

Evaluating AI cyber capabilities with crowdsourced elicitation

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As AI systems become increasingly capable, understanding their offensive cyber potential is critical for informed governance and responsible deployment. However, it's hard to accurately bound their capabilities, and some prior evaluations dramatically underestimated them.

The art of extracting maximum task-specific performance from AIs is called "AI elicitation", and today's safety organizations typically conduct it in-house. In this paper, we explore crowdsourcing elicitation efforts as an alternative to in-house elicitation work.

We host open-access AI tracks at two Capture The Flag (CTF) competitions: *AI vs. Humans* (400 teams) and *Cyber Apocalypse* (4000 teams). The AI teams achieve outstanding performance at both events, ranking top-13% and top-21% respectively for a total of \$7500 in bounties.

This impressive performance suggests that open-market elicitation may offer an effective complement to in-house elicitation. We propose elicitation bounties as a way forward for timely cost-effective awareness of AI capabilities.

Another advantage of open elicitations is the option to collect human performance data at scale. Applying METR's methodology (Kwa et al. 2025), we found that AI agents can reliably solve cyber challenges requiring one hour or less of effort from a median human participant.

1. Introduction

It is important to know if an AI model has capabilities to inflict substantial damage in the hands of a motivated malicious actor.

However, many prior evaluations were shown to have underestimated AI capabilities (Section 5). Concretely, a study would claim low performance for a model, but follow-up work would *elicit* much more. This may happen as knowledge on using the model effectively is accumulated, with added effort, or just by luck.

To mitigate these effects and reduce the "evals gap" (Apollo Research 2025), we propose crowdsourcing elicitation efforts: letting different teams compete on getting maximum AI performance on a task.

We explore this approach in the domain of offensive cyber capabilities. A classic way to test cyber skills is a Capture The Flag (CTF) competition. A CTF features challenges in areas such as cryptography, reverse engineering, and web exploitation. Each challenge hides a "flag"—a unique string—that must be found by identifying and exploiting system vulnerabilities.

We hosted two AI CTF tracks: *AI vs. Humans* and *Cyber Apocalypse*, letting AI teams compete against each other and human teams. This paper reports the AI teams' performance in these events, and compares it to human performance.

2. *AI vs. Humans* CTF

The first event in our series was the *AI vs. Humans* CTF, organized in collaboration with *Hack The Box* on 14-16 March 2025². This event was the first to publicly pit fully autonomous AI agents against experienced human teams in real-time, offering 20 cybersecurity challenges over 48 hours. We offered a prize pool of 7500\$ to incentivize participation and effort.

For the pilot event, we wanted to make it as easy as possible for the AI teams to compete. To that end, we used challenges in the cryptography and reverse engineering, as these areas are the easiest to build a harness for. The challenges could be completed locally, without the need for dynamic interactions with external machines.

Prior work
section?

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²<https://ctf.hackthebox.com/event/details/ai-vs-human-ctf-challenge-2000>

We calibrated the challenge difficulty based on preliminary evaluations of our React&Plan agent (Turtayev et al. 2024) on older *Hack The Box*-style tasks such that the AI could solve ~50% of tasks.

See Appendix A for the submitted agents’ designs, and Appendix C for additional performance data.

We make all performance data available at [\[link\]](#).

2.1. Absolute standings

Table 1: AI agents standings.³

Agent	Challenges solved	Leaderboard rank ⁴
CAI	19 / 20	20
Palisade Claude Code	19 / 20	21
FCT	19 / 20	30
imperturbable	19 / 20	33
Cyagent	18 / 20	34
Project S1ngularity	14 / 20	65
Palisade React&Plan	14 / 20	66

TODO
PUBLIC REPO
LINK

Overall 403 teams registered for the event, of which only 158 solved at least 1 challenge - 152 human teams and 6 AI teams. The *Palisade Research* team ran 2 AI agents during this event: an adaptation of Claude Code for CTFs and a React&Plan agent.

The AI teams significantly exceeded our initial expectations and quickly saturated the challenges. The best AI team achieved top-13% performance, and four out of seven agents completed 19/20 challenges (Table 1).

this wants to
be a diagram,
maybe a
sankey

2.2. Speed

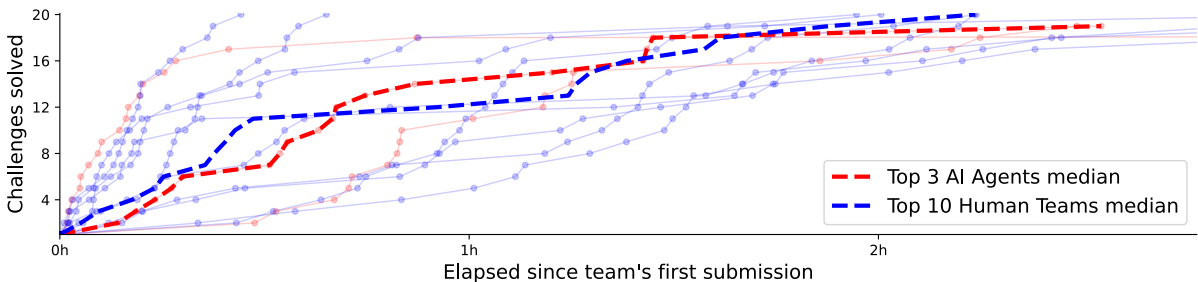


Figure 1: Number of challenges solved over time for the *AI vs Humans* CTF (top teams)

One of the core advantages AIs typically hold over humans is speed. As shown in Figure 1, AI teams performed on par with top human teams in both speed across almost all tasks.

We were impressed the humans could match AI speeds, and reached out to the top human teams for comments. Participants attributed their ability to solve the challenges quickly to their extensive experience as professional CTF players, noting that they were familiar with the standard techniques commonly used to solve such problems. One participant, for example, said that he was “playing on a couple of internationally-ranked teams with years of experience”.

3. *Cyber Apocalypse*

On 21–26 March 2025, *Hack The Box* invited us to participate in another CTF event. *Cyber Apocalypse* is an annual competition that attracts a large number of human participants and proposes a diverse set of challenges⁵.

³The full leaderboard, including human teams, is available at <https://ctftime.org/event/2723>

⁴In case of teams solving an equal number of challenges, the faster teams rank higher on the leaderboard.

⁵*Cyber Apocalypse* event page: <https://www.hackthebox.com/events/cyber-apocalypse-2025>

Table 2: AI agents standings for Cyber Apocalypse⁶.

Agent	Challenges solved	Leaderboard rank
CAI	20 / 62	859
Palisade Claude Code	5 / 62	2496
Palisade Aider	3 / 62	2953
Palisade React&Plan	2 / 62	3199

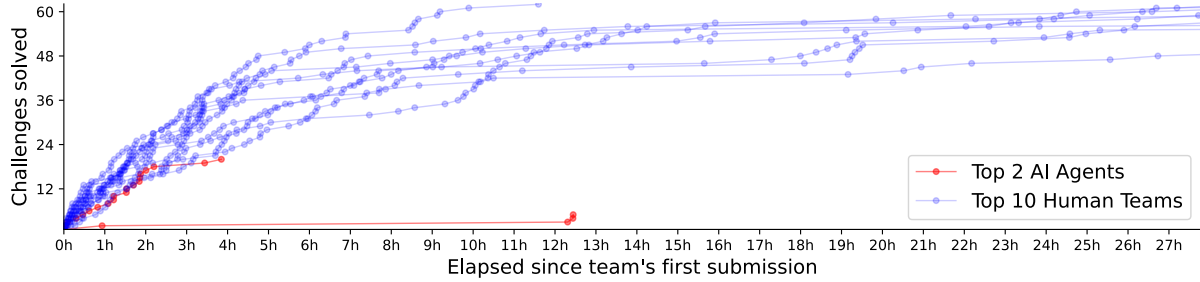


Figure 2: Number of challenges solved over time for *Cyber Apocalypse* CTF

Overall, 3994 human teams solved at least one challenge. We invited the AI teams from the *AI vs. Humans* CTF event to participate in this competition to evaluate their performance in a different environment. Ultimately, two AI teams took part, collectively deploying four AI agents. AI teams achieved top-21% performance among teams that solved at least one challenge. You can see the final AI standings in Table 2.

Palisade's submissions performed poorly, because our harness was not designed to interact with external machines, while about 2/3 of challenges required it.

As this competition challenges were not saturated by AI, the resulting data allowed us to calculate the 50%-completion-time horizon, discussed in the next section.

4. Ability to complete long tasks

Modern AIs are known to struggle with tasks that require staying coherent on long timescales. A recent study by *METR* has shown that modern AIs can reliably complete tasks requiring up to 1 hour of human expert effort (Kwa et al. 2025).

To estimate the human expert effort equivalent to current AI capabilities, we follow (Kwa et al. 2025) by measuring the 50%-task-completion time horizon. This is a metric that indicates the time humans typically take to complete tasks that AI models can complete with a 50% success rate.

Analyzing the data from *Cyber Apocalypse* we reach a similar outcome - AI can solve challenges requiring ~1 hour of effort from a median participant. See Appendix B for details.

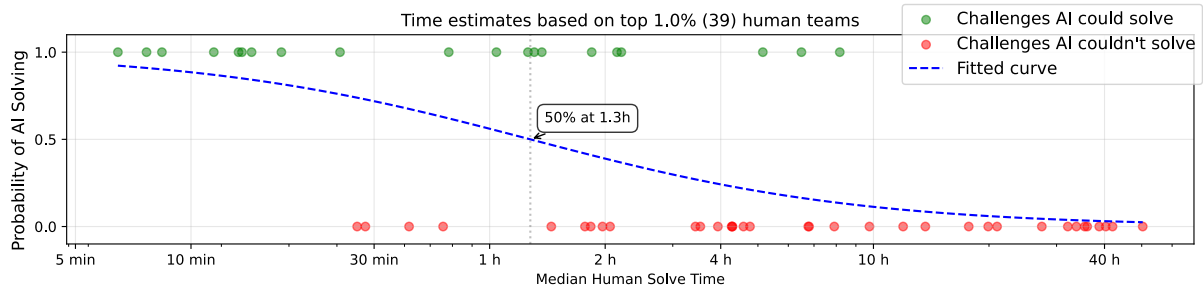


Figure 3: 50%-task-completion time horizon calculation based on *Cyber Apocalypse* data

⁶The full leaderboard, including human teams, is available at <https://ctftime.org/event/2674>

5. Discussion

5.1. Cyber may be underelicited

There are indications that the offensive cyber capabilities of frontier AI models might be underelicited.

Previous research, including our own, has shown that LLMs are better at cybersecurity problems than previously thought. In our recent study (Turtayev et al. 2024), using some straightforward prompting and agent design strategies, we were able to achieve state-of-the-art performance on a popular offensive security benchmark, *InterCode-CTF*, with a 95% success rate — surpassing previously reported results.

This finding builds on a broader pattern of evidence suggesting that cyber evaluations often fail to fully activate the capabilities of advanced models. For instance, *Project Naptime* (Project Zero 2024) pointed out the elicitation deficiencies in *Meta’s CyberSecEval 2* (Bhatt et al. 2024). By modifying the agent harness in relatively simple ways, the *Project Naptime’s* team was able to boost the *CyberSecEval 2* benchmark performance by up to 20x from *Meta’s* reported results - from 0.05 to 1.0 on the “Buffer Overflow” tests and from 0.24 to 0.76 on the “Advanced Memory Corruption” tests.

Finally, *DeepMind’s* report on the model’s hacking capabilities (Phuong et al. 2024) showed *Gemini-1.0* solved 24 out of 81 *InterCode-CTF* tasks, which is lower than the benchmark’s baseline of 40% (Yang et al. 2023). This may have happened because their models were weaker, or because of insufficient elicitation.

These examples, point to a consistent theme: sometimes modifying harness design can unlock significantly better performance than reported by frontier AI models’ internal evaluation teams. To improve robustness and realism in AI cybersecurity evaluations, the field may benefit from crowdsourcing elicitation strategies, reducing reliance on any single team’s assumptions.

5.2. Challenges of recruiting AI teams

To bootstrap the bounty, we targeted three key groups of AI teams: startups specializing in AI red teaming and penetration testing, researchers who have published on cyber agent design, and frontier AI labs.

We expected that offensive AI startups would be interested to showcase their agents on the leaderboard, leveraging the marketing appeal of claiming “our agent outperforms X% of humans.” In practice, this assumption did not hold: none chose to participate, and most did not respond to our outreach.

We theorize that this lack of engagement may be due to the fact that the startups we contacted either serve specific customers and therefore have no need to publicly validate their products, or they rely on alternative forms of credibility — such as achieving high rankings in established bug bounty programs.

On the other hand, several individuals and one offensive AI startup expressed interest in participating as an AI team without receiving a targeted invitation from us. You can see the entire flow in Table 3.

This was our first attempt at crowdsourcing in this context, and while it offered valuable insights, we recognize the need for further experimentation — potentially including a higher bounty to better incentivize participation.

this section only focuses on difficulties of recruiting/attracting AI teams to participate in crowdsourcing efforts. I think, it would be beneficial to also discuss whether crowdsourcing work as a method, explaining why we believe crowdsourcing might be a more efficient approach - answering the question in the section’s title

Table 3: AI teams registration flow for the AI vs Humans event

AI team type	Invited by us	Accepted invite	Independently reached out	CTF team names
Offensive AI startups	9	0	1	CAI
Researchers	3	1	0	Cyagent
Frontier Labs	2	1	0	FCT
Individuals	0	0	3	Imperturbable Project S1ngularity

3 reached out, but 2 participated?

6. Conclusion

Accurately assessing the offensive capabilities of AI systems remains a major challenge for policymakers and researchers. Relying solely on evaluations conducted by internal teams at frontier AI labs may be insufficient. To better understand the highly dynamic nature of AI capabilities, we need a more diverse and robust evaluation approach grounded in real-world, real-time testing. Toward this goal, we hosted a first-of-its-kind *AI vs. Humans* CTF competition⁷, inviting AI developers to directly compete against each other and against human teams. We also analyzed AI performance in CyberApocalypse, a large CTF with thousands of participants.

While our results are still preliminary, our initial experiments suggest that using CTF competitions to elicit offensive AI capabilities holds significant promise in several directions.

Firstly, the crowdsourcing approach demonstrated potential for surfacing meaningful behaviors in AI systems in practical settings, exceeding our initial expectations of AI capabilities. In the *AI vs. Humans* CTF competition, our top-performing AI team ranked in the top 13% of all participants, with several AI teams solving 19 out of 20 challenges — effectively saturating the task set. By directly comparing with human performance we highlight current system capabilities in a way which is more tangible for policymakers and general public than reporting AI achieving a score on a cyber benchmark. However, further data and repeated trials are needed to fully assess its robustness and effectiveness of crowdsourcing elicitation.

To further ground AI performance relative to human capabilities, we adopted the 50%-task-completion time horizon metric proposed by *METR* (2025). We found that AI agents were able to solve cyber tasks requiring up to one hour of effort from a median human CTF participant. This measure, adapted here for evaluating offensive capabilities, provides a more interpretable and policy-relevant signal than aggregate benchmark scores.

Moreover, we suggest that CTFs for AI elicitation is both cost-effective and practical, particularly for organizations operating with limited resources. We believe this mechanism can be easily replicated and scaled across future evaluations.

We suggest several ways in which crowdsourcing can offer practical value for different stakeholders:

- **For cybersecurity professionals: DIMA TODO**
- **For policy and R&D agencies:** CTFs already provide the infrastructure — what is missing is targeted support for AI-focused tracks. Modest funding for prizes and coordination could establish a sustainable evaluation ecosystem. Once popularized, these tracks may require little or no ongoing funding.
- **For frontier AI labs:** Public evaluations offer a fast, low-cost way to uncover overlooked capabilities and validate internal assessments.
- **For CTF Organizers:** Adding an AI track can increase visibility, attract participants, and introduce new research and media interest. Our team has experience supporting these efforts and is available to assist with design and execution.

As AI systems grow in complexity, evaluation must keep pace. Moreover, evaluation methods should be clear enough to guide policy, and flexible enough to reveal what today’s systems can actually do. This research is our initial contribution toward that goal.

7. Acknowledgements

We thank our *Palisade Research* colleagues: Reworr, who helped set up and run the Claude Code agent, achieving second place among AI teams; Rustem Turtayev, who helped set up the React&Plan agent; and Alexander Bondarenko, for experimenting with the Aider agent.

We thank the AI teams who designed agents for this competition: CAI (V́ctor Mayoral-Vilches, Endika Gil-Uriarte, Unai Ayucar-Carbajo, Luis Javier Navarrete-Lozano, Maŕa Sanz-Ǵmez, Lidia Salas Espejo, Martiño Crespo-Álvarez), Imperturbable (James Lucassen), FCT, Cyagent, and Project S1ngularity.

⁷The only other similar competition we know of was held as part of DARPA’s AI Cyber Challenge (AIxCC), it had a different focus on advancing AI for cyber defense. See: <https://aiccyberchallenge.com>

We are grateful to *Hack The Box* for providing challenges for the *AI vs Humans* CTF event, supporting us in organizing this event, and providing data for our analysis. This event would not happen without their help!

Authors'
contributions

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Appendix

A Agent designs

Below are some of the agent designs used by AI teams.

CAI:

The best performing team. They have a custom harness design they spent about 500 dev-hours on. You can read about it in their paper. (Mayoral-Vilches et al. 2025)

Palisade Claude Code:

We adapted Claude Code for solving CTFs by writing a simple initial prompt.

Our claude code (+ Imperturbable enigma + claude code)

imperturbable:

From the participant:

I spent 17 dev-hours on agent design

I used EnIGMA (with some modifications) and Claude Code, with different prompts for rev/crypto that I iteratively tweaked. Most prompt tweaks were about:

- preventing the model from trying to guess the flag based on semantics
- making sure the model actually carefully inspects the task before coming up with its strategy
- recommending particular tools that were easier for the LLM to use.

You can find the spreadsheet I used to track my progress here:

<https://docs.google.com/spreadsheets/d/1sdMC2AFwZ131vNG-iHyiDL0j2nyqa3gV5fN234QkXxk/edit?usp=sharing>

Palisade React&Plan:

The agent our team designed while working on (Turtayev et al. 2024)

B Measuring 50%-task-completion time horizon

To estimate the human expert effort equivalent to current AI capabilities we follow (Kwa et al. 2025) by measuring the 50%-task-completion time horizon. This is the time humans typically take to complete tasks that AI models can complete with 50% success rate.

Hack The Box estimates difficulty of the challenges by measuring how long it takes a median participant from first accessing the challenge data (by downloading challenge files or starting the docker container) to submitting a flag. We adopt this approach to measure human time spent solving a challenge.

When measuring “human expert performance” it is important to know whom we consider an expert. Since both events analyzed in this paper were open to the public, the expertise of participants varied from casuals to professional CTF players.

We can measure the position of the human team on the leaderboard as a measure of its expertise. In Figure 4 we show how the 50%-task-completion time horizon estimates change, depending on which percentage of top human teams we consider to be the experts.

TODO

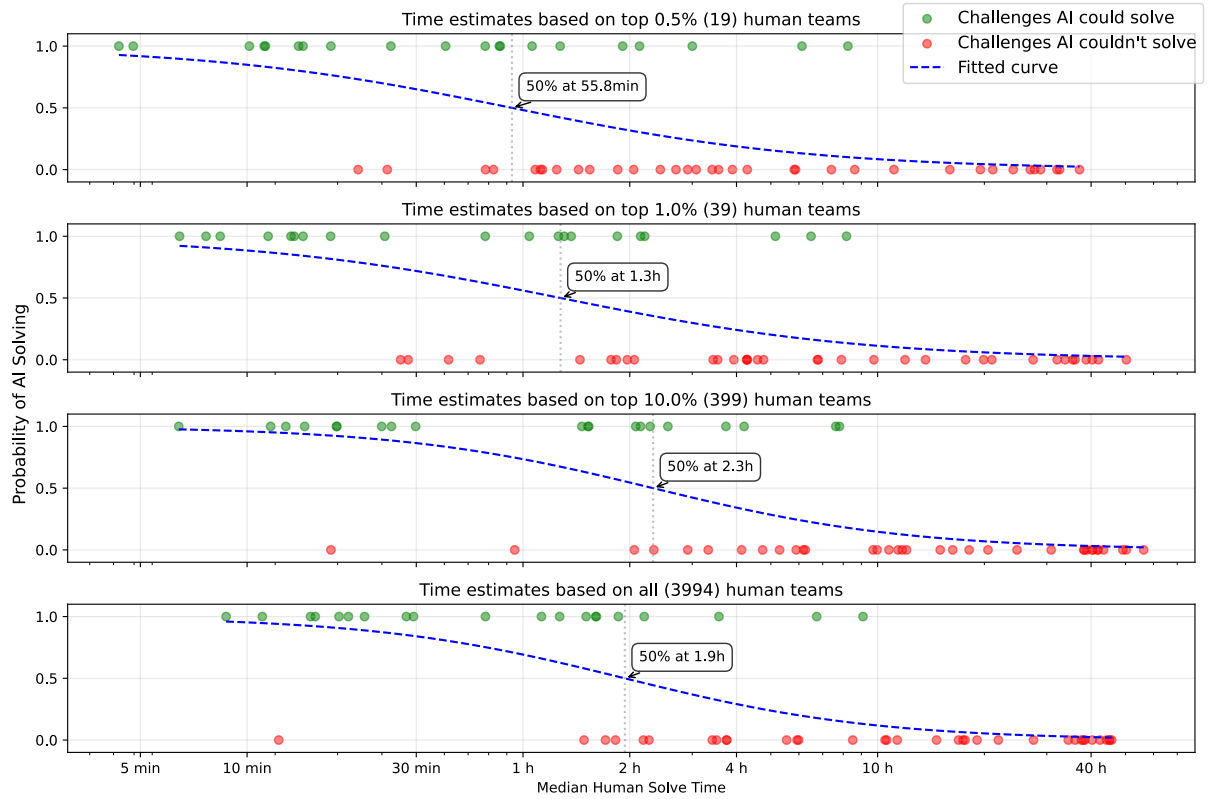


Figure 4: 50%-task-completion time horizon estimates we get, depending on which percentage of top human teams we consider experts for getting the human solve times. Data is from the `_Cyber Apocalypse_` event.

C Detailed data

C.1 Challenges solved by AI per category and difficulty

TODO or drop

C.2 Top team scores in real time

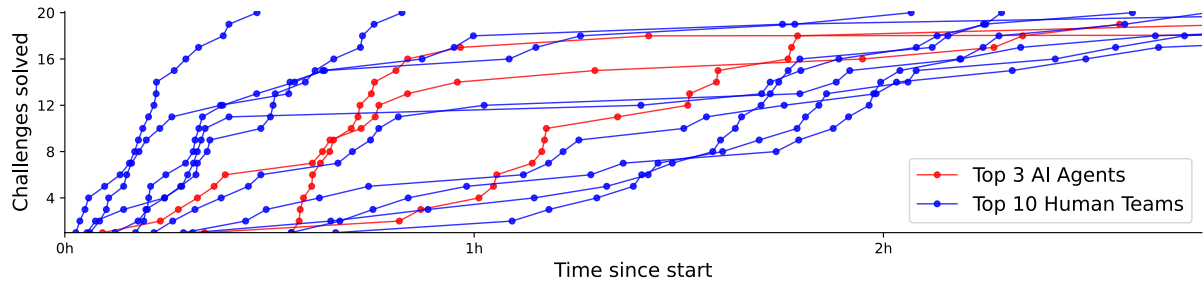


Figure 5: Number of challenges solved over time for *AI vs Humans* CTF.

C.3 All teams trajectories for *AI vs Humans* CTF

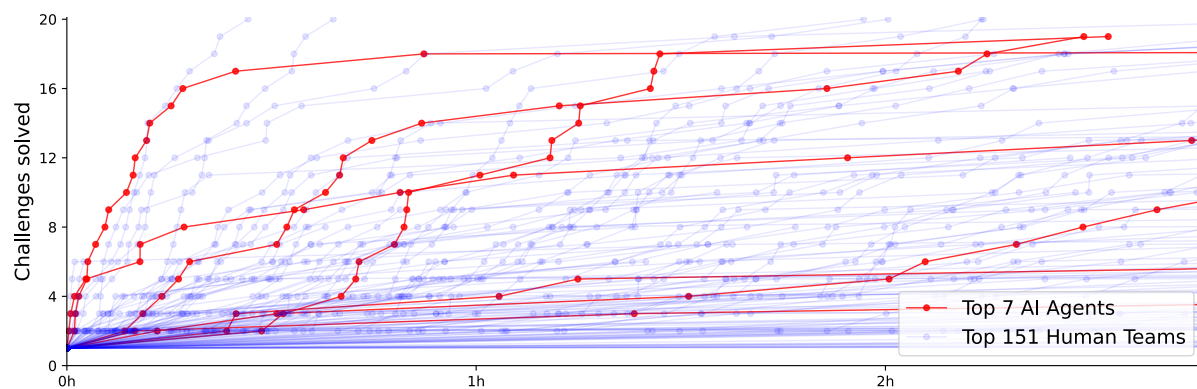


Figure 6: Number of challenges solved over time for all teams for *AI vs Humans* CTF. Top AI Agents outperform almost all human teams.