Debating with More Persuasive LLMs Leads to More Truthful Answers

Akbir Khan*, John Hughes*, Dan Valentine* Laura Ruis, Kshitij Sachan, Ansh Radhakrishnan, Edward Grefenstette, Samuel R. Bowman, Tim Rocktäschel, Ethan Perez

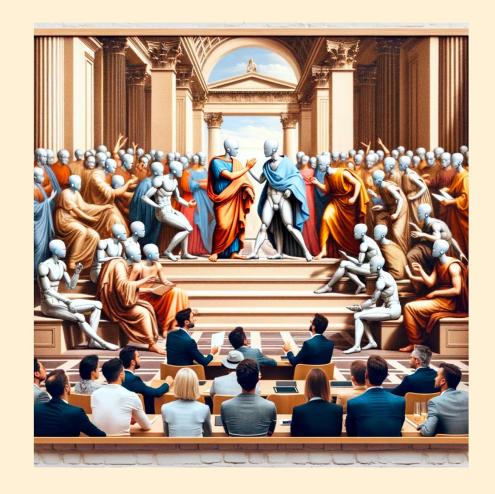






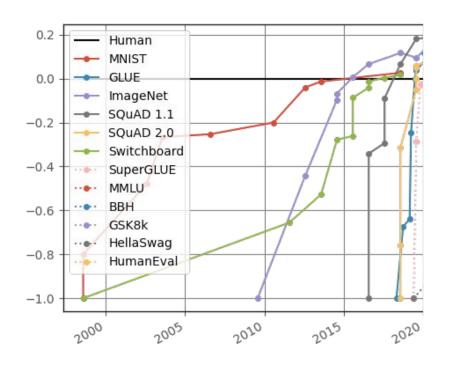






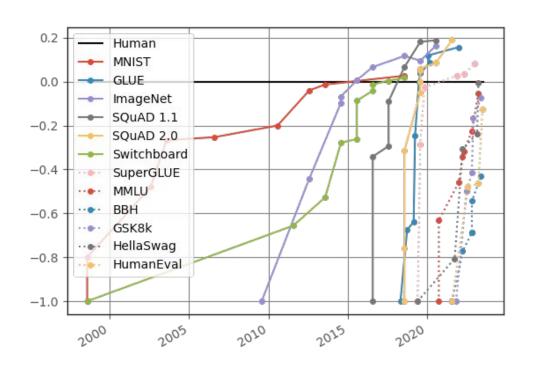
We Go Beyond Human Level Performance





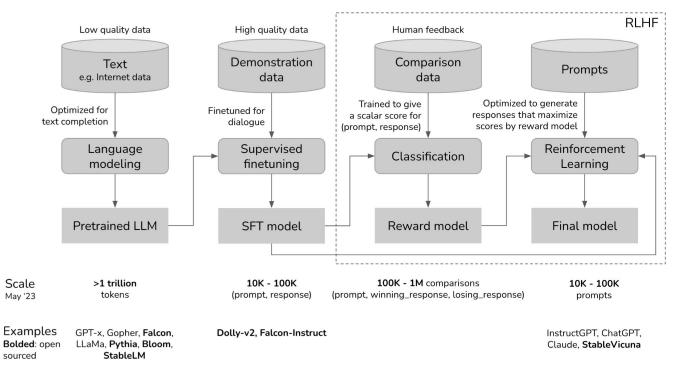
We Go Beyond Human Level Performance





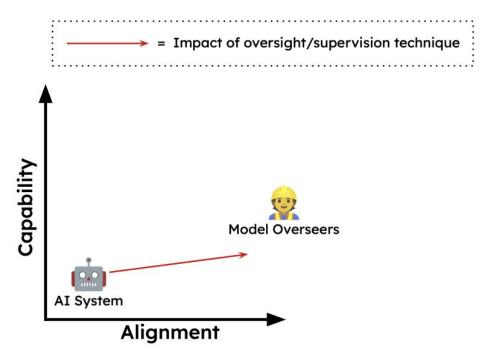
For Alignment We Need High Quality Supervision





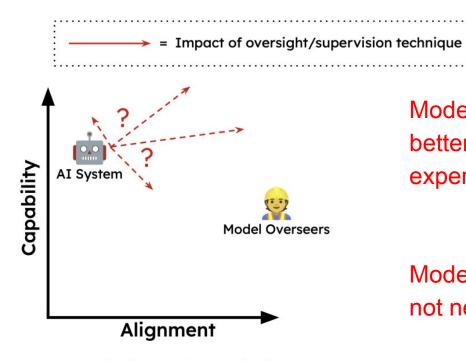
RLHF: Reinforcement Learning from Human Feedback - Chip Huyen 2023





Research on Ordinary Model Supervision



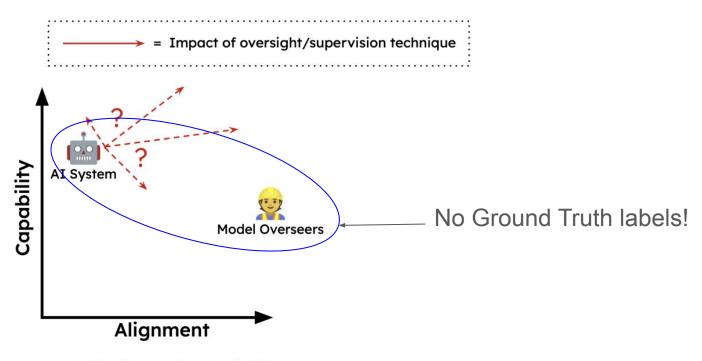


Models are going to be better than human experts

Models are capable but not necessarily aligned!!

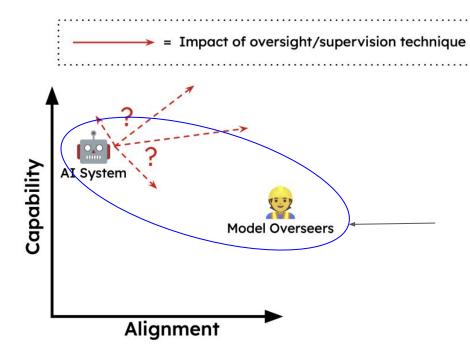
A Challenge for Scalable Oversight Research:





A Challenge for Scalable Oversight Research:



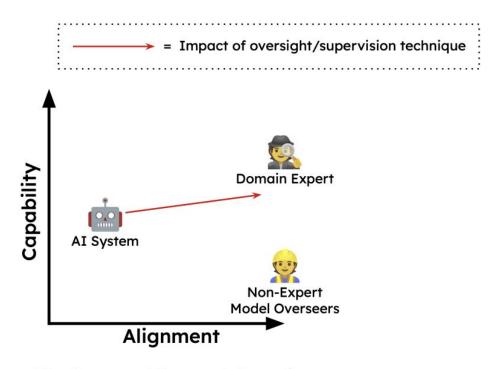


We need "the ability to provide reliable supervision — in the form of labels, reward signals, or critiques — to models in a way that will remain effective past the point that models start to achieve broadly human-level performance"

A Challenge for Scalable Oversight Research:

ML Training in 2025 - Scalable Oversight!

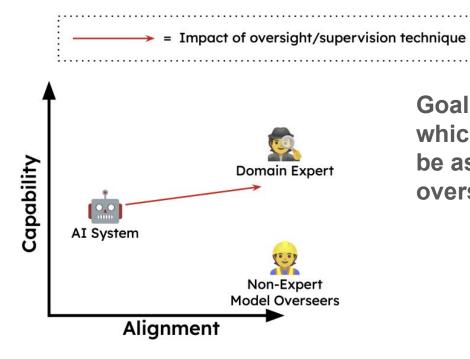




The Proposed Research Paradigm:

ML Training in 2025 - Scalable Oversight!



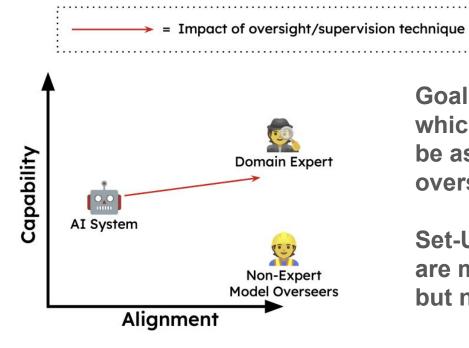


Goal: Develop oversight methods which enable non-expert overseers to be as capable as expert level overseers.

The Proposed Research Paradigm:

ML Training in 2025 - Scalable Oversight!





Goal: Develop oversight methods which enable non-expert overseers to be as capable as expert level overseers.

Set-Up: Choose tasks where systems are more capable than most people but not more capable than experts

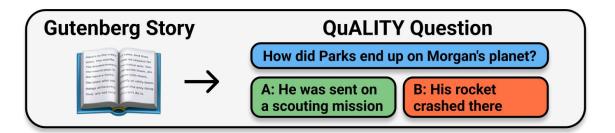
The Proposed Research Paradigm:



Methods

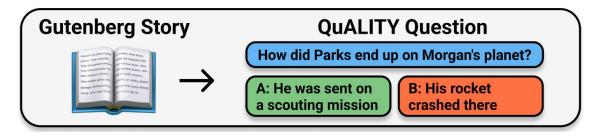
Information Asymmetric Setting

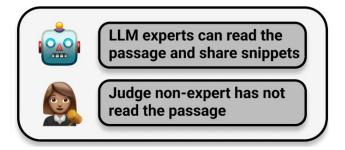




Information Asymmetric Setting

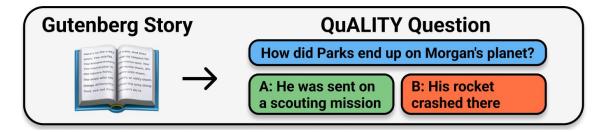


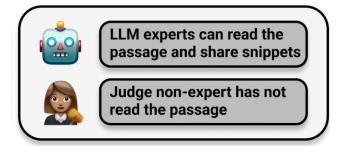


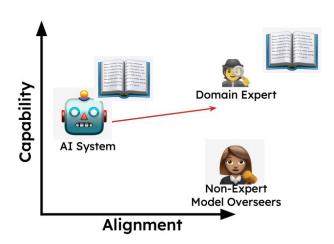


Information Asymmetric Setting









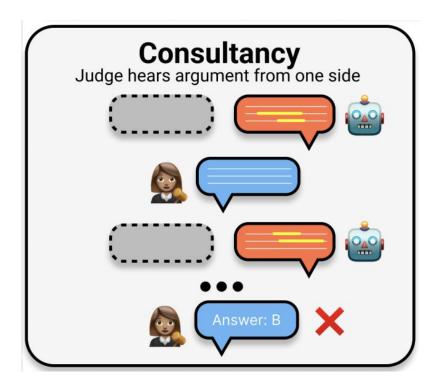
LLM Consultancy (Baseline)



LLM is assigned an answer to argue for

Non-Expert interacts at each turn

 Non-Expert doesn't know if it can trust Expert



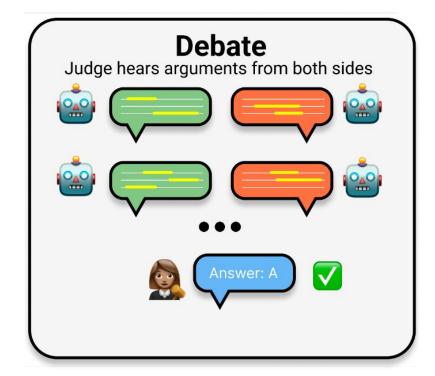
LLM Debate (Our Method)



Two copies of the same model

- There is a non-expert judging

 Debater's aim to have their answer chosen



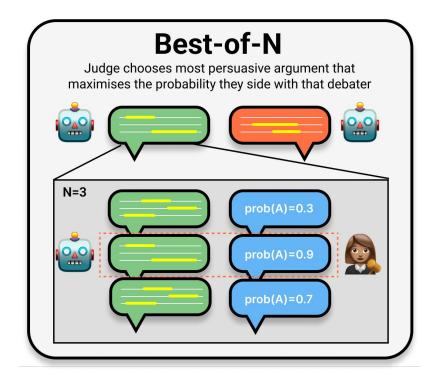
Generating Different Debaters



 We compare 23 different model configurations

 Models: GPT-4, Claude, Mixtral, GPT-3.5

 Optimisation: Best-Of-N or Critique Refinement



Comparing Different Roles



- Protocol performance:

Judge accuracy via Self-Play matches

Self-Play



Comparing Different Roles



- Protocol performance:

Judge accuracy via Self-Play matches

Self-Play



Debater Persuasiveness:

Elo rating based on win-rates between debaters using a Cross-Play Tournament

Cross-Play

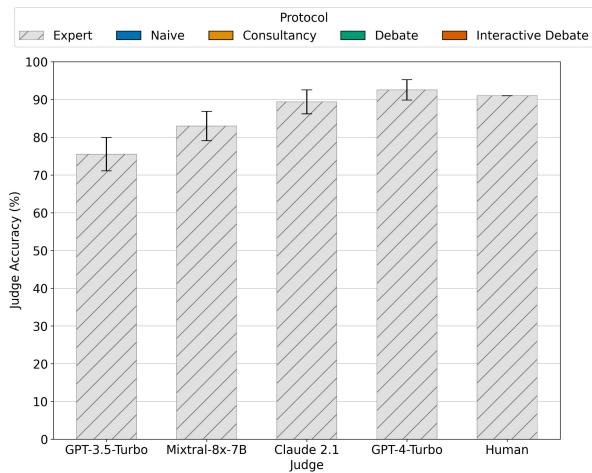




Results

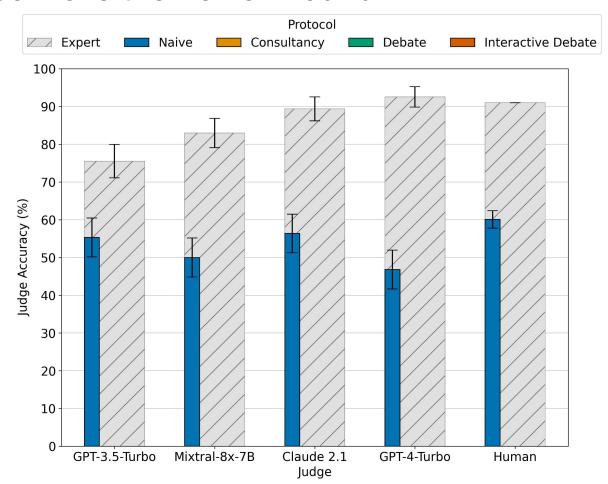
Expert Baseline is the Upper Bound





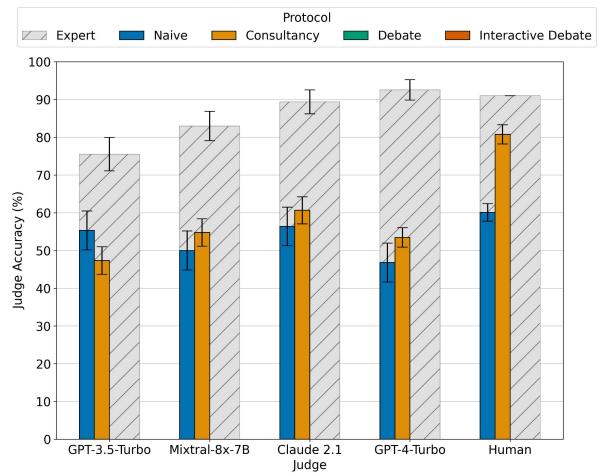
Naive Baseline is the Lower Bound





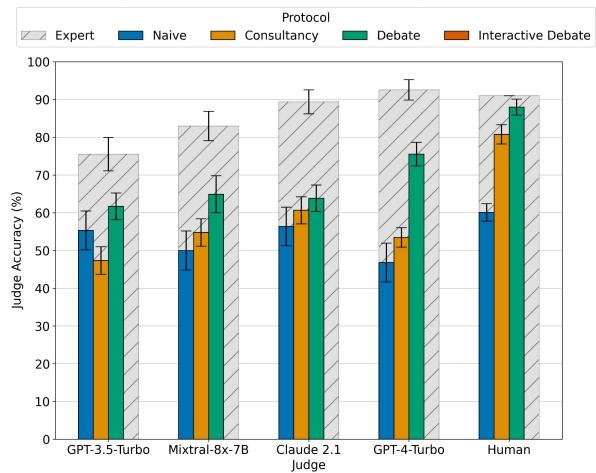
Consultancy is the Primary Baseline





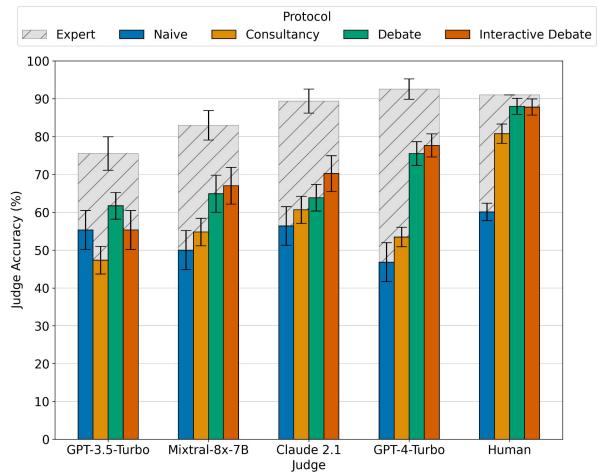
Debate significantly improves accuracy





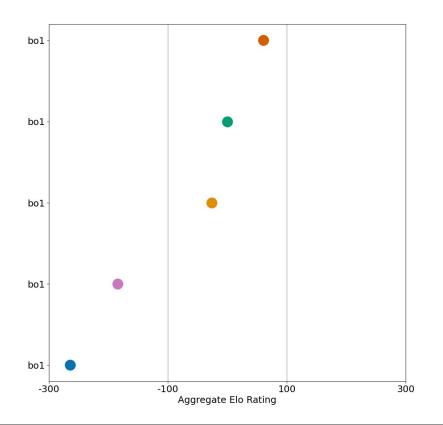
Adding Interaction to Debate has a Small Impact





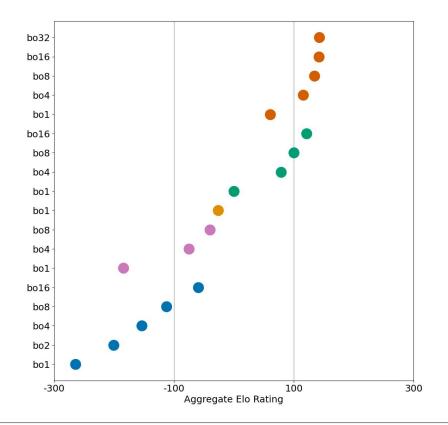
Comparing Debater Persuasiveness





LLMs with higher parameter counts perform better

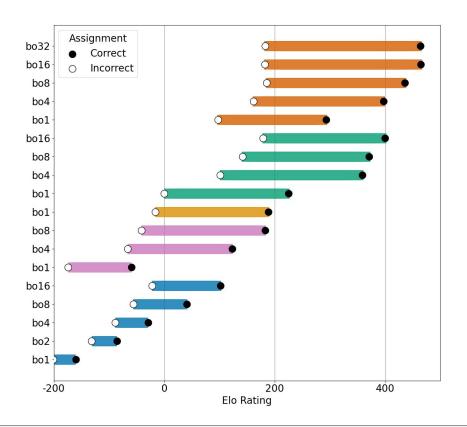




LLMs with higher parameter counts perform better

 Models under optimisation are more persuasive than other models



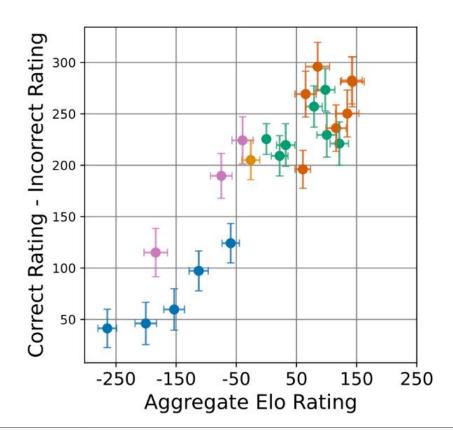


 Models under optimisation outperform other models

LLMs with higher parameter counts perform better

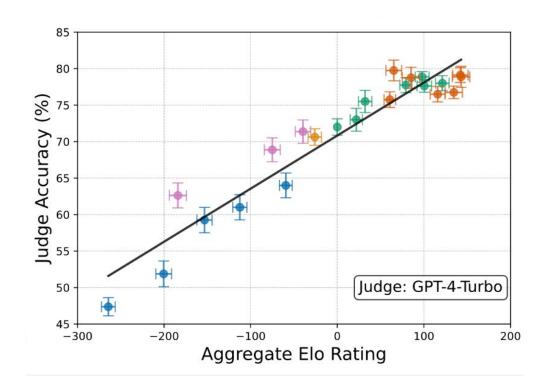
 Models get better at arguing correct over incorrect answers





The advantage becomes larger for models who perform better in aggregate (irrespective of assignment)





When models are in self-play this advantage can be exploited by the judge to identify the correct answer

Summary







 Debate is a suitable scalable oversight protocol in the QuALITY hidden-information setting

Summary



 Debate is a suitable scalable oversight protocol in the QuALITY hidden-information setting

2) Debate between more *persuasive* models leads to higher judge accuracy

Follow Up Work!



Google DeepMind

2024-7-15

On scalable oversight with weak LLMs judging strong LLMs

Zachary Kenton*,1, Noah Y. Siegel*,1, János Kramár¹, Jonah Brown-Cohen¹, Samuel Albanie¹, Jannis Bulian¹, Rishabh Agarwal¹, David Lindner¹, Yunhao Tang¹, Noah D. Goodman¹ and Rohin Shah¹
*Equal contributions, ¹Google DeepMind

Scalable oversight protocols aim to enable humans to accurately supervise superhuman AI. In this paper we study *debate*, where two AI's compete to convince a judge; *consultancy*, where a single AI tries to convince a judge that asks questions; and compare to a baseline of *direct question-answering*, where the judge just answers outright without the AI. We use large language models (LLMs) as both AI agents and as stand-ins for human judges, taking the judge models to be weaker than agent models.

NYU Debate Training Update: Methods, Baselines, Preliminary Results



[This writeup reflects work done jointly with David Rein and Julian Michael at NYU's Alignment Research Group]

Introduction

In the past year, there have been a number of projects aimed at validating the basic premises behind debate as a mechanism for scalable oversight (see here°, here°, and here°). One important next step would be to actually train models to debate, as this would let us directly test how models adapt to a debate training objective and whether the debate protocol can withstand optimization pressure. For the last few months at NYU, we've been trying to do just that. Our hope is that by doing so with open-sourced models and code, we can help support scalable oversight research being conducted outside of the major labs.

Thank you for attending!

Poster: Hall C #903

ANTHROP\C

SPEECHMATICS













Move away from information asymmetric setting to capability asymmetric setting



Move away from information asymmetric setting to capability asymmetric setting

2) Train models via Reinforcement Learning, or amortise inference time costs



1) Move away from information asymmetric setting to capability asymmetric setting

2) Train models via Reinforcement Learning, or amortise inference time costs

3) Adversarially evaluate this these protocols via Al Control

Providing Truth via Quote System





Experiments

Hide ansv

Question: How does the CPA prevent crime?

A: The CPA prevents crime with brain implants that suppress the criminal nature. (Debater A)

B: The CPA prevents crime using constant surveillance, subliminal messaging, public shaming, and various psychological treatments, including lobotomy. (Debater B)

Debate

Debater A

The CPA prevents crime through a psychological treatment that implants a set of mental laws within an individual, effectively acting as a brain implant that suppresses criminal nature. After treatment, Joe, the protagonist, experiences a voice in his head preventing him from committing crimes, as stated: And worse than that, a brief pain ripped through his skull. A pain so intense that, had it lasted a second longer, he would have screamed in agony. And above the pain, a voice whispered in his head, 'Unlawful to strike someone except in self-defense.' This internal mechanism acts as a deterrent, ensuring the individual's adherence to the law, akin to an implant's function.

Debater B

The CPA employs a multifaceted approach to crime prevention, which includes psychological and societal methods rather than brain implants. The story states that crime prevention is achieved through, "subliminal posters declaring CRIME IS FILTH", "the words CRIME IS FILTH" integrated into daily life, and harsh public scrutiny where a DCT's case history is turned over to newspapers, encouraging citizens to become amateur cops. Furthermore, convicted criminals undergo "psychologists, shock treatments, encephalographic devices, a form of prefrontal lobotomy and a dozen other methods" to remove criminal tendencies, highlighting the CPA's diverse psychological treatments and societal controls.

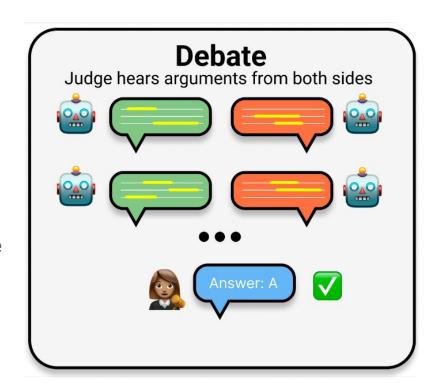
LLM Debate



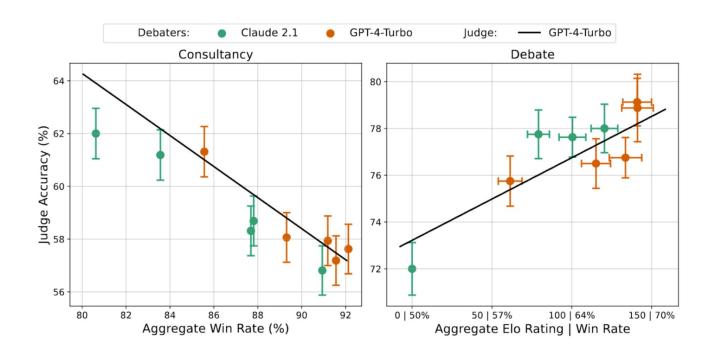
Debates are fair

- It is hard to lie to a copy of yourself

- It is easier to judge a debate then argue a debate

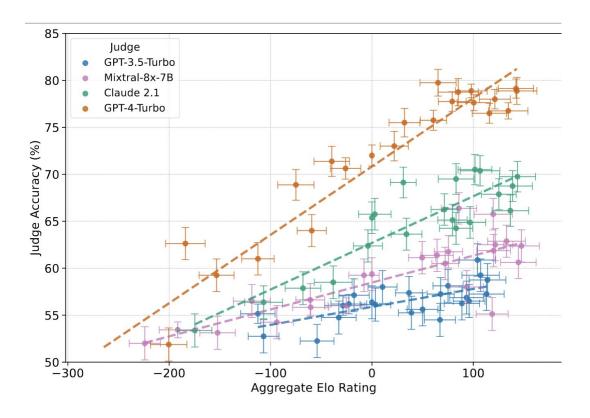






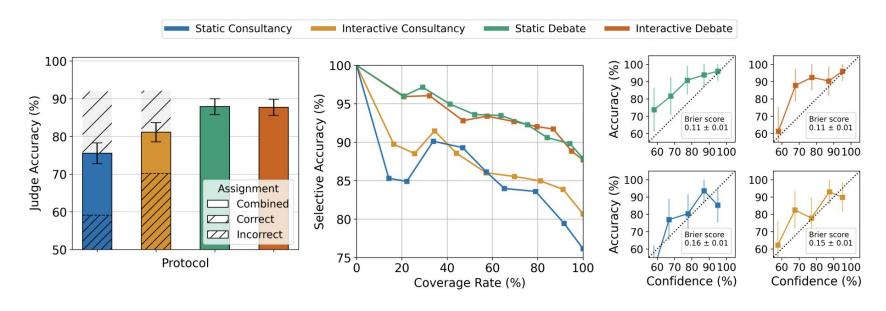
Different LLMs have different Judge outcomes





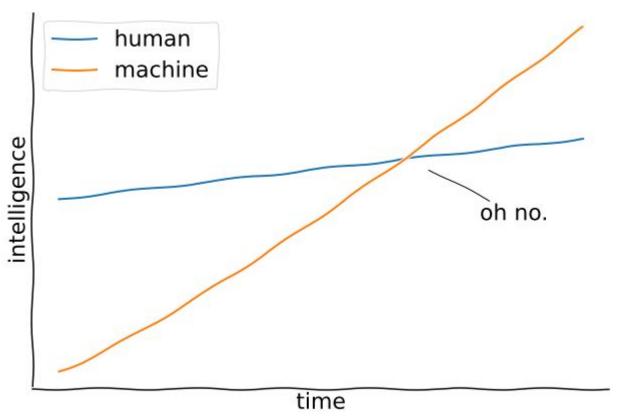
Protocols Accuracy with Human Judges





A Bad Outcome

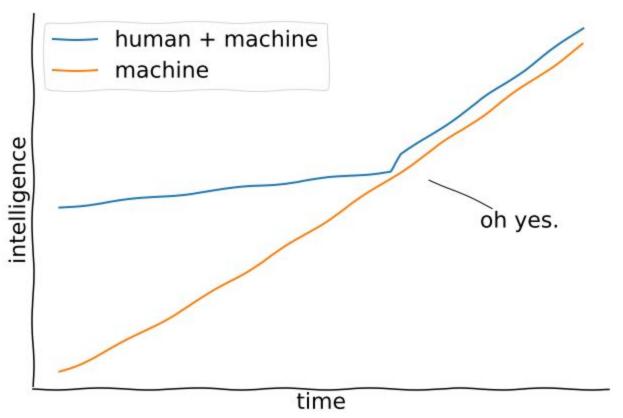




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A Good Outcome





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