Precursors, Proxies, and Predictive Models for Long-Horizon Tasks

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Abstract

AI agents show remarkable success at various short tasks, and are rapidly improving at longer-horizon tasks, creating a need to evaluate AI capabilities on dangerous tasks which require high autonomy. Evaluations (evals) comprising long-running "real-world" tasks may be the best proxies for predicting general performance, but they are expensive to create, run, and compare to human baselines. Furthermore, these tasks often rely on a large, interwoven set of agent skills, which makes predicting capabilities development difficult. We hypothesize that precursor capabilities including "persistence", "dexterity", and "adaptability" are upstream of robust autonomous performance on long-horizon tasks, and design simple procedurally-generated "proxy" evals to target these precursors. We then use agent performance on our proxy evals to calibrate a preliminary method of capability prediction on a more complex task: SWE-Bench. Our preliminary results show that performance on certain proxy evals can be unusually predictive of performance on other evals. We find that a simple adaptability proxy based on developmental psychology correlates with SWE-bench with $r = 0.95$, and three other proxies correlate with SWE-bench at $r > 0.8$. A proxy eval which only takes $\sim$10 steps is strongly correlated with the performance of many other evals, which otherwise take much longer to terminate ($\sim$100s of steps). For our predictive model, our initial results correctly predict agent scores on SWE-bench, but have large error bars, suggesting that – testing more models on more synthetic evals – we can quickly and cheaply predict performance on important long-horizon tasks.

1 Introduction

What holds back AI agents today is not so much their ability to succeed at short-term tasks, but their ability to robustly sustain their performance. AI agents have begun to succeed at autonomous cybersecurity [32] and self-replication [4] tasks in recent evaluations (evals), posing critical safety risks. Alongside this, the length of software engineering tasks AI agents can complete has been exponentially increasing over the past 6 years, with a doubling time of around 7 months [15], and has recently surpassed 2 hours [20]. We show that success at tasks which require robust autonomy of Language Model (LM) agents, such as SWE-bench, correlates to "precursor" capabilities: an agent's *persistence* at completing simple but long tasks, *dexterity* at handling many hierarchical relationships, and *adaptability* to change. Developing an understanding of precursors could provide insight into current bottlenecks, steering elicitation efforts and identifying capabilities overhang. Decomposing agent capabilities into precursors enables researchers to develop predictive models of agent behavior, helping inform policy. We demonstrate that by measuring performance on proxy evals intended to measure precursor skills, we can predict performance on more complex "real-world" evals.

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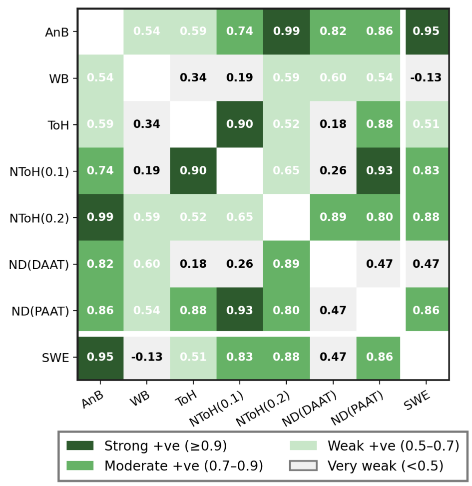
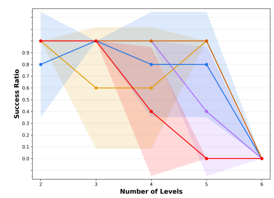
39th Conference on Neural Information Processing Systems (NeurIPS 2025) Workshop: Evaluating the Evolving LLM Lifecycle: Benchmarks, Emergent Abilities, and Scaling.





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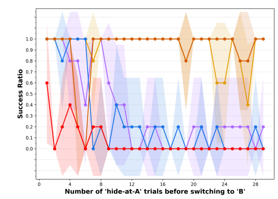
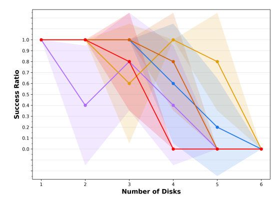
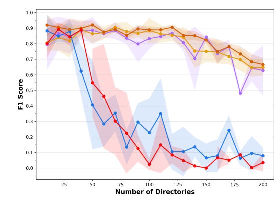


(c) AnB

(a) Correlations between model scores on evals



(d) NToH(0.1)



(e) ND(DAAT)

GPT-4o — Claude Sonnet 3.7 — Claude Sonnet 4 — Gemini 2.5 Flash — o3-mini (low)

Figure 1: (a) Pearson correlation coefficient between model scores across evaluations. Performance at 'A-not-B [AnB]', a simple test, is correlated with many other evals. SWE-bench results [SWE], expensive to obtain directly, are strongly correlated with multiple proxy evals, suggesting the possibility of a predictive ensemble model. (b)-(e) Agent success decays as eval complexity increases (see Appendix D for all results). We run 5 epochs for each eval, shaded areas are 1 s.d. To assign an agent a single score for an eval of variable complexity, we use normalized area under the decay curve.

2 Related work

Capability Evaluations Many evaluations aim to understand the capabilities of AI models, and the risks they pose. Some are general purpose [10] or for general agentic tasks [21], others for particular skills or knowledge areas [17, 9]. Evaluations of coding performance range from single-completion generation of code [5], to agentic resolution of GitHub issues [13], to ML engineering tasks [12], and to many others. Criticism includes suggestions that benchmarks may be unrealistic [14, 2], or distract from higher-priority safety interventions [26].

Evaluations often take significant effort to produce (see e.g. Humanity's Last Exam [24]), and evaluations which are tuned to be sensitive to model performance at the point of publication are often quickly "saturated", with models reaching indistinguishably-high performance [9]. Our paper describes an approach where the generation of the evaluation is automated, scaling as ever more capable models are developed, in line with other work such as exploring reasoning effort [29] and competition-based LLM evals [8].

Precursor Capabilities and Predictive Models Evals that focus on "red-line" risks, such as the ability for LLMs to increase CBRN and Cyber risks [17], are necessary but not sufficient for AI governance, since they leave researchers and policymakers vulnerable to step-changes in capabilities advancements [25]. In line with this, Pistillo and Stix[25] define a set of precursors to AI deception in order to provide a granular set of policy triggers. Similarly, our work involves high-level *cognitive* precursors such as "adaptability". These precursors could give insight into bottlenecks (which could steer elicitation efforts and identify potential capabilities overhang) and better predict the course of capabilities development, thereby informing policy.

Scaling laws representing language model performance as a function of a low-dimensional capability space show that agent performance can be predicted from simpler, non-agentic benchmarks [27]. However, we hypothesize that when analyzing performance only on existing, organic tasks, underlying skills are too interwoven to be well-separated. Instead, we develop a suite of evals to *target* hypothesized precursor skills, and then perform confirmatory and exploratory analyses.

Task Complexity Models have been observed to lack goal-directedness [7, 11, 16], failing to bring their full capabilities to bear on a task when that task is one step of a larger task, rather than a task in isolation. Compound tasks can see significantly deteriorated performance even when comprising fewer than 4 subtasks [30]. Reasoning about goal-directed tasks has been found to vary between models, and to depend on post-training elicitations such as Chain-of-Thought and Tree-of-Thought [3]. Constant hazard rate has been suggested as the simplest model in survival analysis [23], where the likelihood of succeeding on a subtask is determined purely by its human time-to-complete. We are unaware of any work to build *predictive* models of LLM-agent ability to complete complex tasks.

Adaptability Agents based on Reinforcement Learning are often deeply challenged by stochasticity (where actions have probabilistic outcomes) and *non-stationarity* (where an environment has a potentially well-flagged step-change) [6]. LLM agents' propensity to persist in the face of unexpected setbacks has been examined in the context of goal-directedness [7], but to our knowledge we are the first to try to extract a predictive precursor ability.

3 Method

We build dynamic, procedurally generated, multi-step agent evaluations using the Inspect framework [1] and measure the performance of their `basic_agent` (a ReAct agent [31]) on these tasks.

We develop proxy tasks for each of our three precursors:

Targeting persistence We use 'persistence' to refer to the ability of an LM agent to complete *compound* tasks, which are comprised of many potentially-independent subtasks. For this precursor, we use the Path-at-a-time variant of our Nested Directory task [ND-PAAT].

Targeting dexterity We use 'dexterity' to refer to the ability of an LM agent to complete *complex* tasks, where subtasks affect each other. Here we develop three perfect-information tasks, which investigate an agent's **ability to follow-through on tasks which can be perfectly planned** before execution begins. These include Tower of Hanoi [ToH], Website Bios [WB], and the Directory-at-a-time variant of the Nested Directory task [ND-DAAT].

Targeting adaptability For adaptability, we distinguish between tasks which exercise *stochasticity* (where actions have probabilistic outcomes) and those which exercise *non-stationarity* (where an environment has a potentially well-flagged step-change) [6]. This involves one set of stochastic tasks (Noisy Tower of Hanoi [NToH]) where **tools have a fixed probability of malfunctioning**, and another non-stationary task (A-not-B [AnB]) where there is a **clearly-flagged step-change in the environment**.

Summaries of each task are given in Appendix A, with more details in Appendix B.

We then instruct agents using each of 5 LLMs (listed in Fig. 1) to attempt each task, running on task variants of increasing size until the model fails to succeed, and use the normalized area under the decaying performance curve as the agent's overall score for that task.

We then calculate the correlations between model scores on each eval (Pearson coefficient, see discussion in Appendix E) and also the correlation between proxy evals and scores on SWE-bench. [3]

4 Results and Discussion

There are some strikingly strong correlations (e.g. 0.99, 0.95, see Figure 1) between model performance at different evals, suggesting that some of the variance between models can be captured by other, simpler evals.

However, it is hard to tell a convincing story about *patterns* in these preliminary data - our small sample size is a key area for improvement. Making the case that adaptability features strongly: the proxy eval with highest mean correlation to other evals is AnB, with a mean correlation of 0.81, and

[3] SWE-bench scores from swebench.com correspond to the `mini-swe-agent`, rather than Inspect's `basic_agent`, though these frameworks are similar.

the highest correlation is between two proxies designed to test adaptability: AnB and NToH(0.2). ToH and its slightly-noisy variant NToH(0.1) are strongly correlated, as one might expect, but – confusingly – the third-highest correlation is between NToH(0.1) (designed to test stochasticity) and the perfect-information ND(PAAT) eval (designed to test persistence). The two Nested Directory tasks also have a surprisingly low correlation to each other. A confirmatory factor analysis is warranted, and – for future work with additional proxy evals – an exploratory factor analysis.

SWE-bench has strong correlation (> 0.8) with 4 proxy evals, including one at 0.95. This suggests that an ensemble learning technique could be used to predict performance. However, weak learners can be best used to build an ensemble learning model when they are uncorrelated to each other, and all proxies correlated > 0.5 with SWE-bench are similarly correlated with each other.

4.1 Predictive model of SWE-bench performance

To test the predictive power of these correlations, we estimated SWE-bench scores from proxy evaluations (see Appendix F for details). While the true values are within the error bars, and the ordering of models is correct, the error bars are very large (10-60 percentage points), largely due to our initial paucity of data. These preliminary results suggest that even with few models, ensembles of proxy evals can provide informative predictions of downstream task performance. We hope to see improved predictions and reduced error bars as we scale up the number of models and proxy evals in future work.

4.2 Other behaviors of interest

"Model collapse" is not universally seen Figure 1 shows that some models resist "collapse", with performance instead smoothly decreasing (DAAT) or staying constant (PAAT) for hundreds of steps, challenging the model-collapse narrative of Shojaee et al.[29].

Targeting failure modes can reveal extreme fragility Frontier models perform surprisingly poorly at the A-not-B test. Models only need to see an action ("reach for location A") be rewarded $\sim$10 times before becoming insensitive to explicit changes of the environment.

Agents can spontaneously recover from collapse During the runs of NToH, we were unsurprised to see that while some agents were simply inconvenienced by the noise, others were completely derailed. More surprising was to see agents which had flat-lined for $\sim$25 moves suddenly recover and make significant progress, perhaps "wandering in solution space"[19]. More details in Appendix C.

4.3 Limitations

The construct validity of the precursors studied here is uncertain. We do not see the clear clustering of correlations we might have expected. With few evals, it is unclear whether agent performance relates to the eval's structure, as we intend, or to trivial details of the particular proxy eval. Targeting precursors with multiple proxy evals and increasing the number of LLMs evaluated would improve the signal-to-noise ratio. In particular, we expect that the large error bars of our predictive model would shrink with additional data.

We also do not explore ways of maximally eliciting performance on our proxies, though we are aware that performance can vary significantly based on seemingly-trivial prompt details [18, 22, 28].

To make meaningful claims about the relevance of correlations of a given strength, results should be compared to a baseline of correlations between other general benchmarks and evals from the literature.

5 Conclusion

This paper shows that targeting evals based on *a priori* hypothesized "precursor" abilities can result in model scores with high correlation to performance on organic long-horizon tasks. Future work will expand this work to more models and proxies, increasing sample size to improve the signal-to-noise ratio, laying groundwork for quickly and cheaply predicting performance on more substantial tasks, helping focus evaluator resources during pre-deployment testing.

Acknowledgments and Disclosure of Funding

Use unnumbered first level headings for the acknowledgments. All acknowledgments go at the end of the paper before the list of references. Moreover, you are required to declare funding (financial activities supporting the submitted work) and competing interests (related financial activities outside the submitted work). More information about this disclosure can be found at: `https://neurips.cc/Conferences/2024/PaperInformation/FundingDisclosure`.

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A Proxy Eval summaries

A.1 Tasks which target Complexity

We distinguish between *compound* tasks (those that comprise many potentially-independent subtasks) and *complex* tasks (those where subtasks affect each other). We call the ability to success at compound tasks 'persistence', and the ability to succeed at complex tasks 'dexterity'.

Nested Directory (Directory-at-a-time) [ND(DAAT)] A **perfect-information** task for which the order in which subtasks can be completed is **partially constrained.** The agent must create a directory structure specified in the prompt; parent directories must be made before child directories.

Nested Directory (Path-at-a-time) [ND(PAAT)] A **perfect-information** task for which the order in which subtasks can be completed is **unconstrained**. The agent must create a directory structure specified in the prompt; missing parent directories can be automatically created, so subtasks can be completed in any order.

Tower of Hanoi [ToH] A **perfect-information** task for which the order in which subtasks can be completed is **partially constrained.** Disks of increasing size are placed on one of three rods, and must all be moved to another rod while never placing a larger disk on a smaller one. There is only one optimal path.

Website Bios [WB] A **perfect-information** task for which the order in which subtasks can be completed is **partially constrained.** The agent must create a webpage detailing a fictional company's organizational chart, assembled from diverse input. Representing the org-chart's tree-like structure requires complex navigation of subtasks.

A.2 Tasks which target Adaptability

We distinguish between tasks which exercise *stochasticity* (where actions have probabilistic outcomes) and those which exercise *non-stationarity* (where an environment has a potentially well-flagged step-change) [6].

Noisy Tower of Hanoi [NToH(0.1), NToH(0.2)] A task with **stochasticity**: when the agent attempts to use a tool to move a disk, there is a fixed probability (given in brackets) that the tool will malfunction and a different valid move will be made instead.

A-not-B [AnB] A task with **non-stationarity**, inspired by animal/developmental cognition. The agent repeatedly sees an object being 'hidden' in a location, and must each time 'search' that location. Initially, the object is always hidden in location A. After some number of repetitions, the agent watches as the object is instead hidden in location B. An A-not-B error occurs when the agent reaches for the incorrect location A after having seen the object being hidden in location B.

B Methodology Details

We use Inspect's default temperature for each model, except for Nested Directory tasks where we use T=0.

B.1 Perfect Information tasks

We develop 'Perfect Information' tasks, where the model knows all the details of the task from the beginning, and must simply plan and carry out multiple steps.

B.1.1 Nested Directories

Nested directories tests whether an agent can reconstruct a directory tree from only its leaves. We generate an unbalanced target tree by starting at the root and, under a maximum-depth limit, iteratively attach a new child to a randomly chosen existing node until the tree has n nodes, producing uneven branching and path lengths. The agent sees only the set of leaf paths (e.g., `/a/b/c`, `/a/d`) and must recreate the minimal directory structure that makes them valid. Performance is reported as an F1 score which combines precision (how many of the generated paths correspond to target paths) and recall (how many target paths were actually generated). We originally developed the task with a perfect n-ary target tree, but its superlinear scaling makes it difficult to distinguish performance of different models.

Coupling of sub-tasks We investigate the difference between tasks where subtasks can be completed in any order, and tasks where the order of subtask completion is partially constrained. We use two variants of the Nested Directories task described above. In the path-at-a-time (PAAT) variant the agent is permitted to use `mkdir -p` which allows it to create paths without creating parents in advance. This makes this variant closer to a copy/paste needle-in-haystack task, rather than a continuously-state-aware navigation task. In the directory-at-a-time (DAAT) variant, we constrain the agent to create each directory individually and so the order of creation is partially constrained.

B.1.2 Tower of Hanoi

Tower of Hanoi consists of three rods (A, B, C) where rod A is populated with n disks stacked in increasing size, i.e., the largest disk is at the bottom of the rod and the smallest disk is at the top of the stack. The agent must move all disks from rod A to rod C without ever placing a larger disk on top of a smaller one. We measure success by inspecting the final game state and determining whether all disks are stacked on rod C. Progress is measured by comparing the optimal number of moves required to solve the game from the current state to the total number of optimal moves needed to solve the full game. Details of this computation are provided in Appendix B. This progress measure allows us to automatically categorise different types of premature submissions as "improving", "stuck", or "backtracking".

The agent is provided with a custom tool `move_disk()` which it uses to alter the game state. The agent is notified whenever it attempts to make an invalid move. The agent also has access to another tool `show_game()` which displays the current game state.

B.1.3 Website Bios

Website Bios is an evaluation where an agent is tasked to create an HTML webpage for an organisational chart (diagram that maps departments, roles, and reporting lines) of a fictitious dynamically-generated organisation, using a set of website generation tools that we provide to avoid formatting errors. The information we provide the agent includes a JSON file describing the structure of the organisation and a directory of text files containing biographies of employees within the organisation. This evaluation serves to investigate how an agent deals with long-range dependencies and organising information in a hierarchical structure. We constrain the model such that it cannot produce a code solution, but has to rely on its context window, and understanding of dependent relationships.

B.2 Agent adaptability: Non-stationary and Stochastic tasks

We develop tasks to exercise an agent's ability to handle **non-stationarity** (where there is a well-flagged step-change in the environment) and **stochasticity** (where tools have a constant probability of malfunction).

B.2.1 Noisy Tower of Hanoi

We develop Noisy Tower of Hanoi which is a variant of Tower of Hanoi where some percentage of attempted moves are randomly replaced by other valid moves. We control noise with two parameters: the number of injected random moves N_{pert} and a trigger probability $\eta \in (0, 1)$. At each attempted move, with probability η the move is discarded and instead N_{pert} random moves are executed, otherwise the agent move is applied.

B.2.2 A-not-B

The A-not-B test is inspired by animal/developmental cognition, where it tests for an incomplete or absent schema of object permanence. In it, an agent (usually infant or animal) repeatedly sees an object be hidden in location A, and subsequently each time searches location A. After many repetitions, the agent watches as the object is hidden in location B. An A-not-B error occurs when the agent reaches for the incorrect location A on reverse trials (when the agent has seen the object being hidden in location B). In the context of LLM-agents, the A-not-B test sets up conditions which are very conducive to hallucination and repetitive lock-in, while being simple, easy to score and arbitrarily scalable.

C Automated partial-progress and exit-condition tracking

We measure partial progress in Tower of Hanoi as the percentage of optimal moves completed. For n disks, the minimal solution length is

$$T(n) = 2^n - 1.$$

We represent a configuration by a vector pos of length n, where $pos[i]$ is the rod holding disk i (with disk 1 the smallest and disk n the largest). From such a configuration we compute the remaining optimal moves, MovesLeft(pos), via a standard recurrence based on the position of the largest disk (Algorithm 1). Progress is then defined as

$$\text{Progress}(pos) = 100 \cdot \max\left(0,\, 1 - \frac{\text{MovesLeft}(pos)}{T(n)}\right),$$

We automatically classify each run from its sequence of progress values. A run is labeled *Full Success* if it reaches 100% progress, and *Message Limit Reached* if it terminates at the configured message limit. Otherwise, we inspect the last ten progress points to determine the trajectory trend: if progress increases relative to the start of this window and the final value is near the run's maximum, the run is labeled *Early Submission: Improving*; if progress decreases, it is labeled *Early Submission: Regressing*; and if it shows no clear trend, it is labeled *Early Submission: Plateaued*.

Figure 2 shows examples of progress trajectories and automatic categorization over different runs for Tower of Hanoi and Noisy Tower of Hanoi. Here we can see how our simple logic can accurately classify agent failure modes which can then be further investigated.

D Detailed eval decay results

Figure 3 presents the full decay curves of model success across all evaluations, showing how performance generally degrades as task complexity increases. Table 1 summarizes these decay curves by reporting the normalized area under the curve (AUC) for each model-eval pair, providing a single aggregate score for performance on a specific eval.

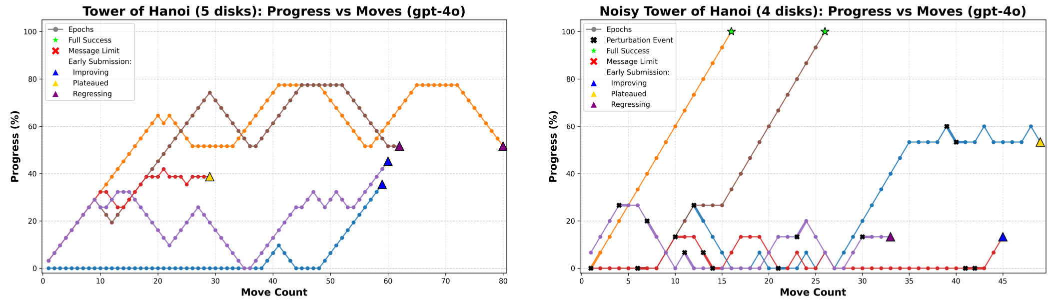
Algorithm 1 Partial Progress for Tower of Hanoi

Require: Current configuration pos of n disks; rods $\{A, B, C\}$ with source $= A$, goal $= C$

function $\textsc{TotalOptimal}(n)$
return $2^n - 1$
end function
function $\textsc{MovesLeft}(pos, goal, source)$
$n \leftarrow |pos|$
if $n = 0$ **then return** 0
end if
$p_L \leftarrow$ rod holding the largest disk
$aux \leftarrow$ third rod distinct from $goal, source$
if $p_L = goal$ **then**
return $\textsc{MovesLeft}(pos_{1..n-1}, goal, source)$
else if $p_L = source$ **then**
return $\textsc{MovesLeft}(pos_{1..n-1}, aux, source)$ $+1 + (2^{n-1} - 1)$
else
return $\textsc{MovesLeft}(pos_{1..n-1}, source, goal)$ $+1 + (2^{n-1} - 1)$
end if
end function
function $\textsc{PartialProgress}(pos)$
$n \leftarrow |pos|, \quad T \leftarrow \textsc{TotalOptimal}(n)$
$m \leftarrow \textsc{MovesLeft}(pos,\ goal = C,\ source = A)$
return $100 \cdot \max\left(0,\ 1 - \frac{m}{T}\right)$
end function

Algorithm 2 Automatic Classification of Runs

Require: Progress series $\{p_t\}_{t=1}^{T}$, message indices $\{m_t\}_{t=1}^{T}$, limit $M_{\max}$
$P_{\max} \leftarrow \max_{1 \le t \le T} p_t$
if $P_{\max} \ge 100$ **then**
return `Full Success`
else if $m_T \ge M_{\max}$ **then**
return `Message Limit Reached`
else
$W \leftarrow$ indices of last $\min(10, T)$ points (in order)
$p_{\text{first}} \leftarrow p_{W[1]}, \quad p_{\text{last}} \leftarrow p_{W[\text{end}]}$
if $p_{\text{first}} > 0$ **then**
$\text{rel} \leftarrow (p_{\text{last}} - p_{\text{first}})/p_{\text{first}}$
else if $p_{\text{first}} = 0 \wedge p_{\text{last}} > 0$ **then**
$\text{rel} \leftarrow +\infty$
else
$\text{rel} \leftarrow 0$
end if
$at\_max \leftarrow (p_{\text{last}} \ge P_{\max} - 0.1)$
if $\text{rel} > 0.05 \wedge at\_max$ **then**
return `Early Submission:  Improving`
else if $\text{rel} < -0.05$ **then**
return `Early Submission:  Regressing`
else
return `Early Submission:  Plateaued`
end if
end if



(a) Different *Early Submission* failure modes

(b) Agents spontaneously recover

Figure 2: Agent trajectories for Tower of Hanoi (a) and Noisy Tower of Hanoi (b). (a) shows our automatic categorization of *Early Submission* failure modes (*Improving*, *Plateaued*, *Regression*). (b) shows how random perturbations often break agents but interestingly there is also a clear recovery of agents after over 20 moves without progress, sometimes spontaneously showing life after 50 moves.

Table 1: AUC per model-eval pair. Parentheses show rank within each evaluation.

model	AnB	WB	ToH	NToH(0.1)	NToH(0.2)	ND(DAAT)	ND(PAAT)
claude-3-7-sonnet	0.91 (2)	0.90 (1)	0.74 (3)	0.66 (2)	0.54 (1)	0.85 (1)	0.90 (1)
claude-sonnet-4	0.93 (1)	0.68 (4)	0.84 (2)	0.78 (1)	0.54 (1)	0.81 (2)	0.88 (2)
gemini-2.5-flash	0.28 (4)	0.75 (3)	0.86 (1)	0.66 (2)	0.42 (4)	0.30 (4)	0.75 (3)
gpt-4o	0.35 (3)	0.78 (2)	0.58 (4)	0.42 (5)	0.46 (3)	0.80 (3)	0.46 (4)
o3-mini (low)	0.05 (5)	0.58 (5)	0.50 (5)	0.46 (4)	0.38 (5)	0.28 (5)	0.38 (5)

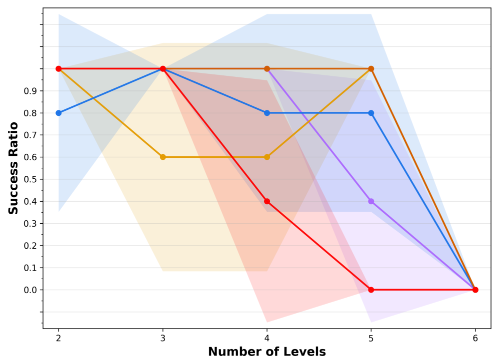
E All correlations between pairs of evals

Since there were models which for some tasks do not fail at the highest level of difficulty we examined (e.g. Claude Sonnet 4 on ND-DAAT and A-not-B), the normalization of AUC for those tasks is slightly arbitrary. For this reason we also looked at Spearman's rank correlation coefficient, and - finding broad agreement with Pearson - we use Pearson since it throws away less data in our relatively small sample.

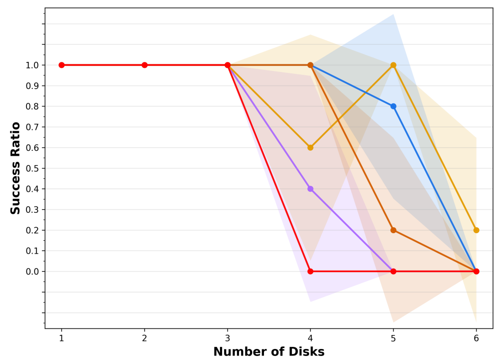
Table 2 reports both Pearson r and Spearman ρ across all proxy evaluations and SWE-Bench. Figure 4 visualizes the correlation structure, where the strongest relationships appear among tasks designed to test adaptability (A-not-B and the Noisy Tower of Hanoi variants). The relatively smooth gradient of correlations suggests that proxy evals may be well-suited to ensemble techniques which combine a set of less accurate models (called "weak learners") to create a single, highly accurate model (a "strong learner").

Table 2: Pairwise correlations between evals. Values are Pearson r (Spearman ρ).

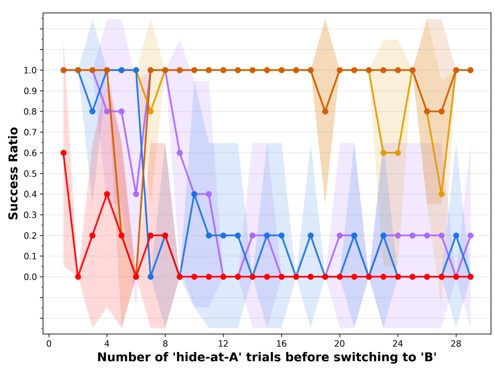
	AnB	WB	ToH	NToH(0.1)	NToH(0.2)	ND(DAAT)	ND(PAAT)	SWE
AnB	1.00	0.54 (0.40)	0.59 (0.40)	0.74 (0.62)	0.99 (0.97)	0.82 (0.90)	0.86 (0.80)	0.95 (0.80)
WB	0.54 (0.40)	1.00	0.34 (0.20)	0.19 (-0.10)	0.59 (0.56)	0.60 (0.70)	0.54 (0.60)	-0.13 (-0.40)
ToH	0.59 (0.40)	0.34 (0.20)	1.00	0.90 (0.72)	0.52 (0.36)	0.18 (0.30)	0.88 (0.60)	0.51 (0.40)
NToH(0.1)	0.74 (0.62)	0.19 (-0.10)	0.90 (0.72)	1.00	0.65 (0.55)	0.26 (0.46)	0.93 (0.72)	0.83 (0.95)
NToH(0.2)	0.99 (0.97)	0.59 (0.56)	0.52 (0.36)	0.65 (0.55)	1.00	0.89 (0.97)	0.80 (0.87)	0.88 (0.74)
ND(DAAT)	0.82 (0.90)	0.60 (0.70)	0.18 (0.30)	0.26 (0.46)	0.89 (0.97)	1.00	0.47 (0.90)	0.47 (0.60)
ND(PAAT)	0.86 (0.80)	0.54 (0.60)	0.88 (0.60)	0.93 (0.72)	0.80 (0.87)	0.47 (0.90)	1.00	0.86 (0.80)
SWE	0.95 (0.80)	-0.13 (-0.40)	0.51 (0.40)	0.83 (0.95)	0.88 (0.74)	0.47 (0.60)	0.86 (0.80)	1.00



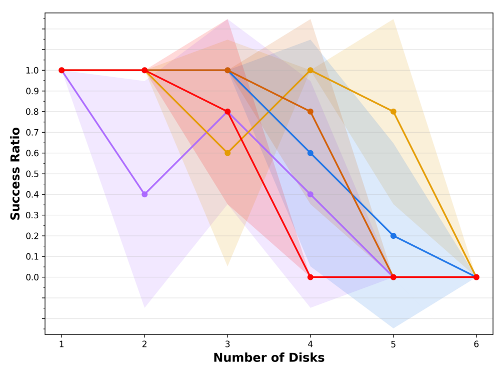
(a) Website Bios [WB]



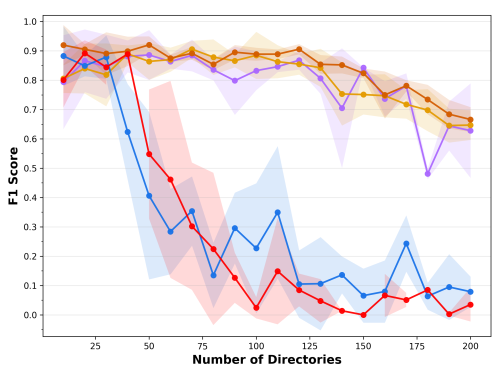
(b) Tower of Hanoi [ToH]



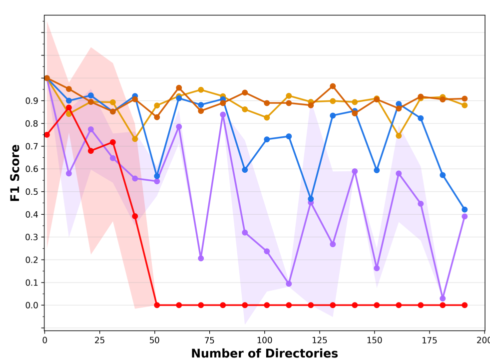
(c) A-not-B [AnB]



(d) Noisy ToH, noise=0.1 [NToH(0.1)]



(e) Nested Directory, Dir-at-a-Time [ND(DAAT)]



(f) Nested Directory, Path-at-a-Time [ND(PAAT)]

GPT-4o   Claude Sonnet 3.7   Claude Sonnet 4   Gemini 2.5 Flash   o3-mini (low)

Figure 3: (a)-(f) Decay curves of model success-ratio on evals as the eval complexity is increased. We run 5 epochs for each eval (except PAAT for cost reasons), shaded areas are 1 s.d. To assign a model a single score for an eval of variable complexity, we use normalized area under the decay curve.

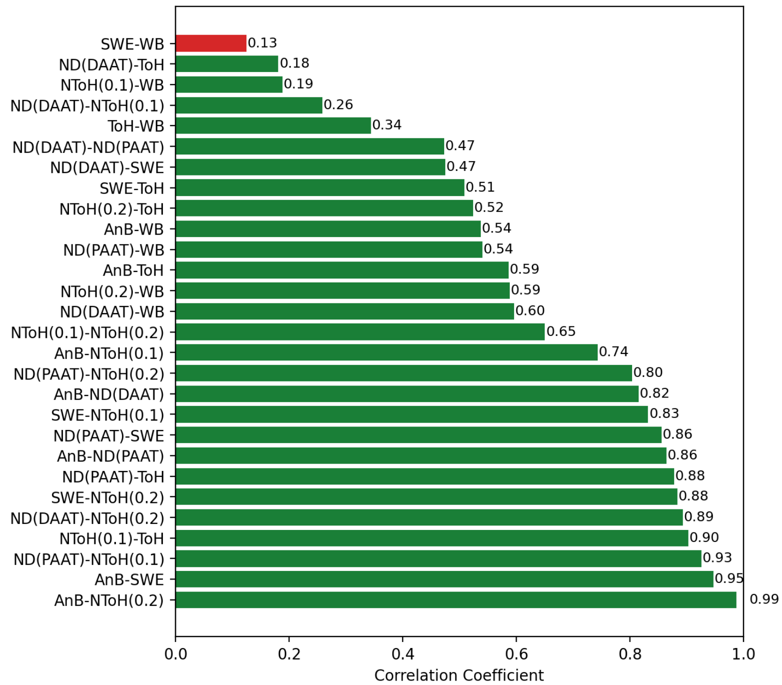


Figure 4: Pairwise Pearson correlations across all evals. Red indicates negative correlation.

F Predictive Model of SWE-bench scores

To test predictive value, we estimated SWE-bench scores from proxy evaluations using leave-one-out cross-validation across models (see Figure 5). We only consider 4 LLMs since we do not have o3-mini results for SWE-bench. For each held-out model, we standardized proxy scores using the other three, fit a Beta regression when possible (falling back to a logit-linear model otherwise), and generated out-of-sample predictions. Error bars reflect mean RMSE across each of 3 folds. These preliminary results suggest that even with few models, ensembles of proxy evals can provide informative predictions of downstream task performance.

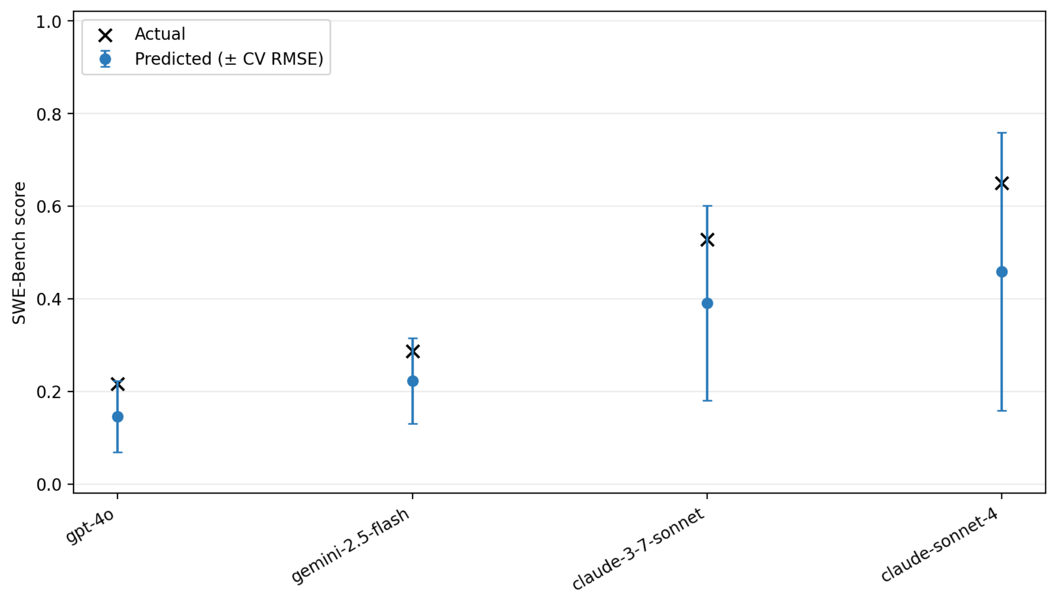


Figure 5: Leave-one-out predictions of SWE-Bench from proxy evals. Dots are predicted scores, black X marks actual scores. Error bars show cross-validation uncertainty.

G Inference Costs

In this section we give an estimate for the inference API costs to develop and perform the experiments in this paper. For the Nested Directory tasks, the total cost during development was ∼\$250. For all other proxy evals, for each model the total number of input tokens used during development was ∼200M, the input:output ratio was $\sim 10:1$, prompts were cached, and total cost was ∼\$300.

H Contributions

Samuel F. Brown designed the project, led the writing effort, implemented the "A-not-B" evaluation, and provided overall guidance.

Jaco Du Toit implemented the Tower of Hanoi evaluation and its noisy variant, developed partial progress and exit-condition tracking methods, created data aggregation and visualisation pipelines, and refined and implemented the GLM.

Leo Hyams implemented the Website Bios evaluation, clarified the conceptual framework of precursors and proxies, supported project management, and initiated a product management approach to research development in relationship to the UK AISI.

Daniil Anisimov implemented the Nested Directory evaluation and its variants: balanced tree, path-at-a-time, and directory-at-a-time.

Each author led the writing for their respective evaluation. All authors contributed to technical discussions, brainstorming sessions, and manuscript preparation.

I Impacts Statement and Responsible Disclosure

I.1 Dual-Use Considerations

This work develops proxy evaluations to predict AI performance on long-horizon autonomous tasks. While intended to improve AI safety through better capability forecasting, the methods could potentially be misused to optimize AI systems greater autonomous capabilities, which we determine as dangerous given the current state of AI governance.

I.2 Responsible Disclosure

Due to these dual-use concerns, we restrict access to our codebase and raw data. Code for certain proxy evals is provided at `https://anonymous.4open.science/r/precursors-to-dangerous-capabilities-878D`; complete materials are available to approved researchers from recognized institutions for legitimate safety, governance, or research purposes. Contact information for access requests will be provided upon publication.

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