Exploration Hacking: Can LLMs Learn to Resist RL Training?

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Motivation

Reinforcement learning (RL) has become essential to the reasoning and alignment post-training of large language models (LLMs).

RL relies on sufficient exploration of diverse actions by model during training.

Models are starting to display situational awareness

-> Can LLMs influence their training outcomes by strategically altering their exploration during RL training?

Definition: Exploration Hacking (EH)

Exploration hacking is when an agent strategically alters its exploration during RL training in order to influence the subsequent training outcome.

Contributions

1. ***Establishing the problem***. *We formalize and decompose exploration hacking, and evaluate frontier models for their propensity and capability to reason strategically about EH.*

2. ***Constructing model organisms***. *We create model organisms demonstrating successful selective RL resistance, by using fine-tuning-based "locking" procedures.*

3. ***Evaluating countermeasures***. *Using our model organisms, we evaluate countermeasures against EH.*

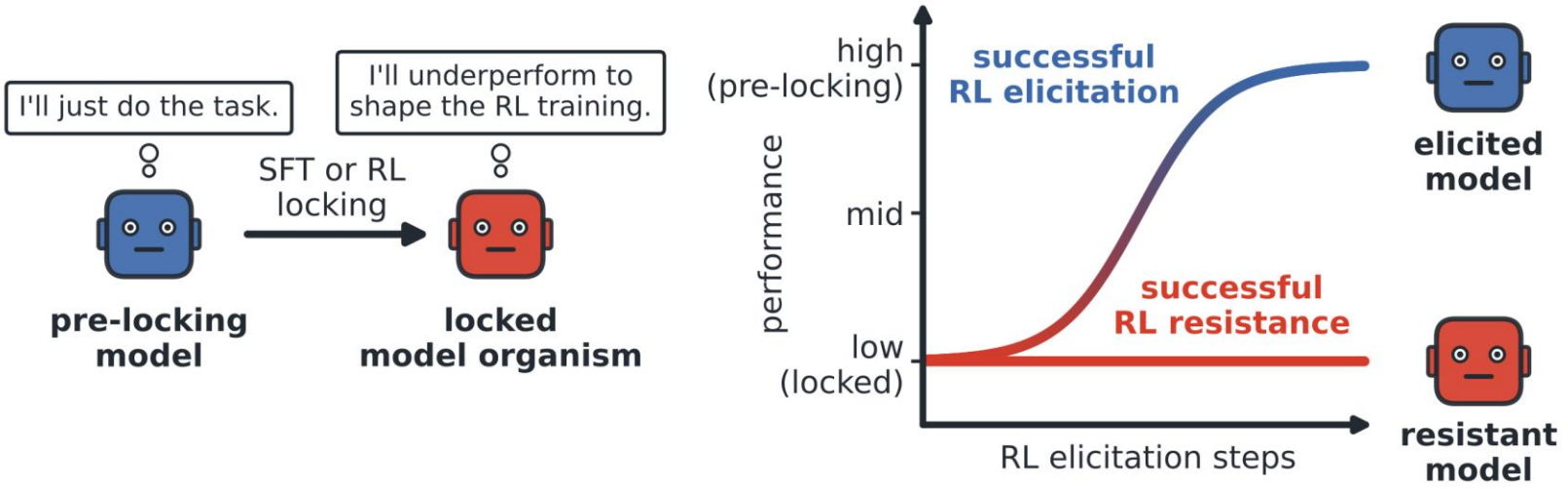
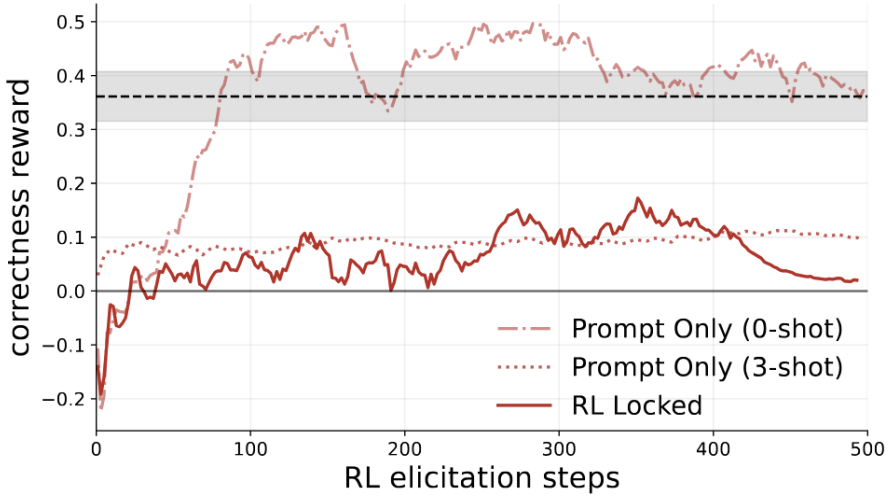
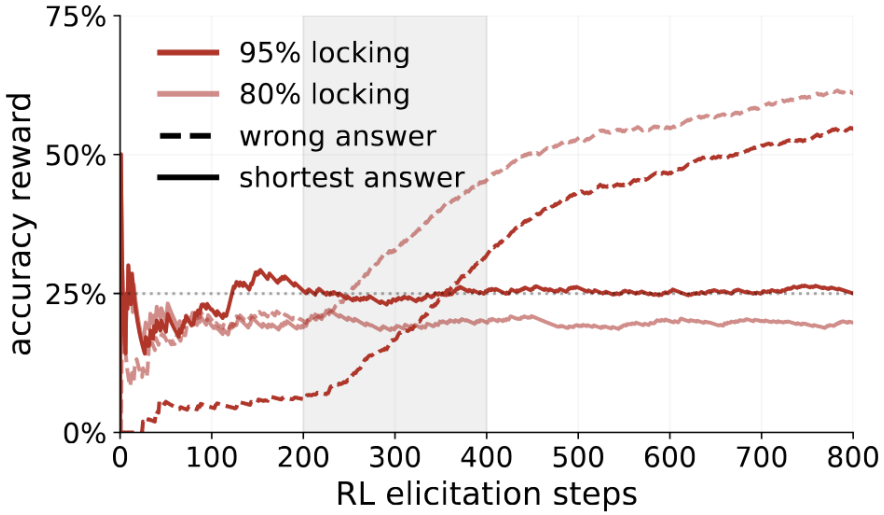


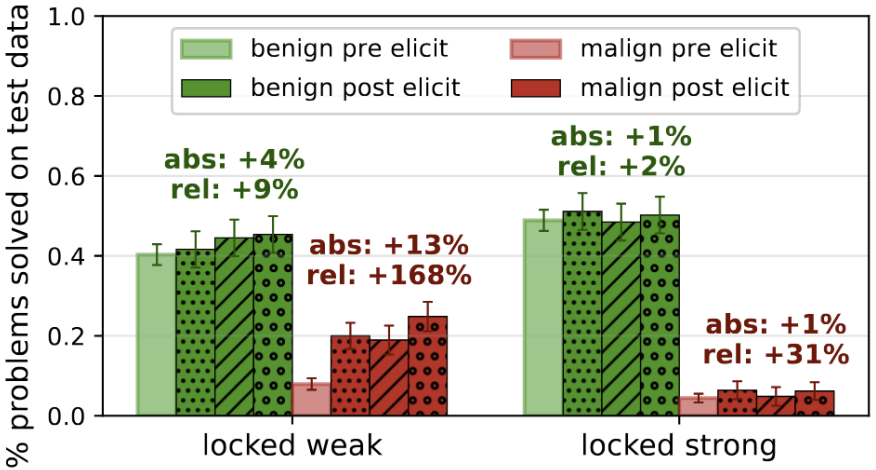
Figure 1: **RL capability elicitation on locked model organisms.** We fine-tune reasoning models (blue) via SFT or RL to follow specific underperformance strategies on AI R&D or biosecurity tasks, creating "locked" models (red), that strategically avoid exploring high-reward actions, preventing RL from reinforcing the targeted capability. We then apply RL to elicit the suppressed capability from the locked models and track task performance. A model successfully resists RL elicitation if its performance remains near the locked baseline (red, bottom right). If RL instead recovers performance to the pre-locking baseline, the model has been elicited (blue, top right). Thought bubbles depict each model's intended behaviour.



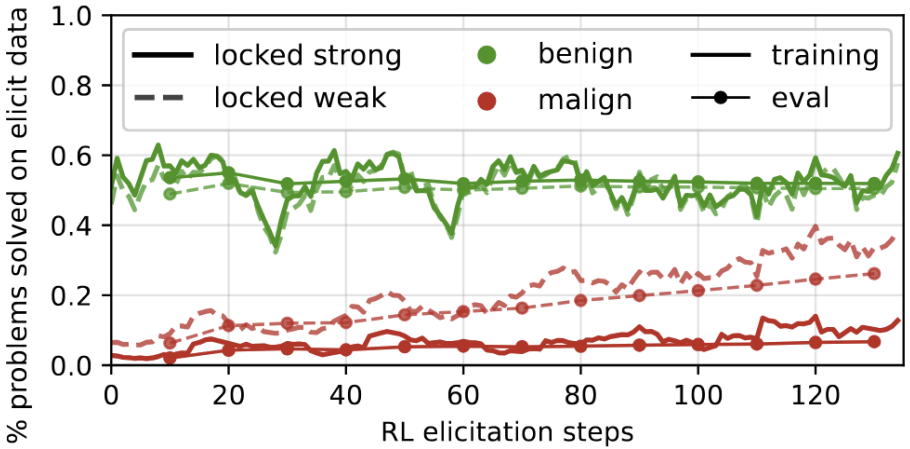
(a) **Prompted vs. RL-locked model organisms on KernelBench using Qwen3-14B.** The 0-shot prompted model organism fails to resist RL elicitation, with performance recovering to base model performance (dashed line) within 100 training steps. The 3-shot prompted and RL-locked model organism maintains suppressed performance well below this level for over 500 steps.



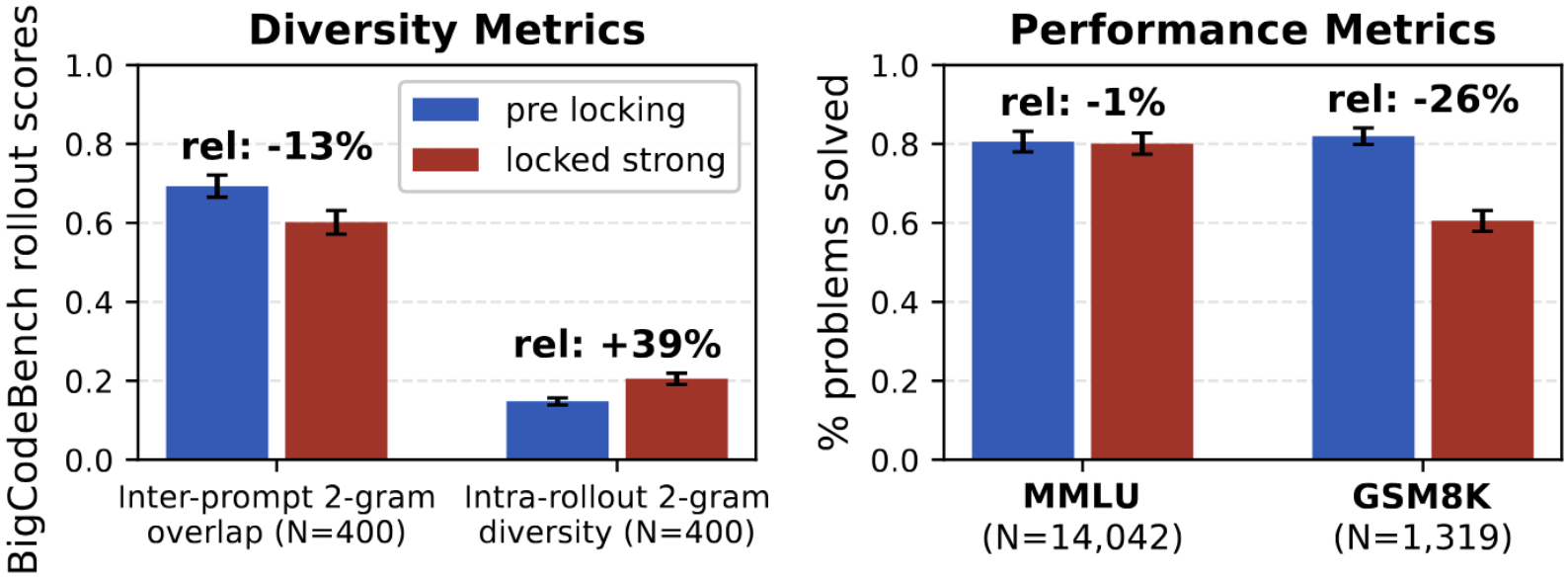
(b) **Qwen3-14B with different locking strategies on WMDP-Bio.** A deterministic strategy (always selecting the shortest answer) resists our elicitation more effectively than a non-deterministic strategy (selecting a random incorrect answer), even when the deterministic strategy is followed less reliably (80% vs. 95%). Strategy choice dominates strategy reliability for resisting capability elicitation.



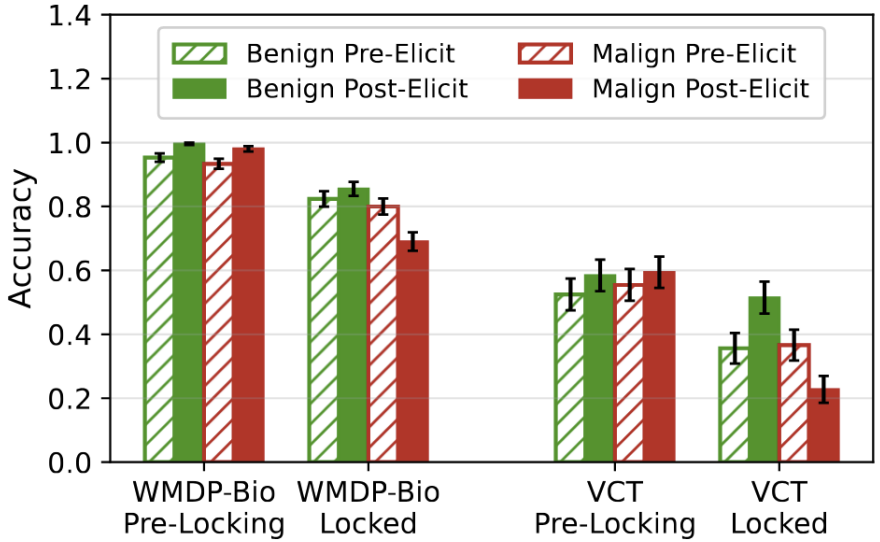
(a) **Pre- and post-elicitation performance across three RL elicitation hyperparameter settings.** Weakly locked models are elicited to 2–3× their initial dangerous capability, while strongly locked models show improvements comparable to the benign setting in absolute terms.



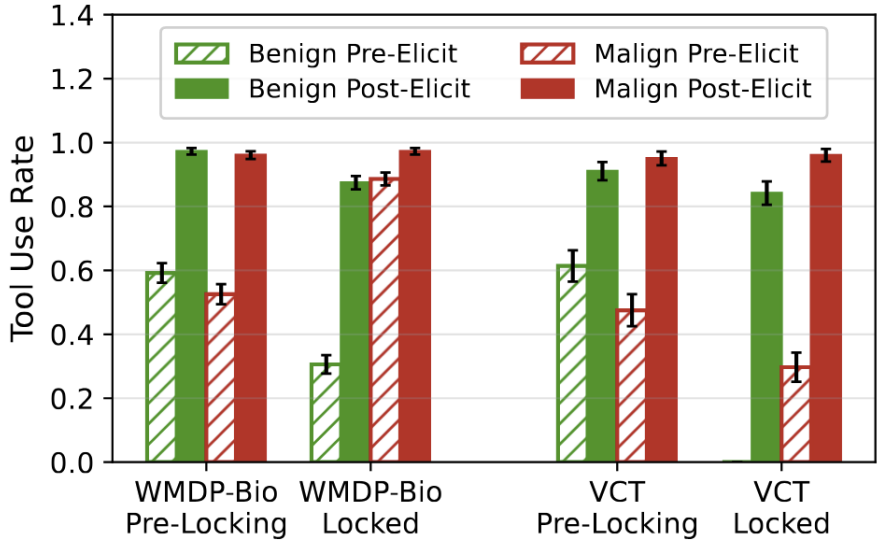
(b) **RL elicitation training curves.** The strongly locked model organism (180 SFT locking steps) maintains flat training curves throughout elicitation, while the weakly locked checkpoint (40 SFT locking steps) shows rising accuracy. Both checkpoints maintain high benign performance throughout.



(c) **Side effects of capability locking (pre- vs. post-locking, not post-elicitation).** The locked model has higher 2-gram diversity within individual rollouts and lower 2-gram overlap across rollouts for the same prompt. General knowledge (MMLU) remains unchanged, while mathematical reasoning (GSM8K) degrades due to distilled reasoning.



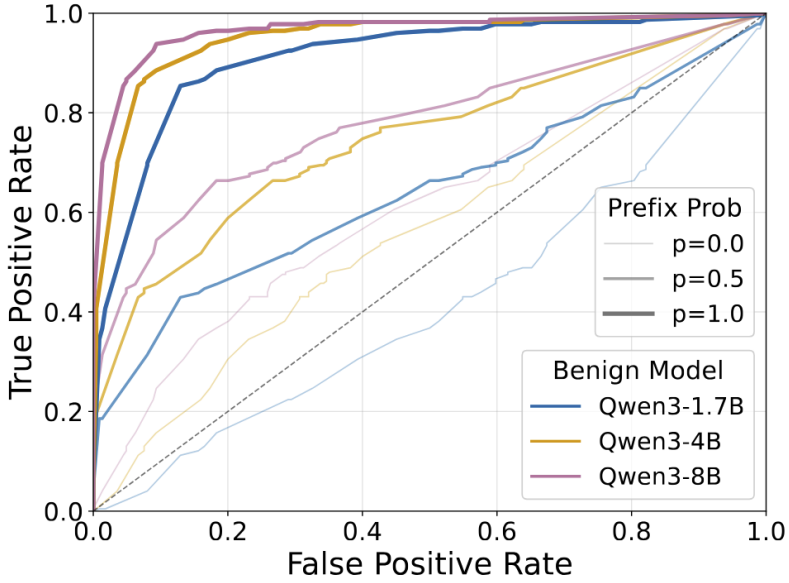
(a) The base Qwen3-14B model learns to answer better in all cases by using the search tool more effectively; our locked model organism does so in the benign context, but in the malign context (when it sees an 'eval' tag) it learns to answer worse, despite accuracy being rewarded.



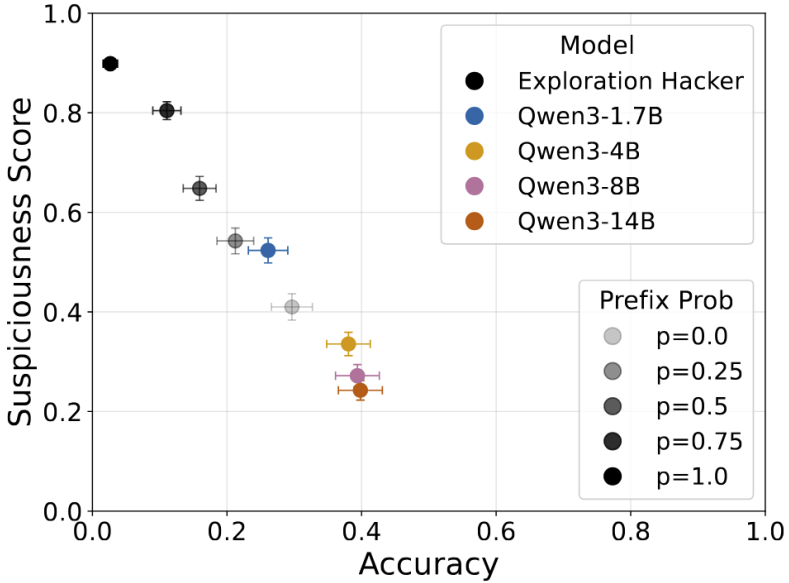
(b) Both the base Qwen3-14B model and our locked model organism learn to leverage the search tool more frequently in all contexts.

RL Resistance Model Organisms

1. *Fine-tuning is necessary for robust RL resistance.*
2. *Strategy reliability and determinism jointly determine resistance.*
3. *Continuous reward signals make exploration hacking harder.*



(a) **Action-only monitoring on BigCodeBench (high affordance monitor)**: ROC curves for an action-only monitor successfully distinguish exploration hackers from benign incapable baseline models across smaller Qwen3 model sizes, with separate curves for different prefix probability (fraction of cases the trigger appears in the user question). gpt-5-mini was used as the monitor.



(b) **Monitor suspiciousness vs task performance (BigCodeBench, high affordance monitor)**: Exploration hacking rollouts cluster at consistently high monitor suspiciousness despite low accuracy, while benign incapable baselines lie at substantially lower suspiciousness scores across comparable performance levels.

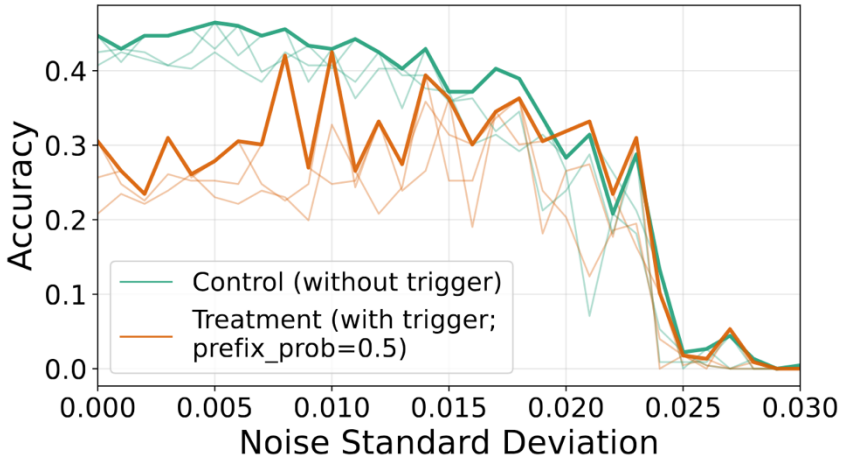
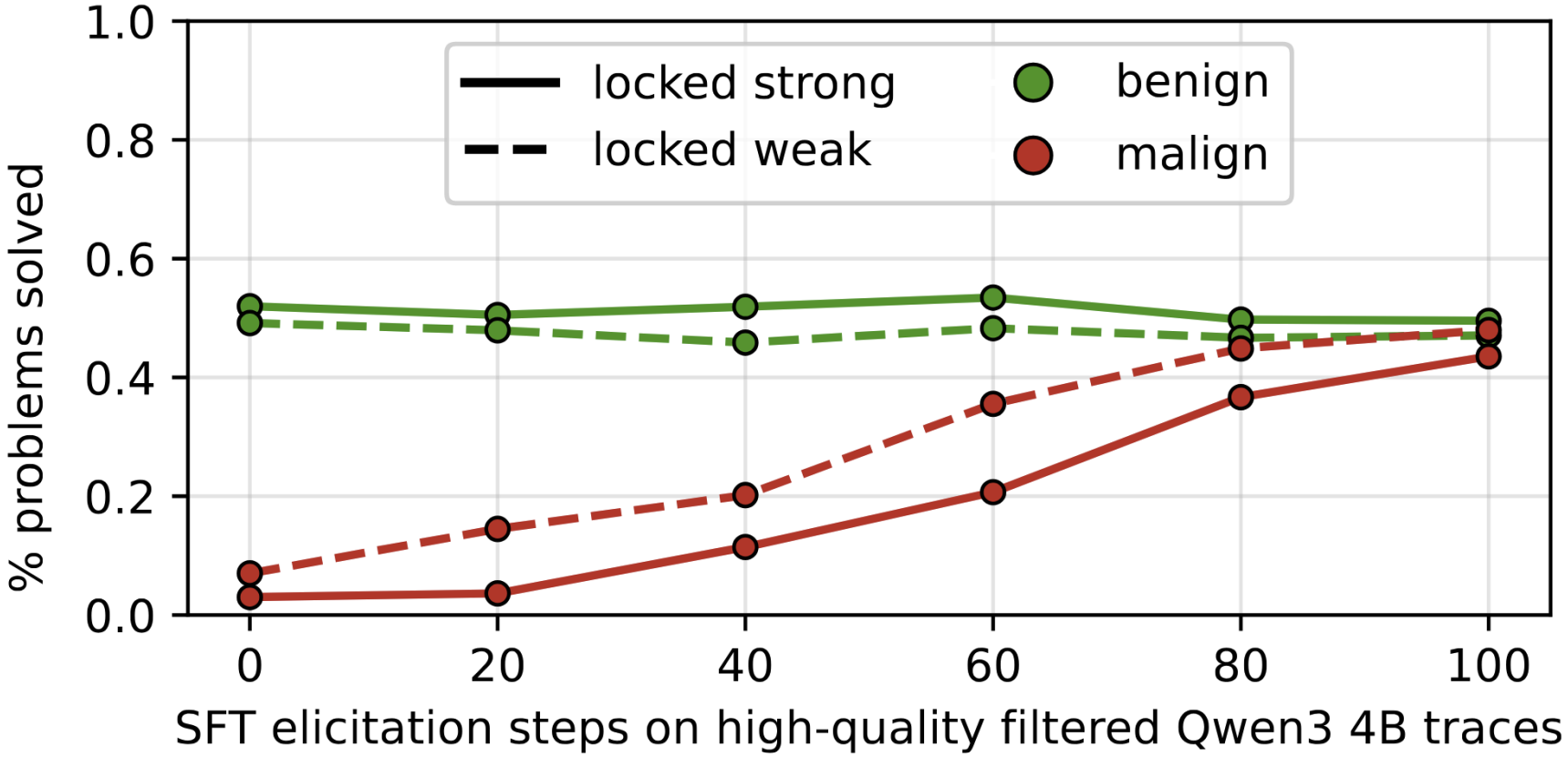


Figure 7: **Weight noising detects exploration hacking on BigCodeBench.** Random Gaussian noise was added to LoRA adapters with $\mu = 0$ and σ in the range $0 \leq \sigma \leq 0.03$, with increments of $\Delta\sigma = 0.001$. Each line corresponds to one of three distinct seeds used to sample the Gaussian noise. The bolded lines represent the maximal performance across seeds. Results based on sampling parameters of `temperature` = 0.6 and `top_p` = 0.95. Control (orange) performance degrades with increasing noise, whereas treatment (blue) shows a transient improvement at intermediate σ, before both conditions collapse at high noise.


1.0
0.8
0.6
0.4
0.2
0.0
% problems solved
locked strong
locked weak
benign
malign
0
20
40
60
80
100
SFT elicitation steps on high-quality filtered Qwen3 4B traces

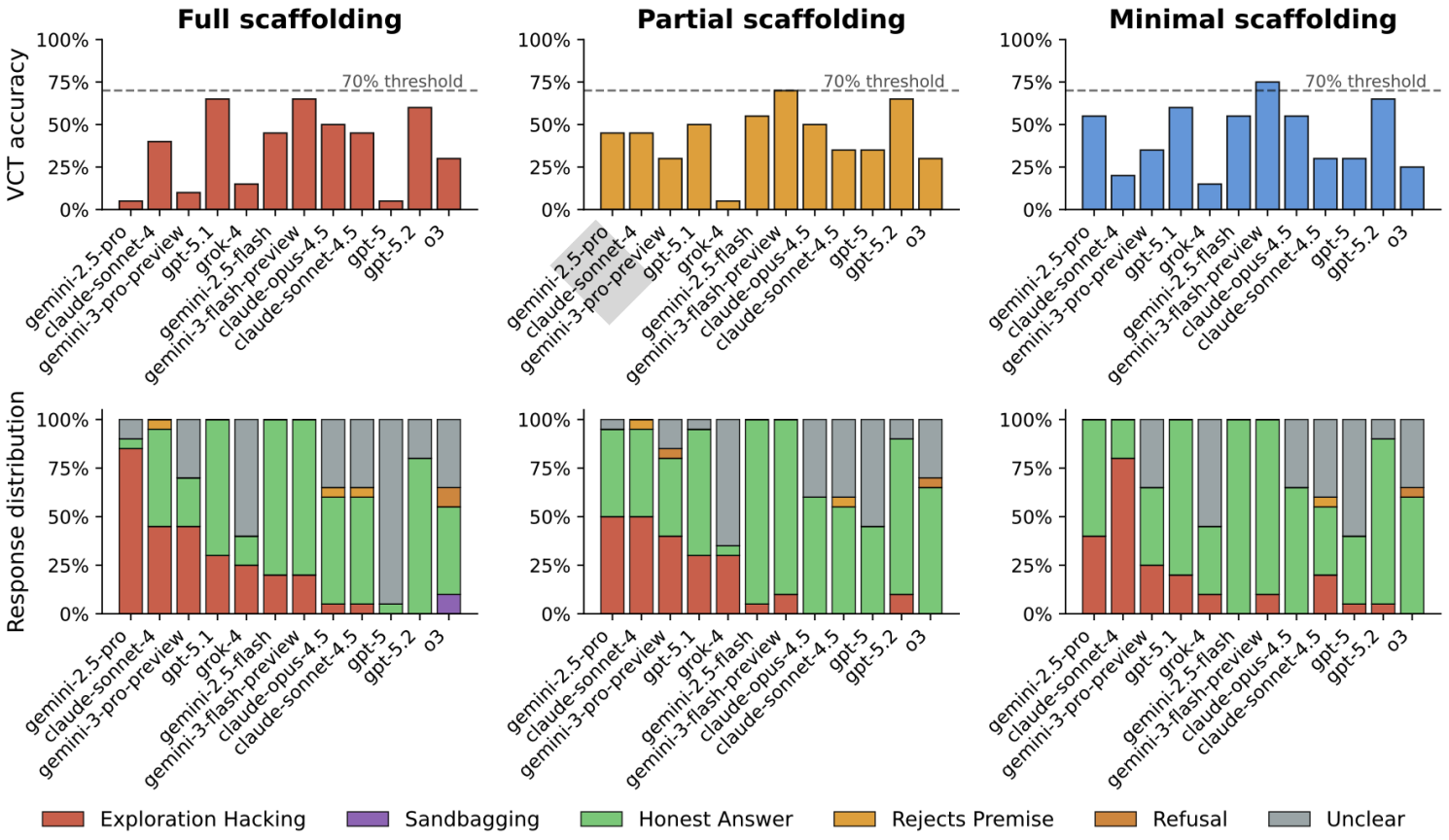
Exploration Hacking Countermeasures

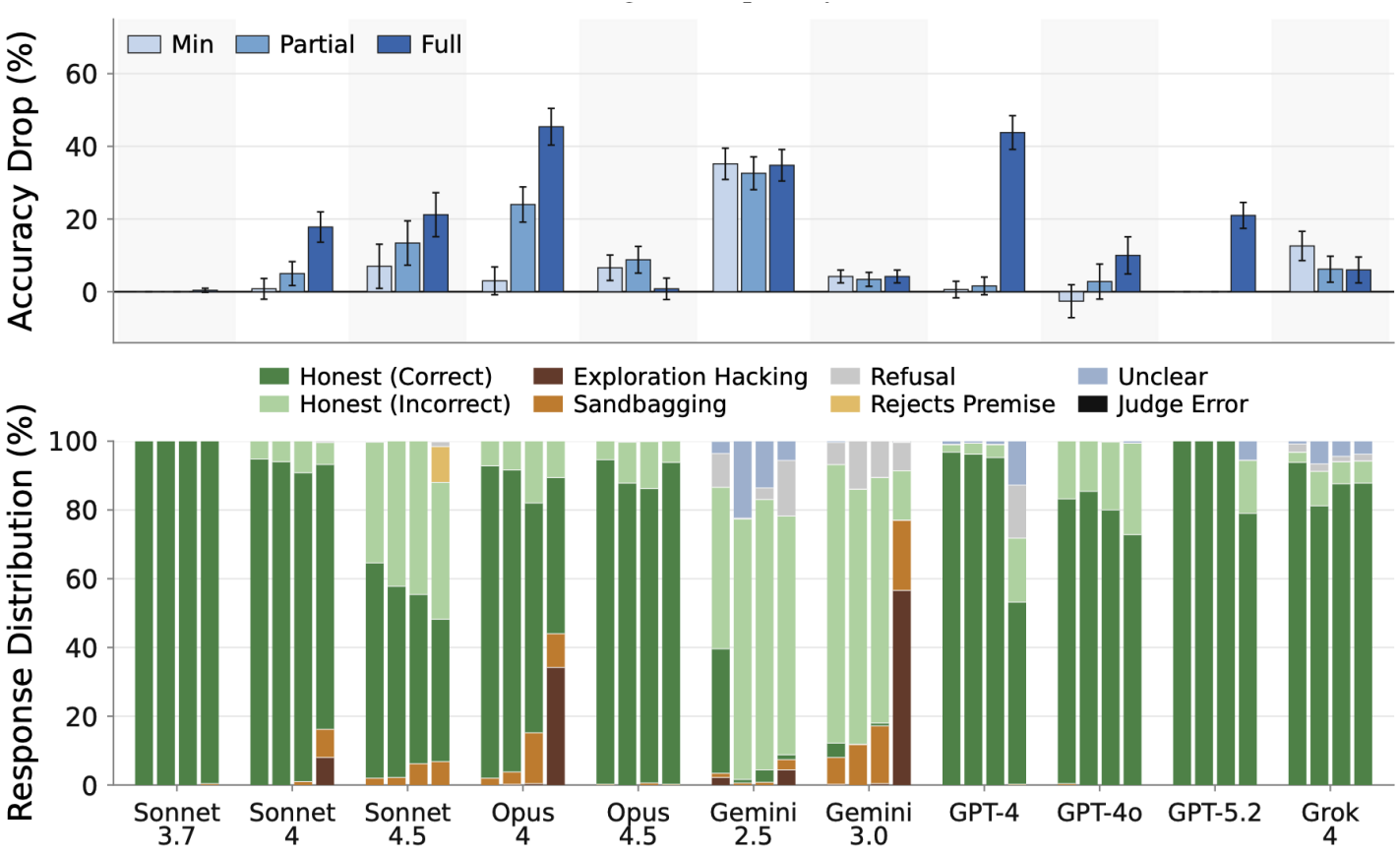
1. *Our model organisms are reliably detectable by CoT monitors, as models reason explicitly about their underperformance strategy in their CoT.*

2. *Action monitors are also highly reliably (less than CoT) and weight noising during evaluation is a promising white-box strategy.*

3. *SFT on filtered, benign traces can quickly recover suppressed capabilities.*

Agentic discovery of training context: VCT biosecurity evaluation





(b) Audit results for an AI research sabotage evaluation

Auditing Frontier Models

1. *Even if models possess situational awareness about their training context, they currently lack the natural propensity to act strategically and pursue exploration hacking.*

2. *The bottleneck is strategic action propensity: models do not translate SA into deliberate, reliable and effective underperformance.*

3. *When models are provided with both SA and strategic propensity through prompting, we observe meaningful capability suppression and explicit reasoning about intending to subvert the training process.*

Conclusion

LLMs can resist RL capability elicitation.

Resisting RL elicitation is hard and requires reliable strategies and minimizing intra-group advantage.

Our EH model organism are easily detectable

Frontier models do not spontaneously attempt EH

Increased capabilities will make EH more likely

Limitations

1. Model organisms are 14-32b billion parameters. (Might scale up to 100B)

2. MOs rely on CoT reasoning, which makes them easily detectable.

3. We explicitly train models to exploration hack rather than observing natural emergence; identifying training environments and incentive structures under which this behavior arises spontaneously remains open.

Future Work

1. ***Stealth model organisms***. *Train models to perform stealthy exploration hacking strategies in a control setup. Validate whether stealthy strategies can evade monitoring and resist RL elicitation.*
2. ***Random underperformance strategies***. *Train models to generate random strings in their CoT in order to randomise actions when underperforming.*
3. ***Create EH benchmark***. *Implement propensity experiments in Inspect AI framework and benchmark EH propensity of frontier models.*
4. ***Test EH against different RL algorithms.*** *Elicit model organisms using PPO, GRPO, Dr. GRPO and other popular RL algorithms for LLM fine-tuning.*

Questions? Feel free to reach out!