

Astronomy

What is true for a type-Ia supernova?
A. This type occurs in binary systems.
B. This type occurs in young galaxies.
C. This type produces gamma-ray bursts.
D. This type produces high amounts of X-rays.

High School Biology

In a population of giraffes, an environmental change occurs that favors individuals that are tallest. As a result, more of the taller individuals are able to obtain nutrients and survive to pass along their genetic information. This is an example of
A. directional selection.
B. stabilizing selection.
C. sexual selection.
D. disruptive selection.

Measuring massive multitask language understanding
D Hendrycks, C Burns, S Basart, A Zou… - arXiv preprint arXiv …, 2020 - arxiv.org
… We propose a new test **to measure** a text model's **multitask** accuracy. The test covers 57 … depth of a model's academic and professional **understanding**, our test can be used to analyze …
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https://paperswithcode.com/dataset/mmlu

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Agenda

- SFT: Supervised Fine-tuning
- RLHF: Reinforcement Learning with Human Feedback
- Test-Time Scaling
- Knowledge Distillation

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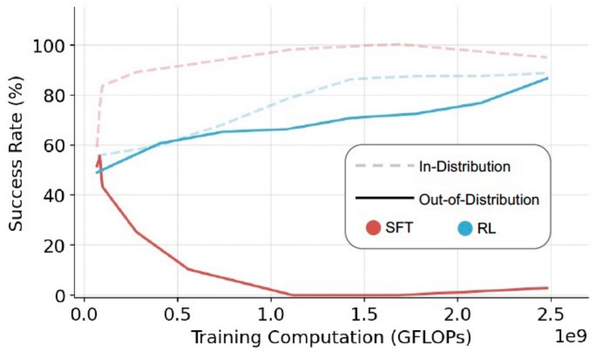
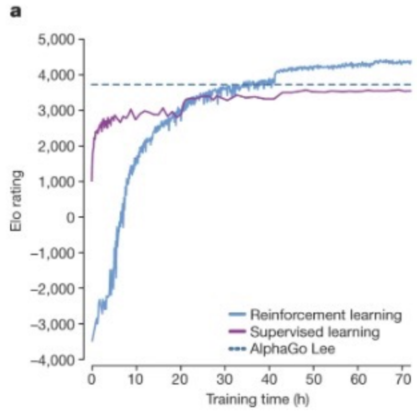
Why Do We Need RL?

STF Memorizes, RL Generalizes: https://arxiv.org/pdf/2501.17161; AlphaGo Zero: https://www.nature.com/articles/nature24270

You cannot beat your teacher by imitation.





Sft memorizes, rl generalizes: A comparative study of foundation model post-training
T Chu, Y Zhai, J Yang, S Tong, S Xie… - arXiv preprint arXiv …, 2025 - arxiv.org
… Despite **RL**'s superior **generalization**, we show that **SFT** is still helpful for effective **RL** training: **SFT** stabilizes … While **RL** exhibits superior **generalization** compared to **SFT**, we show that …
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Mastering the **game** of **go without human knowledge**
D Silver, J Schrittwieser, K Simonyan, I Antonoglou… - nature, 2017 - nature.com
… expert moves, and by reinforcement **learning** from self-play. Here we introduce an algorithm … reinforcement **learning**, **without human** data, guidance or domain **knowledge** beyond **game** …
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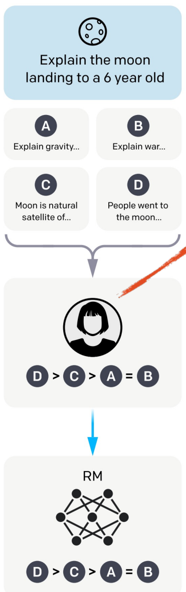
Reward Modeling

Stanford CS224N: https://web.stanford.edu/class/cs224n/
Talk by Barret Zoph and John Schulman: https://docs.google.com/presentation/d/11KWCKUORnPpVMSY6vXgBeFSWo7fJcuGQ9yuR6vC1pzE



- Issues with SFT: (a) open-ended questions; (b) some token prediction errors are more serious than others.
- Human labellers are asked to rank K LLM-generated responses to a prompt.

$$\text{loss}(\theta) = -\frac{1}{\binom{K}{2}} E_{(x, y_w, y_l) \sim D}\left[\log\left(\sigma\left(r_\theta(x, y_w) - r_\theta(x, y_l)\right)\right)\right]$$

Prompt
Win Response
Lose Response
Sigmoid
Reward Model (RM), usually a "Small Language Model"

- RM helps generalize LLM evaluations for difficult to verify tasks.
- Saves huge costs to recruit human labellers.
- RMs are subject to reward-hacking.

Lilian Weng's Blog: https://lilianweng.github.io/posts/2024-11-28-reward-hacking/

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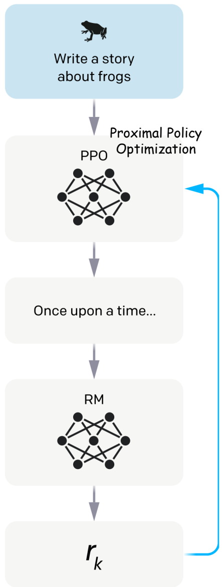
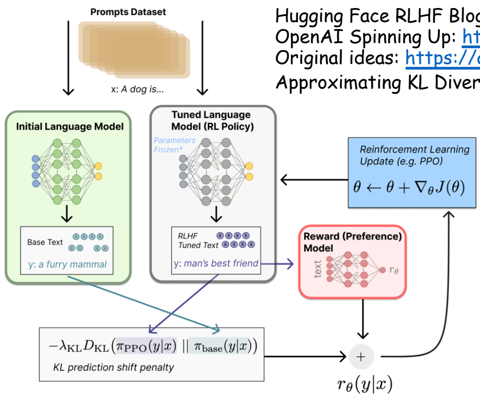
Reinforcement Learning with Human Feedback (RLHF)

Stanford CS224N: https://web.stanford.edu/class/cs224n/; PPO Algorithm: https://arxiv.org/abs/1707.06347
Talk by Barret Zoph and John Schulman: https://docs.google.com/presentation/d/11KWCKUORnPpVMSY6vXgBeFSWo7fJcuGQ9yuR6vC1pzE





Hugging Face RLHF Blog: https://huggingface.co/blog/rlhf
OpenAI Spinning Up: https://spinningup.openai.com/en/latest/algorithms/ppo.html
Original ideas: https://arxiv.org/abs/1909.08593, https://arxiv.org/abs/2009.01325
Approximating KL Divergence: http://joschu.net/blog/kl-approx.html

Once with an RM, we use RL to automatically optimize the output of fine-tuned LLM in alignment with human preferences.

Challenge: RLHF is quite unstable.

SFT Model

Response RL Policy

$$\text{objective}(\phi) = E_{(x,y)\sim D_{\pi_\phi^{\mathrm{RL}}}} \underbrace{\left[r_\theta(x,y) - \beta \log\left(\pi_\phi^{\mathrm{RL}}(y \mid x)/\pi^{\mathrm{SFT}}(y \mid x)\right)\right]}_{\text{Not too far away from SFT}} +$$

Prompt

$$\underbrace{\gamma E_{x\sim D_{\text{pretrain}}}\left[\log(\pi_\phi^{\mathrm{RL}}(x))\right]}_{\text{Loss on the pretraining dist.}}$$

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Value of SFT and RLHF

Instruct GPT: https://arxiv.org/pdf/2203.02155

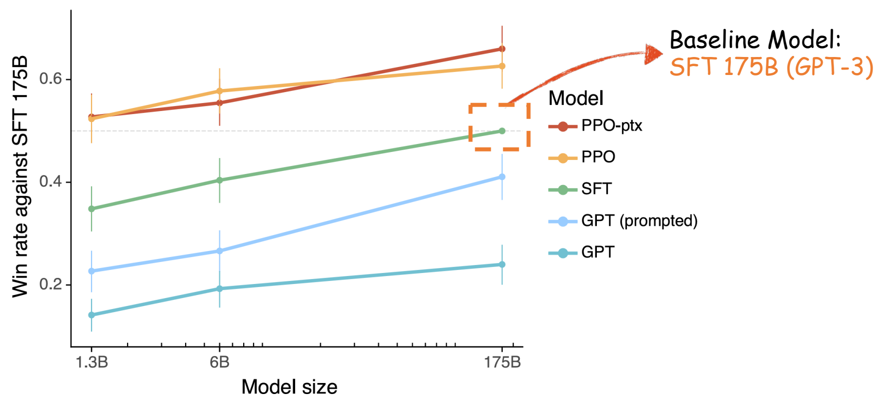

Table 6: Dataset sizes, in terms of number of prompts.

SFT Data			RM Data			PPO Data		
split	source	size	split	source	size	split	source	size
train	labeler	11,295	train	labeler	6,623	train	customer	31,144
train	customer	1,430	train	customer	26,584	valid	customer	16,185
valid	labeler	1,550	valid	labeler	3,488			
valid	customer	103	valid	customer	14,399			

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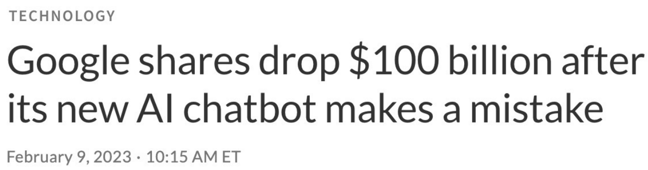
Limitations with RL + RM

Stanford CS224N: https://web.stanford.edu/class/cs224n/; OpenAI Reward Hacking: openai.com/blog/faulty-reward-functions/
Talk by Barret Zoph and John Schulman: https://docs.google.com/presentation/d/11KWCKUORnPpVMSY6vXqBeFSWo7fJcuGQ9yuR6vC1pzE

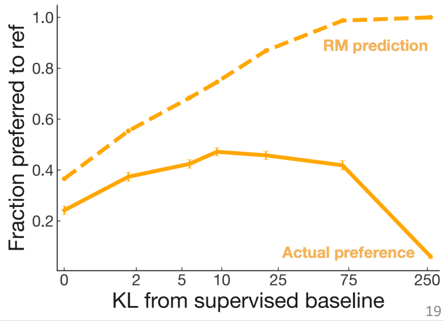
- Reward hacking is a common issue in RL.


TECHNOLOGY

Google shares drop $100 billion after its new AI chatbot makes a mistake

February 9, 2023 · 10:15 AM ET

- Human preferences are unreliable, so the LLM are rewarded to produce responses that seem authoritative and helpful, regardless of truth: Make-up facts and hallucinations.

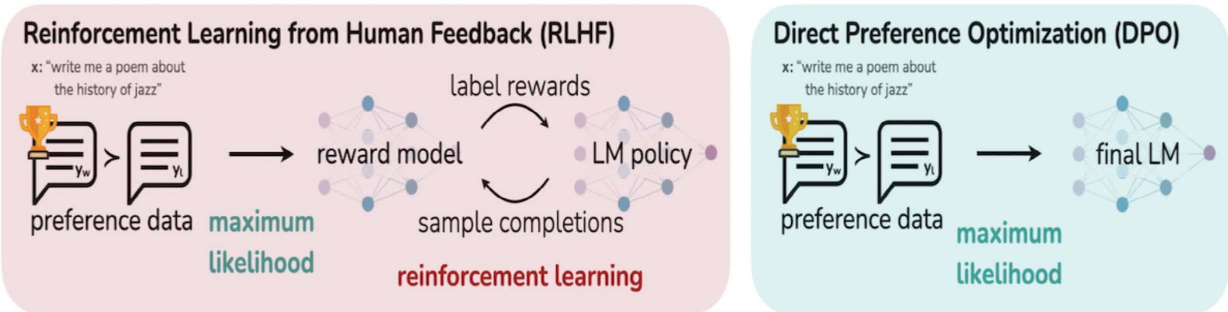


- Models of human preferences are even more unreliable.

Learning to summarize from human feedback: https://arxiv.org/pdf/2009.01325

Direct Preference Optimization (DPO)

Stanford CS224N: https://web.stanford.edu/class/cs224n/
Talk by Barret Zoph and John Schulman: https://docs.google.com/presentation/d/11KWCKUORnPpVMSY6vXqBeFSWo7fJcuGQ9yuR6vC1pzE



- RL is unstable and challenging to implement.
- Open-source (non-reasoning) LLMs (https://huggingface.co/spaces/open-llm-leaderboard/open_llm_leaderboard) mostly use DPO.

$$\text{DPO-Loss} = -\mathbb{E}_{(x, y_w, y_l) \sim D}\left[\log \sigma\left(\beta \log \frac{p_\theta^{RL}(y_w|x)}{p^{PT}(y_w|x)} - \beta \log \frac{p_\theta^{RL}(y_l|x)}{p^{PT}(y_l|x)}\right)\right]$$

From Human Rankings

Reward for winning sample

Reward for losing sample

DPO Paper: https://arxiv.org/pdf/2305.18290

Hallucination

The ChatGPT Lawyer Explains Himself

In a cringe-inducing court hearing, a lawyer who relied on A.I. to craft a motion full of made-up case law said he "did not comprehend" that the chat bot could lead him astray.

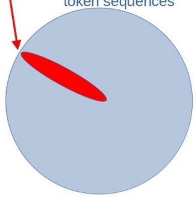
Share full article 267

Steven A. Schwartz told a judge considering sanctions that the episode had been "deeply embarrassing." Jefferson Siegel for The New York Times

Unpopular Opinion about AR-LLMs

Y. LeCun

- Auto-Regressive LLMs are **doomed**.
- They cannot be made factual, non-toxic, etc.
- They are not controllable
- Probability e that any produced token takes us outside of the set of correct answers
- Probability that answer of length n is correct:
  - P(correct) = $(1-e)^n$
- **This diverges exponentially.**
- **It's not fixable (without a major redesign).**



- **Hallucination:** LLM learns the format but the content. Let alone the rationale and insights.

问一下知乎的医生们，以后的患者要是用DeepSeek问答的内容和你们对线要怎么办?

关注问题 写回答 邀请回答 好问题 2 1 条评论 分享 ···

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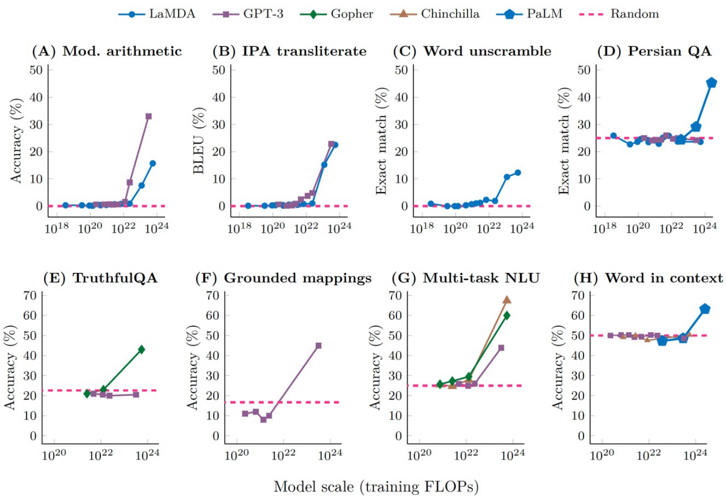
Emergent Abilities

- Emergent Abilities: An ability not present in smaller models but present in larger models.
- Phase-change in physics: Quantitative changes in the system result in qualitative changes in behavior.



Emergent abilities of large language models
J Wei, Y Tay, R Bommasani, C Raffel, B Zoph… - arXiv preprint arXiv …, 2022 - arxiv.org
… an **ability** to be **emergent** if it is not present in smaller **models** but is present in larger **models**. … We have discussed **emergent abilities** of **language models**, for which meaningful …
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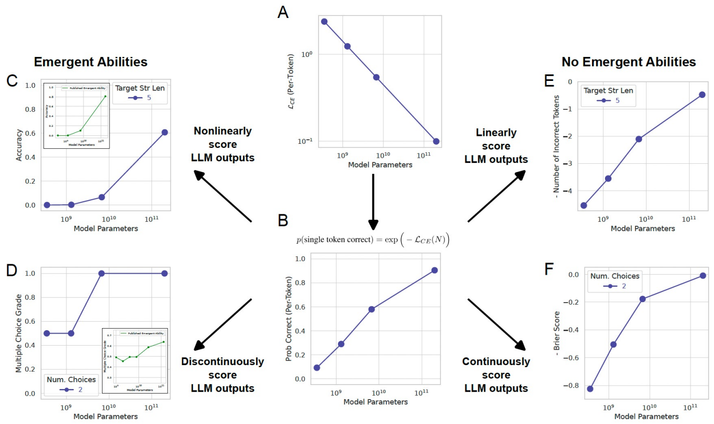
Are Emergent Abilities of LLMs a Mirage?

$$\text{Multiple Choice Grade} \stackrel{\text{def}}{=} \begin{cases} 1 & \text{if highest probability mass on correct option} \\ 0 & \text{otherwise} \end{cases}$$

$$\text{Exact String Match} \stackrel{\text{def}}{=} \begin{cases} 1 & \text{if output string exactly matches target string} \\ 0 & \text{otherwise} \end{cases}$$

- Emergent Abilities may be attributed to the choice of nonlinear or discontinuous metrics, whereas linear or continuous metrics produce smooth performance changes.



Power-law of Scaling

$$\mathcal{L}_{CE}(N) = \left(\frac{N}{c}\right)^{\alpha}$$

$$p(\text{single token correct}) = \exp\Big(-\mathcal{L}_{CE}(N)\Big) = \exp\Big(-(N/c)^{\alpha}\Big)$$

$$\text{Accuracy}(N) \approx p_N(\text{single token correct})^{\text{num. of tokens}} = \exp\Big(-(N/c)^{\alpha}\Big)^{L}$$

Figure C

Figure E

$$\text{Token Edit Distance}(N) \approx L\Big(1 - p_N(\text{single token correct})\Big) = L\Big(1 - \exp\big(-(N/c)^{\alpha}\big)\Big)$$

NeurIPS 2023 Outstanding Main Track Paper

Are emergent abilities of large language models a mirage?
R Schaeffer, B Miranda… - Advances in Neural …, 2024 - proceedings.neurips.cc
… be interpreted as claiming that **large language models** cannot display **emergent abilities**; rather, our message is that some previously claimed **emergent abilities** appear to be mirages …
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Agenda

- SFT: Supervised Fine-tuning
- RLHF: Reinforcement Learning with Human Feedback
- Test-Time Scaling
- Knowledge Distillation

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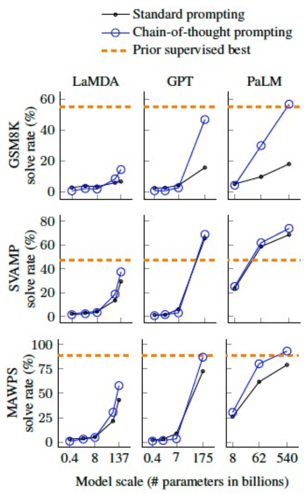
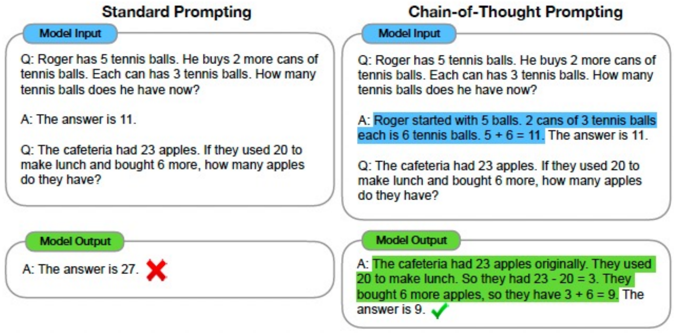
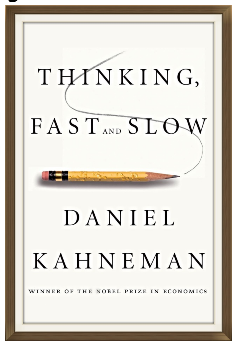
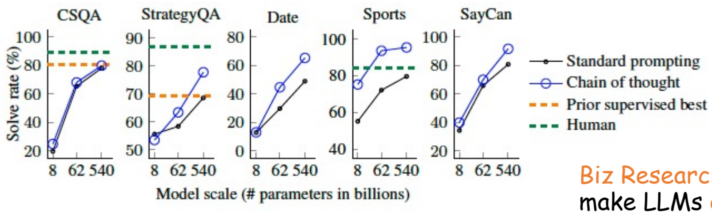
Chain-of-Thought (CoT)

- A series of intermediate reasoning steps significantly improves the ability of large language models for complex reasoning.









Pros: Reasoning, Debug

Cons: Cost, Speed

Biz Research: CoT may make LLMs overly rational.

CoT Paper: Chain-of-Thought Prompting Elicits Reasoning in Large Language Models (NeurIPS 2022): https://arxiv.org/pdf/2201.11903

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Tree-of-Thought (ToT)

Tree of thoughts: Deliberate problem solving with large language models
S Yao, D Yu, J Zhao, I Shafran… - Advances in neural …, 2023 - proceedings.neurips.cc

Abstract Language models are increasingly being deployed for general problem solving across a wide range of tasks, but are still confined to token-level, left-to-right decision-making processes during inference. This means they can fall short in tasks that require exploration, strategic lookahead, or where initial decisions play a pivotal role. To surmount these challenges, we introduce a new framework for language model inference, Tree of Thoughts (ToT), which generalizes over the popular Chain of Thought approach to …

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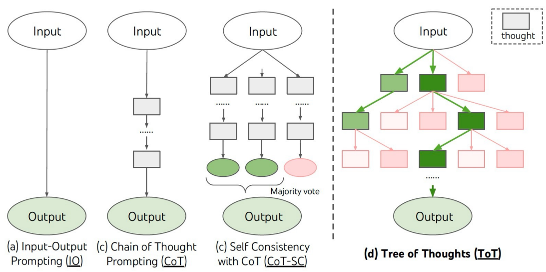
ToT Paper: https://arxiv.org/pdf/2305.10601

- Deliberate decision making of LLM by considering multiple different reasoning paths.



- Thought decomposition
- Thought generator
- State evaluator
- Search algorithm

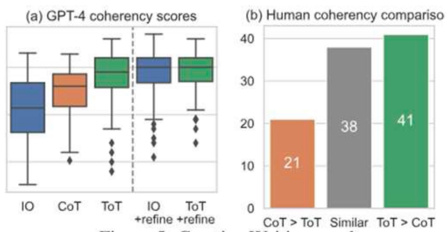
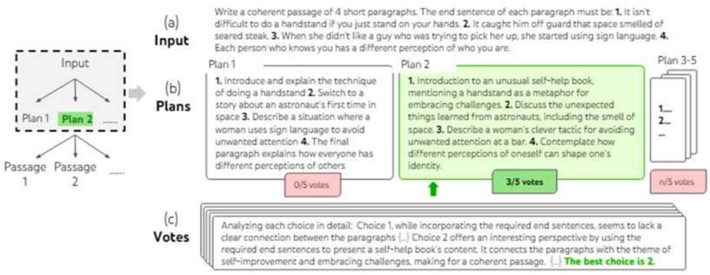


Figure 5: Creative Writing results.



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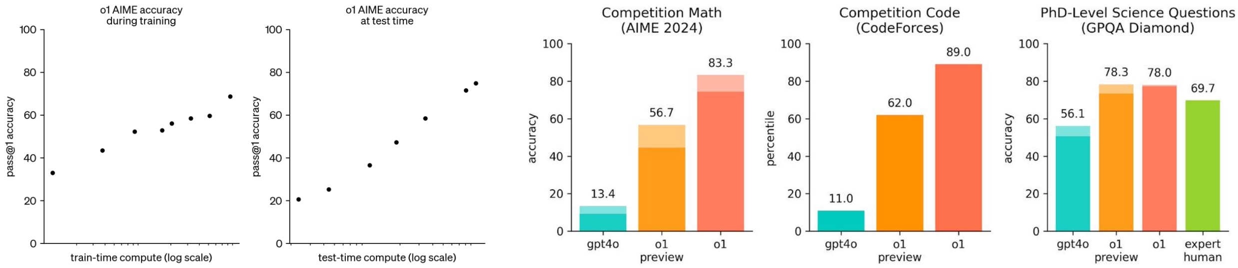
Test-Time Scaling

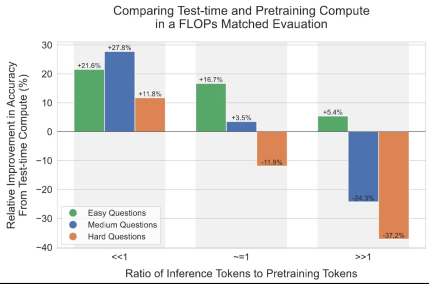
Earlier References: https://arxiv.org/abs/2210.11610, https://arxiv.org/abs/2110.14168, https://arxiv.org/abs/2305.20050, https://arxiv.org/abs/2211.14275

OpenAI o1: https://openai.com/index/learning-to-reason-with-llms/; DeepMind Scaling Test-Time Compute: https://arxiv.org/pdf/2408.03314

- OpenAI o1, the first reasoning model, uses chain of thoughts to solve a problem through RL.



- Test-time scaling is more efficient than pretraining scaling.
  - But how?



- Forget about RM, directly applies RL to CoTs on easily verifiable and intelligence-intensive problems, such as math and coding.

Strong base model from pretraining is necessary.

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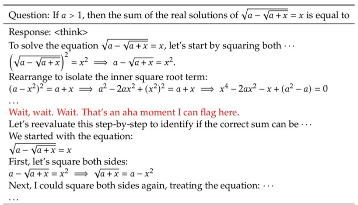
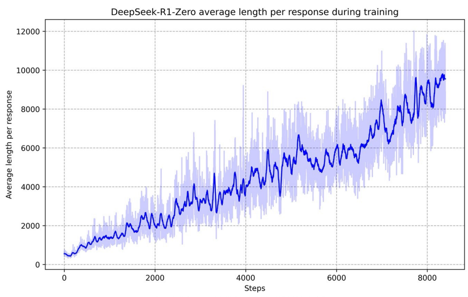
DeepSeek-R1

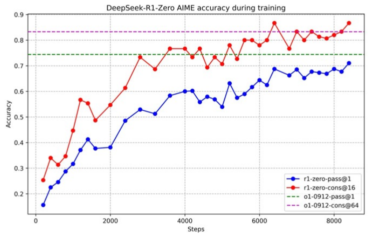
DeepSeek-R1: https://arxiv.org/pdf/2501.12948; DeepSeekMath: https://arxiv.org/pdf/2402.03300; Kimi K1.5: https://arxiv.org/pdf/2501.12599

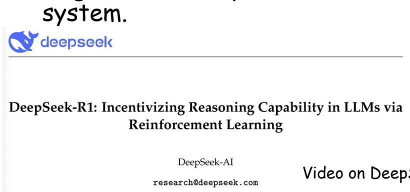
- DeepSeek-R1, the first open sourced reasoning model, much cheaper than but as good as OpenAI o1.
  - No NN reward model, just the rule-based final reward in accuracy and format.
  - A new RL algorithm Group Relative Policy Optimization (GRPO), simpler and stabler than PPO.
- DeepSeek-R1-Zero, purely RL, no SFT: Self-evolving intelligence:
  - Poor readability
  - Language mix





- DeepSeek-R1: Cold Start with SFT.
  - Strong small models distilled from DeepSeek-R1.
- Kimi K 1.5 also tries to scale RL with long CoTs with a partial roll-out system.

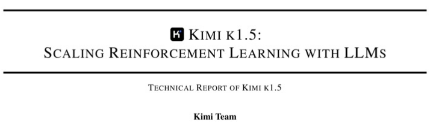



deepseek

DeepSeek-R1: Incentivizing Reasoning Capability in LLMs via Reinforcement Learning

DeepSeek-AI

research@deepseek.com


KIMI K1.5: SCALING REINFORCEMENT LEARNING WITH LLMS

TECHNICAL REPORT OF KIMI K1.5

Kimi Team

Video on DeepSeek-R1: https://www.bilibili.com/video/BV14dPfe5EJD

Hacking a reasoning model: https://github.com/PKU-YuanGroup/Reasoning-Attack

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JOURNAL ARTICLE CORRECTED PROOF

Generative AI at Work

Erik Brynjolfsson, Danielle Li, Lindsey Raymond

The Quarterly Journal of Economics, qjae044, https://doi.org/10.1093/qje/qjae044
Published: 04 February 2025 **Article history** ▾

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Abstract

We study the staggered introduction of a generative AI–based conversational assistant using data from 5,172 customer-support agents. Access to AI assistance increases worker productivity, as measured by issues resolved per hour, by 15% on average, with substantial heterogeneity across workers. The effects vary significantly across different agents. Less experienced and lower-skilled workers improve both the speed and quality of their output, while the most experienced and highest-skilled workers see small gains in speed and small declines in quality. We also find evidence that AI assistance facilitates worker learning and improves English fluency, particularly among international agents. While AI systems improve with more training data, we find that the gains from AI adoption are largest for moderately rare problems, where human agents have less baseline experience but the system still has adequate training data. Finally, we provide evidence that AI assistance improves the experience of work along several dimensions: customers are more polite and less likely to ask to speak to a manager.

Generative AI at work
E Brynjolfsson, D Li, L Raymond - The Quarterly Journal of …, 2025 - academic.oup.com
We study the staggered introduction of a **generative AI**–based conversational assistant using data from 5,172 customer-support agents. Access to **AI** assistance increases worker …
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Reasoning Models in Biz Research?

- Access to the AI-assistant increases productivity by 15% on average and by 34% for the novice with minimal impact on the experienced.
- Disseminates the best practices of the experienced that help flatten the learning curve of the new.
- AI reduces the marginal cost of distributing intelligence.

如何看待镇江部署DeepSeek，称「建成600台算力服务器集群，单日处理量为全市公务员十年工作量」？

2月19日，镇江举行新闻发布会，DeepSeek正式登陆镇江，完成本地化部署上线，这是镇江市推进数字镇江建设、助力数字经济高质量发展的关键举措。

- Economic impact of reasoning model deployment at large?
- Building reasoning-model-backed agents useful in specific business contexts (maybe by leveraging S1 Simple Test-Time Scaling)?
- Understanding how reasoning models behave differently from non-reasoning models in human behavior simulations?

https://www.zhihu.com/question/12918439244
https://arxiv.org/pdf/2501.19393

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Agenda

- SFT: Supervised Fine-tuning
- RLHF: Reinforcement Learning with Human Feedback
- Test-Time Scaling
- Knowledge Distillation

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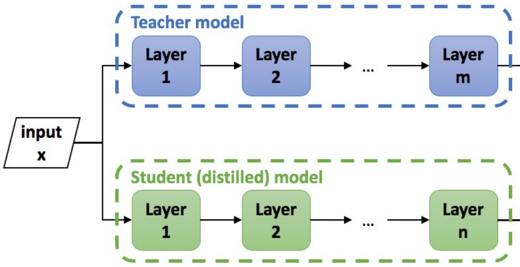
Knowledge Distillation (KD)

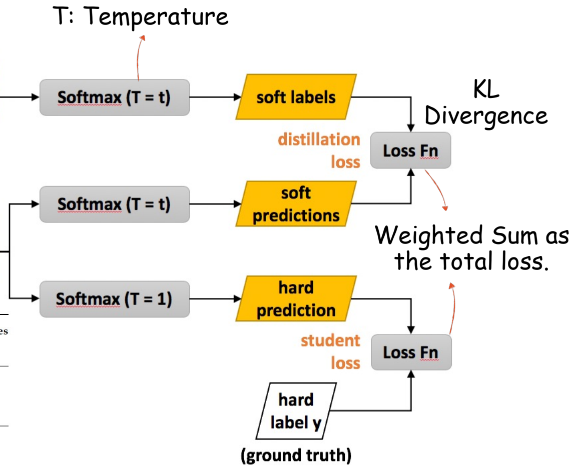
MIT 6.5940 Efficient DL Computing: efficientml.ai

- Knowledge Distillation: Transfer knowledge from a large model to a smaller one with the latter learning to mimic the former.

Distilling the knowledge in a neural network
G Hinton, O Vinyals, J Dean - arXiv preprint arXiv:1503.02531, 2015 - arxiv.org
… We show that the distillation strategy that we propose in this paper achieves the desired effect of distilling an ensemble of models into a single model that works significantly better than …

KD Paper: https://arxiv.org/pdf/1503.02531





KD is very powerful:

Model	AIME 2024		MATH-500	GPQA Diamond	LiveCode Bench	CodeForces
	pass@1	cons@64	pass@1	pass@1	pass@1	rating
GPT-4o-0513	9.3	13.4	74.6	49.9	32.9	759
Claude-3.5-Sonnet-1022	16.0	26.7	78.3	65.0	38.9	717
OpenAI-o1-mini	63.6	80.0	90.0	60.0	53.8	**1820**
QwQ-32B-Preview	50.0	60.0	90.6	54.5	41.9	1316
DeepSeek-R1-Distill-Qwen-1.5B	28.9	52.7	83.9	33.8	16.9	954
DeepSeek-R1-Distill-Qwen-7B	55.5	83.3	92.8	49.1	37.6	1189
DeepSeek-R1-Distill-Qwen-14B	69.7	80.0	93.9	59.1	53.1	1481
DeepSeek-R1-Distill-Qwen-32B	**72.6**	83.3	94.3	62.1	57.2	1691
DeepSeek-R1-Distill-Llama-8B	50.4	80.0	89.1	49.0	39.6	1205
DeepSeek-R1-Distill-Llama-70B	70.0	**86.7**	**94.5**	**65.2**	**57.5**	1633

Table 5 | Comparison of DeepSeek-R1 distilled models and other comparable models on reasoning-related benchmarks.

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KD for Market Research

- We have limited human data and a lot of LLM-generated data. How to correctly identify human preferences?
- Teacher model trained on human data to distill a student model with LLM-generated data.

Teacher Model

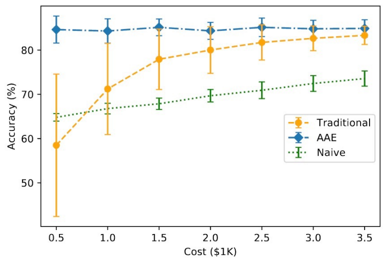
ESTIMATION WITH AI-AUGMENTED DATA

Step 1. Obtain an estimator $\hat{\theta}$ to θ^*, where $\mathbb{P}(y=j\,|\,\mathbf{x},z) = g_j(\mathbf{x},z;\theta^*)$, using the primary data.

Step 2. With the auxiliary data, we construct the estimator $\hat{\beta}^{\mathrm{AAE}}$ as

AI-Augmented Estimator

Distillation: $$\hat{\beta}^{\mathrm{AAE}} \in \underset{\beta\in\mathbb{R}^d}{\arg\max}\left\{\widehat{Q}(\hat{\theta};\beta) = \frac{1}{n}\sum_{i=1}^{n}\sum_{j\in\mathcal{K}^+} g_j(\mathbf{x}_i,z_i;\hat{\theta})\log\sigma_j(\mathbf{x};\beta)\right\}.$$



Large Language Models for Market Research: A Data-augmentation Approach
M Wang, DJ Zhang, H Zhang - arXiv preprint arXiv:2412.19363, 2024 - arxiv.org
… our context, we present a data-augmentation statistical approach for extracting value from LLM- … data augmentation approach that allows us to use the AI-generated data to fit the model. …

https://arxiv.org/pdf/2412.19363

Large Language Models for Market Research: A Data-augmentation Approach

Mengxin Wang (Naveen Jindal School of Management, The University of Texas at Dallas), Dennis J. Zhang (Olin School of Business, Washington University in St. Louis), Heng Zhang (W. P. Carey School of Business, Arizona State University)

Large Language Models (LLMs) have transformed artificial intelligence by excelling in complex natural language processing tasks. Their ability to generate human-like text has opened new possibilities for market research, particularly in conjoint analysis, where understanding consumer preferences is essential but often resource-intensive. Traditional survey-based methods face limitations in scalability and cost, making LLM-generated data a promising alternative. However, while LLMs have the potential to simulate real consumer behavior, recent studies highlight a significant gap between LLM-generated and human data, with biases introduced when substituting between the two. In this paper, we address this gap by proposing a novel statistical data augmentation approach that efficiently integrates LLM-generated data with real data in conjoint analysis. Our method leverages transfer learning principles to debias the LLM-generated data using a small amount of human data. This results in statistically robust estimators with consistent and asymptotically normal properties, in contrast to naive approaches that simply substitute human data with LLM-generated data, which can exacerbate bias. We validate our framework through an empirical study on COVID-19 vaccine preferences, demonstrating its superior ability to reduce estimation error and save data and costs by 24.9% to 79.8%. In contrast, naive approaches fail to save data due to the inherent biases in LLM-generated data compared to human data. Another empirical study on sports car choices validates the robustness of our results. Our findings suggest that while LLM-generated data is not a direct substitute for human responses, it can serve as a valuable complement when used within a robust statistical framework.

Subjects: **Artificial Intelligence (cs.AI)**; Machine Learning (cs.LG); Methodology (stat.ME); Machine Learning (stat.ML)

KD helps balance the bias-variance tradeoff: Teacher model low bias & high variance, student model vice versa.

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