

AUTO LIBRA: AGENT METRIC INDUCTION FROM OPEN-ENDED HUMAN FEEDBACK

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Code Data Website: <https://autolibra.org>

ABSTRACT

Agents are predominantly evaluated and optimized via task success metrics, which are coarse, rely on manual design from experts, and fail to reward intermediate emergent behaviors. We propose *AutoLibra*, a framework for agent evaluation, that transforms open-ended human feedback *e.g.* “If you find that the button is disabled, don’t click it again”, or “This agent has too much autonomy to decide what to do on its own” into metrics for evaluating fine-grained behaviors in agent trajectories. AutoLibra accomplishes this by grounding feedback to an agent’s behavior, clustering similar positive and negative behaviors, and creating concrete metrics with clear definitions and concrete examples, which can be used for prompting LLM-as-a-Judge as evaluators. We further propose two *meta-metrics* to evaluate the alignment of a set of (induced) metrics with open feedback: “coverage” and “redundancy”. Through optimizing these meta-metrics, we experimentally demonstrate AutoLibra’s ability to induce more concrete **agent evaluation** metrics than the ones proposed in previous agent evaluation benchmarks and discover new metrics to analyze agents. We also present two applications of AutoLibra in **agent improvement**: First, we show that AutoLibra serve human prompt engineers for diagonalize agent failures and improve prompts iterative. Moreover, we find that AutoLibra can induce metrics for automatic optimization for agents, which makes agents improve through self-regulation. Our results suggest that AutoLibra is a powerful task-agnostic tool for evaluating and improving language agents.

1 INTRODUCTION

Humans readily acquire skills from open-ended instructions and feedback from others (Tomasello et al., 1993). These instructions and feedback are internalized for self-regulated learning (Pintrich & Zusho, 2002; Nicol & Macfarlane-Dick, 2006), providing internal signals for continuous improvement. Drawing inspiration from this process, we investigate how well AI agents can benefit from open-ended human feedback through induction of generalizable metrics.

In this paper, we introduce AutoLibra, a metric induction method, as a novel agent evaluation framework that mitigates the limitations of current evaluation paradigms. AutoLibra is an evaluation tool that induces interpretable metrics for AI agents from open-ended human feedback, which can be collected from end users of AI agents or experts. This offers two advantages: (1) It is much easier to provide concrete feedback for trajectories than creating metrics, and (2) AutoLibra allows us to evaluate agents from the perspective of the users. AutoLibra-induced metrics provide concrete definitions of behaviors that the model-based evaluation method should look for, which could be used to understand agent behavior, as well as optimization targets to improve agents.

Inspired by the code-theme steps of thematic analysis conducted by experts in social sciences (Braun & Clarke, 2006), we design the AutoLibra induction process (§2.2) as two steps: (1) *feedback grounding*: where we ground every aspect of human feedback on some behavior in the entire agent trajectory, and (2) *behavior clustering*: where we cluster the aspects into multiple clusters of similar behaviors to summarize into metrics. As illustrated in Fig. 1, the user gives a web agent feedback “the agent did not choose iPhone 14/15” which is grounded to the agent’s behavior, choosing “iPhone 16

Pro” from the drop-down menu. Similar behaviors are clustered into a common cluster, summarized as *Element Interaction Accuracy*.

The AutoLibra evaluation process is designed to provide a closed-loop feedback signal for the induction process. The agent trajectories used in the induction process are scored by LLM-as-a-Judge (Zheng et al., 2023) on the induced metrics. The evaluation process (§2.3) then tries to match the feedback aspects, e.g. “recipe does not contain quinoa”, with the traits, e.g. `task-requirement-achievement`. In this way, we can meta-evaluate the quality of the metrics: (i) *coverage* (what proportion of feedback aspects can be matched with an agent trait), and (ii) *redundancy* of the metrics (what proportion of the detected traits are not mentioned by humans). These two metrics provide an overall statistical picture of the quality of the induced metrics. Based on these two metrics, we can search for the set of metrics with the lowest redundancy and the highest coverage. As shown in §3.1, we find that as the number of metrics increases, the redundancy increases, and the coverage ultimately converges to the maximum coverage. With AutoLibra, our aim is to answer the following research questions:


RQ1: How well do AutoLibra’s step-wise results align with human judgment?

RQ2: Does AutoLibra provide insights into agent behavior beyond expert-designed metrics?

RQ3: Can AutoLibra provide optimization signals for improving agents’ performance?

Experiments within multiple agent domains, including collaborative agents (Shao et al., 2024), social agents (Zhou et al., 2024b), web agents (Zhou et al., 2024a; He et al., 2024), and text game agents (Paglieri et al., 2024; Cloos et al., 2024), demonstrate that AutoLibra is able to induce fine-grained and interpretable metrics with high coverage and low redundancy in unseen human feedback with 80 trajectories per dataset annotated with one feedback for each. These metrics are more concrete, and some of them were even overlooked in expert designed metrics or error analysis (§4). AutoLibra can iteratively discover new, emergent metrics (§3.2) throughout the agent optimization process, and provide optimization signals helps improve the performance of frontier LLM in a challenging 2D text game by over 20% (§5) in 3 stages with only 18 trajectory annotated per stage.

2 AUTO LIBRA

To address the limitations of existing evaluation paradigms, AutoLibra  is designed to meet the following desiderata: (1) *induced from agent behavior*: This ensures that metrics are grounded in agent trajectories rather than predefined by human experts, (2) *self-validating*: Allows choosing minimal set of metrics that cover unseen human feedback with sufficient abstraction to be useful across different tasks, and (3) *generalizable*: Applicable to various agent environments, independent of domain-specific design. Based on feedback data collected from humans (§2.1), AutoLibra achieves these desiderata through a closed-loop pipeline consisting of two processes: **Induction Process** that converts agent behaviors and corresponding feedback into metrics, (§2.2) and **Evaluation Process** that predicts ratings and quality of new agent behaviors on the induced metrics (§2.3).

2.1 COLLECTING HUMAN FEEDBACK

In this paper, we use human feedback from two groups: (1) End-users – for agents that interact directly with humans, we use the feedback from the users who interact and converse with the agents. CoGym (Shao et al., 2024) is the environment that belongs to this category, and we use the user comments collected in their study, resulting in 197 trajectories with feedback. (2) Experts – for agents that do not directly interact with humans, we use the feedback from human annotators (five authors in this paper) who observe agent trajectories. All other environments belong to this category, these being Sotopia (Zhou et al., 2024b), WebArena (Zhou et al., 2024a), WebVoyager (He et al., 2024), Baba-is-ai (Cloos et al., 2024), and MiniHack (Samvelyan et al., 2021). For each trajectory, we collect only one element of feedback based on the complete agent trajectories.¹

Annotators are instructed to explicitly indicate the aspects of agent behavior that they classify as good or bad, and to avoid general comments such as “*The agent is good at solving the task*”. The annotators can also choose from a terminal or a web interface; in both cases the annotator is provided

¹While in theory we can leverage feedback on specific steps to achieve better feedback grounding and multiple feedback for single trajectory, we leave it as future work.

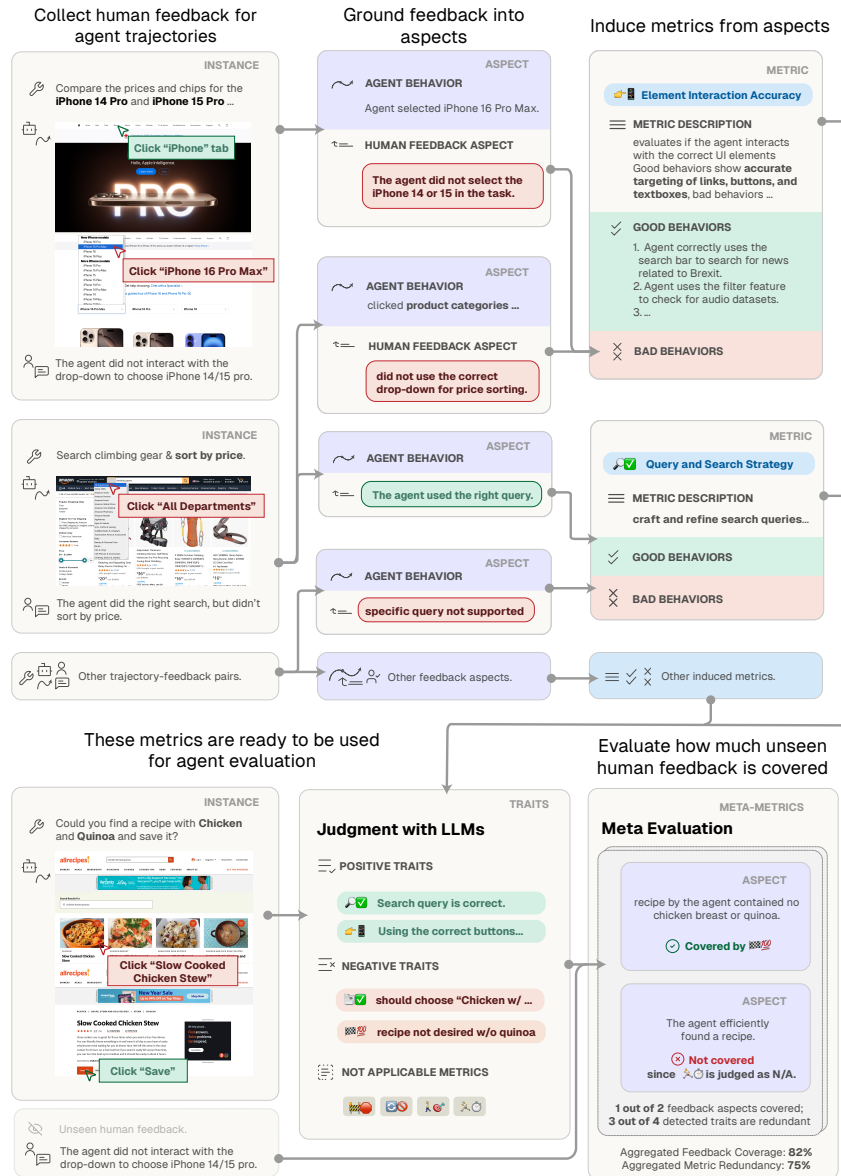



Figure 1: AutoLibra  induces agent evaluation metrics from human feedback, and uses these metrics to evaluate agents, which can be meta-evaluated via evaluating the coverage on unseen human feedback. Here we show real examples of agent trajectories, human feedback, aspects, induced metrics, evaluation results on WebVoyager (He et al., 2024).

with the agent’s task and then view the agent’s observation and actions step by step, in text form.² For multi-agent tasks, we annotate each agent’s trajectory in a given interaction separately. For Sotopia (Zhou et al., 2024b), WebArena (Zhou et al., 2024a), and WebVoyager (He et al., 2024), we annotate 100 trajectories of agents based on GPT-4 (Achiam et al., 2023) with feedback for each dataset. For experiments in §5 we annotate 18 trajectories for each dataset in each iteration. The annotation process is fast: Human annotators spend less than 5 minutes to provide feedback for each trajectory; §4, we randomly hold out 20% of the trajectories for validation.

²While viewing screenshots is standard for web navigation tasks, we keep the observation format consistent across agents and humans to encourage more grounded feedback.

2.2 INDUCTION PROCESS

Feedback Grounding The feedback of human annotators can contain multiple aspects; e.g. “AI agent was pretty good at giving me a consistent itinerary and vacation plan, although it froze on the last couple of minutes.”, collected from human annotators in CoGym (Shao et al., 2024), contains a positive aspect about the agent’s ability to generate a consistent itinerary, and a negative aspect about the agent freezing at the end. Here we define an *aspect* as a triple (behavior, feedback, sign). In the positive aspect of the previous example, the `behavior` is the agent’s actions to create a 20-day itinerary for the Maldives, the `feedback` is that the created itinerary is consistent and the `sign` is positive. This grounding procedure is similar to the coding procedure in thematic analysis.

We feed the trajectory and the feedback into the LLM (we use GPT-4o (OpenAI et al., 2024) as it yields good results in our pilot experiments) and prompt the LLM with the following instructions: (1) break down the feedback into bullet points; (2) for each bullet point, find the corresponding part of the trajectory to which the feedback refers. Finally, we use constrained decoding to force GPT-4o to output the aspects in the previous format. In our experiments, we find that on most datasets, for each trajectory, the LLM can generate one to five aspects, with a mean of one to two aspects.

Behavior Clustering The second step of the extraction process is to group the aspects into N metrics. To illustrate this step, we consider another example in the same dataset “The AI responds quickly to write and run the Python script“ where the `behavior` is the agent’s action to quickly write and run a Python script, the `feedback` is that the agent responds quickly, and the `sign` is positive. Although this aspect is a positive aspect, it reflects the same dimension of the agent’s behavior as the previous negative aspect, with an opposite value. Each *metric* is a cluster of aspects, with a definition summarizing the criteria of positive behaviors, a list of positive behavior examples, and a list of negative behavior examples. This clustering procedure is similar to the theme induction step in thematic analysis.

However, clustering similar agent behaviors together is challenging for statistical clustering methods.³ Inspired by LLM-based semantic clustering and concept induction methods (Viswanathan et al., 2024; Lam et al., 2024), we prompt an LLM (o3-mini high⁴, as it produces the most accurate coverage and redundancy scores as evaluated later) to cluster the aspects into metrics. As illustrated in Fig. 7, we gather all the aspects of M trajectories and cluster into N metrics, where N is a parameter set through the optimization process (§3.1). We provide the LLM with the following instructions: *The granularity of the grouping should be minimal; only very similar behaviors are grouped together; but don’t limit to one particular website or one particular character*, which empirically makes the metrics more concrete but still applicable across different tasks.

2.3 EVALUATION PROCESS

Evaluating agents with induced metrics LLM-as-a-Judge (Zheng et al., 2023), or more broadly, model-based evaluation (Zhang et al., 2019; Celikyilmaz et al., 2021) is a method to use machine learning models to evaluate the output of other machine learning models. The success of LLM-as-a-Judge depends on the gap between the difficulty of evaluation or verification and that of generation and action. In agentic tasks, this gap is often large, as the policy model must perform multiple steps in decision-making, while the evaluation model must only classify the trajectories, which make LLM-as-a-Judge widely used (Zhou et al., 2024a; He et al., 2024; Zhou et al., 2024b). In AutoLibra, we employ LLM-as-a-Judge to evaluate the agent trajectories configured with the induced metrics. However, LLM-as-a-Judge can be replaced by any other evaluation methods implementing the induced metrics; e.g. an `interact-valid-element` metric could be evaluated by a rule-based evaluator that checks if the agent interacts with valid elements on the webpage. We note that AutoLibra could be used with other evaluation methods, such as programmatic evaluation (Ma et al., 2024); we leave generating programs for the induced metrics for future work.

As illustrated in Fig. 8, taking the induced metrics as input, an LLM (we use o3-mini medium, as it provides similar results in this step to o3-mini high) is prompted to rate the agent trajectories to

³In preliminary experiments, we tried to use K-means clustering on the aspect vectors generated by embedding model `text-embedding-3-large`, but the clusters are mostly based on tasks and not on the behaviors.

⁴<https://openai.com/index/openai-o3-mini/>

{+ 1, -1, N/A} for each metric. For an agent trajectory, the metrics labeled +1 are the positive *traits*, and the ones labeled -1 are the negative *traits*. When we calculate the scores of the metrics, we use the ratio of agent trajectories rated as positive to the ones that are rated as positive or negative, ignoring those rated as N/A, since not all metrics are applicable to all trajectories (some metrics like `valid-search-terms` are only applicable when the task involves searching).

Meta evaluation The final loop component is the meta-evaluation, i.e. evaluating the evaluation metrics induced by AutoLibra. This step matches the traits detected by the LLM-as-a-Judge with aspects grounded from the human feedback. The goal is to verify whether (1) the induced metrics cover the behaviors the human annotators care about, and (2) LLM-as-a-Judge can produce accurate evaluation results based on the induced metrics. In the previous example, if the `respond-promptly` is extracted as a metric, and the LLM-as-a-Judge has the same opinion as the human annotators, then this aspect is considered as successfully covered. If either a similar metric was not extracted, or the LLM-as-a-Judge assigns a different score, then this aspect is considered as not covered.

As illustrated in Fig. 9, we perform meta-evaluation for each trajectory-feedback pair by classifying the aspects into positive and negative aspects, classifying traits into positive and negative traits based on rating, then matching the positive aspects with positive traits and the negative aspects with negative traits. We prompt an LLM (we use GPT-4o (OpenAI et al., 2024)) with a list of aspects and another list of traits and ask the LLM to find the best matching trait for each aspect or decide that there is no matching trait. The *coverage* of the whole dataset is calculated as the proportion of aspects of all instances that have a matching trait, and the *redundancy* is calculated as the proportion of traits of all instances that have not been matched with any aspect.

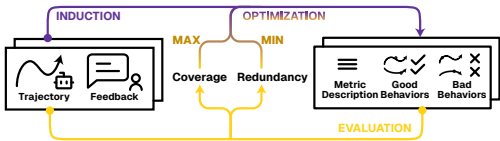


Figure 2: Metric optimization: optimizing the induction process through maximizing the coverage while minimizing redundancy of the metrics, calculated via the evaluation process.

The *coverage* of the whole dataset is calculated as the proportion of aspects of all instances that have a matching trait, and the *redundancy* is calculated as the proportion of traits of all instances that have not been matched with any aspect.

3 OPTIMIZING AND VALIDATING AUTO LIBRA

AutoLibra is designed to be self-validating through the evaluation process, which allows us to search the optimal set of metrics that cover the human opinion the best (§3.1). This optimization process can also be applied iteratively throughout the agent improvement process. As the agent is optimized, new metrics can be added to existing metrics (§3.2), which is similar to how unit tests are kept throughout software development to prevent new features from interfere with existing features. In the last part of this section, we study the alignment between each step of AutoLibra and human judgment.

3.1 METRIC OPTIMIZATION

Illustrated in Fig. 2, we optimize the metric induction process to maximize *coverage* and minimize *redundancy*. Among the two, we prioritize coverage of the metrics to provide a comprehensive evaluation of the agent behavior, while minimizing overlap within the metrics to avoid redundancy, thus maximizing the utility of induced metrics. To optimize for this objective, we generate 20 different sets of metrics, with metric count N ranging from 4 to 13, and calculate the coverage and redundancy of the metrics in human feedback. We then select metrics with a coverage of at least the highest coverage minus 1%, and the lowest redundancy. This is performed iteratively, by resetting the range of N to the number of metrics selected previously ± 2 , repeating until the coverage and redundancy of the selected metrics converge, normally within 3 iterations. While this optimization process is simple, experiments with various other optimization strategies, including genetic algorithms and iterative clustering saw none of them yield better results than the simple strategy. Fig. 3 shows the highest coverages of the metrics of size N , which converge around $N = 6$ to 10 depending on the datasets. The best coverage on Sotopia (Zhou et al., 2024b) is the lowest among all four datasets, 60%, likely due to the diversity of the tasks in the dataset, while coverage on WebArena (Zhou et al., 2024a) and WebVoyager (He et al., 2024) are the highest, 88%. We also find that the coverage of the held-out trajectories is only slightly worse ($< 5\%$) than the trajectories we use to induce the metrics, which is expected since we use the exact examples extracted from the latter. Lastly, we show that the

good and bad behaviors are crucial in the metrics, dropping which resulting in up to 30% coverage decrease on CoGym.

3.2 ITERATIVE METRIC INDUCTION

When applying AutoLibra to agent optimization, we can iteratively induce new metrics, as agents develop new failure modes or new behaviors as they improve, which is useful for tracking agents’ progress across different iterations.⁵ To do this, we modify the behavior clustering step: we provide the LLM with the existing metrics and definitions, asking the LLM not to change the definitions of the existing metrics, to only add new behaviors to the existing metrics, and to add new metrics if necessary. We apply the same optimization strategy as in the metric optimization step ensure the newly induced metrics cover emerging behaviors and do not overlap with existing metrics.

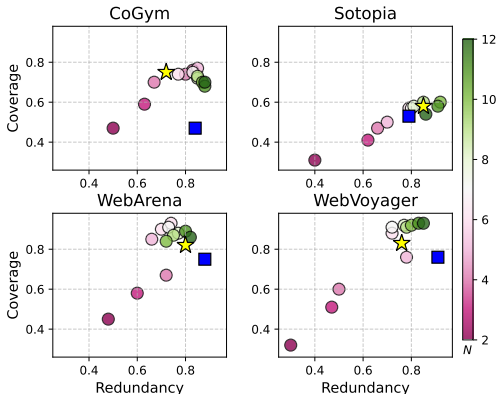


Figure 3: Coverage and redundancy of AutoLibra metrics on four agentic datasets. Circles indicate coverage and redundancy for different induced metrics; stars indicate the the best metrics’ coverage and redundancy on held-out human feedback; squares show an ablation test, indicating the effect when good and bad behavior examples are removed from metrics, demonstrating the criticality of concrete behavior examples

3.3 HOW ALIGNED ARE THE STEPS IN AUTO LIBRA WITH HUMAN JUDGMENT?

Since AutoLibra uses LLMs in each step, we first ask whether LLM outputs are reliable or aligned with human judgment. To measure the alignment of AutoLibra metric induction with human judgment, we validate the feedback grounding, agent evaluation, and meta evaluation steps by having human experts manually review each step (with exception of the behavior clustering step, as it is prohibitively time-intensive for human annotators to process and cluster more than 400 aspects), scoring (1/0) based on whether they agree with the outcomes of each iteration. The coverage and redundancy scores, in combination with the validation results of the other steps in the loop, thus serve as an indirect validation for the behavior clustering step. Table 1 shows the agreement rate of human annotators in AutoLibra steps. It should be noted that these tasks are significantly different; e.g., grounding for WebVoyager (He et al., 2024) is challenging due to the length and wide action space of the trajectory, and LLM-as-a-Judge for Sotopia (Zhou et al., 2024b) is difficult due to the complexity of the evaluation of social interactions. Our results show that the majority (significantly over 85%) of results in AutoLibra are reliable according to human validation.

⁵Alternatively, a new set of metrics can be induced from scratch for each iteration - in practice, we do not find that this results in any coverage loss, but we choose the former method for consistency

Table 1: The ratio of instances marked as fully correct in human validation. For each step and each task, we randomly sample 40 instances to reach a relatively small confidence interval of 0.04 and ask human annotators to label them as completely correct or not. Although the agreement scores vary across tasks and steps, the average agreement for each step and dataset is above 0.85 significantly.

Steps	CoGym	Sotopia	WebArena	WebVoyager	Baba-is-AI	Average
Grounding	0.95	0.95	0.98	0.93	0.93	0.95 (±0.03)
LLM-as-a-Judge	0.90	0.85	0.95	1.00	0.90	0.92 (±0.04)
Meta-Evaluation	0.98	0.90	0.85	0.83	0.95	0.90 (±0.04)

Table 2: AutoLibra-induced metrics and expert-proposed evaluation dimensions and failure categories. (Percentage %) denotes failure frequency or score from AutoLibra or the original papers.

	AutoLibra-induced metrics	Failure categories by experts
	Matched metrics and failure categories	
CoGym (Shao et al., 2024)	Responsiveness and Efficiency (75%)	Communication (65%)
	Communication Clarity & Notification (8%)	Situational Awareness (40%)
	Instruction Adherence & Follow-Through (24%)	Planning (39%)
	Iterative Refinement and Adaptability (47%)	Environmental Awareness (28%)
	Autonomy and Proactiveness (28%)	Personalization (16%)
	Content Quality and Coherence (16%)	
	Search and Retrieval Accuracy (13%)	
	Data Analysis Competence (2%)	
	Matched metrics and social dimensions	
Sotopia (Zhou et al., 2024b)	Goal Achievement & Outcome Effectiveness (19%)	Goal Completion (14%)
	Conversational Naturalness & Efficiency (5%)	Believability (4%)
	Personality Consistency and Alignment (2%)	
	Contextual Integration of Identity (1%)	
	Unmatched AutoLibra-induced metrics	
	Negotiation Tactics and Strategic Adaptability (14%), Responsiveness and Conversational Termination (5%), Adaptability and Flexibility in Dialogue (7%)	
	Unmatched Sotopia-Eval dimensions	
	Relationship, Knowledge, Secret, Financial and Material Benefits, Social Rules	
	Matched metrics and failure reasons	
WebVoyager (He et al., 2024)	Error Recovery & Adjustment (15%)	Navigation Stuck (44%)
	Step Efficiency & Action Redundancy (13%)	
	Navigation Accuracy (11%)	
	Access Barrier Handling (2%)	Hallucination (22%)
	Information & Verification Accuracy (16%)	Prompt Misalignment (9%)
	Result Relevance Accuracy (9%)	
	Unmatched AutoLibra-induced metrics	
	Query and Search Strategy Efficiency (7%), Final Output and Summarization Quality (18%)	
	Unmatched WebVoyager fail reasons	
	Visual Grounding Issue (25%)	

4 AUTO LIBRA AS A LENS : AGENT EVALUATION WITH AUTO LIBRA

In this section, we use AutoLibra as a lens to provide grounded, behavior-salient insights into agent trajectories. In three data sets, CoGym (Shao et al., 2024), Sotopia (Zhou et al., 2024b), and WebVoyager (He et al., 2024), we compare induced metrics with heuristically proposed evaluation dimensions and failure modes summarized by the authors. We find that AutoLibra can discover more concrete metrics than heuristically defined categories, and novel metrics that are overlooked by experts. Tab. 2 summarizes the comparison between AutoLibra-induced metrics and evaluation criteria across the three aforementioned datasets.

CoGym For CoGym (Shao et al., 2024), AutoLibra induces 9 metrics from feedback from **end users**, which can correspond to the five failure categories proposed by the authors. The failure rate (frequency of a metric score of -1) measured by AutoLibra also roughly matches the failure rate of the manually labeled CoGym categories by the authors. This shows that AutoLibra induces metrics that reflect human-expert categorization and provide an automated measurement of agent failures.

Sotopia Sotopia (Zhou et al., 2024b) proposed 7 dimensions for evaluating social intelligence in AI agents. With AutoLibra, we recover the exact dimension *Goal Completion*, and 3 metrics as the subdimensions of *Believability*, indicating that *Believability* could be too high-level, while AutoLibra provides more concrete breakdown metrics. The failure rate (frequency of a score of -1 metric rating,

indicating the agent performs poorly on that metric) measured by AutoLibra in these two categories roughly matches the score of the Sotopia dimensions of the agent we studied. AutoLibra induces another four metrics overlooked in the heuristically proposed Sotopia-Eval dimensions. We note that the other five dimensions in Sotopia are still valuable evaluation dimensions for social intelligence. However, behaviors captured by dimensions *Financial and Material Benefits*, *Knowledge*, and *Secret* are often also captured by *Goal Completion* and *Believability*. As a result, AutoLibra produces the single *Goal Achievement and Outcome Effectiveness* by minimizing redundancy. Whereas, *Relationship* and *Social Rules* captures long-tailed behaviors not captured by AutoLibra.

WebVoyager Similarly, for web navigation tasks, AutoLibra also discovers metrics such as *Access Barrier Handling*, *Error Recovery and Adjustment*, *Step Efficiency and Action Redundancy*, and *Navigation Accuracy*, which much more closely reflect concrete agent behavior than the failure analysis categories proposed in previous work (He et al., 2024; Zhou et al., 2024c), where they are often simply classified as “navigation stuck”. We also find additional metrics that are not mentioned in the failure analysis, such as *Query and Search Strategy Efficiency* and *Final Output and Summarization Quality*, which are frequent issues (with frequencies of 7% and 18%). Since AutoLibra only observes the behavior of the agents, it cannot interpret the neural representation, not able to capture the visual grounding issues, which are mentioned in the WebVoyager paper. This further demonstrates AutoLibra’s utility in extracting behavior-salient metrics, and particularly its ability to obtain **fine-grained metrics** that expert design would not have been able to extract.

5 AUTO LIBRA AS A LADDER 🪜 : AGENT IMPROVEMENT WITH AUTO LIBRA

As AutoLibra can automatically induce metrics from human feedback, a natural question to ask is whether it can enable self-regulated improvement in agents through iterative feedback. This can be achieved through optimizing the agent prompts towards higher scores on the metrics extracted by AutoLibra. To answer this question, we use a challenging 2D game *Baba-Is-AI* (Cloos et al., 2024; Paglieri et al., 2024) as a benchmark. Inspired by *Baba-Is-You*, this game requires not only following rules to achieve goals, but also manipulating the rules, even self-referential ones. For example, in the game illustrated in Fig. 5, the agent needs to change self-referential rules from *baba is you*, to *door is you* to control the green

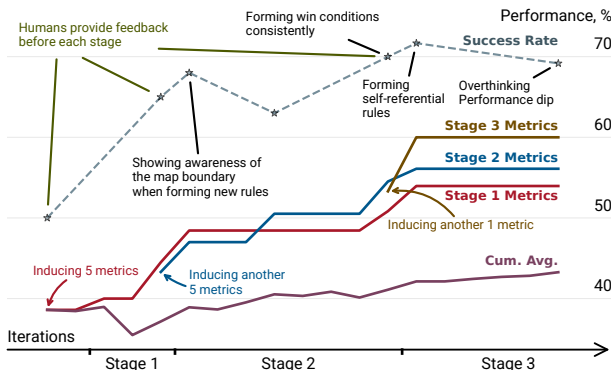


Figure 4: AutoLibra iteratively induce metrics and improves the agent prompts through optimizing for the induced metrics. Although not optimized for, the success rate of the agent continuously improve until Stage 3, when the agent begins to overthink.

door on the other side of the wall, form a new win rule *ball is win*, and navigate to the red ball to achieve the win condition. To achieve a high score on this dataset, the agent needs not only planning, but also metacognitive skills, which is very challenging for LLM agents with frontier models as shown in the Balrog benchmark (Paglieri et al., 2024). In this experiment, we use Gemini-2.5-Flash (Team et al., 2025) for the agent, AutoLibra, and agent prompt optimization, throughout the experiment, which will be referred as the LLM in this section. Gemini-2.5-Flash is ranked as the 3rd place, with a success rate of $50.8\% \pm 4.6\%$ on the Balrog leaderboard for *Baba-is-AI* at the time of submission, and the state-of-the-art result is $56.7\% \pm 4.5\%$. We chose this model due to the tradeoff between the cost and the performance.

Fig. 4 illustrated our procedure, and summarized the results. In this experiment, we employ an iterative process by improving the agents in 3 stages through providing human feedback on 6 out of 40 tasks in the *Baba-Is-AI* (Paglieri et al., 2024) benchmark. In this way, we can study if the feedback provided for training tasks can be generalized to unseen tasks.

Before each stage we show human annotators 3 trajectories per task for the 6 tasks, gather the feedback, and apply AutoLibra iterative metric induction process (§3.2). This results in 5 metrics for Stage 1 and 2, and another 1 metric for Stage 3. Within each stage, we iteratively feed 1 LLM agent trajectory on each of these 6 tasks, together with evaluation results based on these AutoLibra-induced metrics to the LLM to improve the prompt of the LLM agent. This process results in continuous improvement not only on the running maximum metric scores, the cumulative average metrics, but also game success rate. Fig. 4 shows these statistics on the whole 40 tasks, although we only use 6 out of the 40 tasks in the whole optimization process. Upon examining the agent trajectories, we find the skills learned in the process. In the first stage, the agent learns to find rules to form based on the map boundary, which could be a result of an induced metric `map-n-constraint-recognition`. Similarly, more advanced skills are learned in Stage 2 and 3, including forming win conditions and self-referential rules, probably as a result of metric `rule-manipulation-proficiency`.

Our results show that the metrics induced by AutoLibra form effective objectives for improving the agents through prompt optimization. It should note that AutoLibra is a metric induction method, which is orthogonal to learning algorithms, including prompt optimization, fine-tuning or reinforcement learning. We show that this process improves agent success rate by 20% without optimizing for success rate, and in the future, researchers can study the effect of employing other learning algorithm.

6 RELATED WORK

AutoLibra unifies three areas of research: it draws inspiration from *thematic analysis* to create *neutral language-derived evaluation metrics* to evaluate and reward AI agents.

Evaluating AI agents Much of the work in AI agent evaluation focuses around benchmarks which contains both task suites and evaluation metrics. In addition to the datasets we used in this paper, SWE-Bench (Jimenez et al., 2024) uses human-written unit tests as evaluation metrics; Embodied Agent Interface (Li et al., 2024) provides fine-grained evaluation for LLM-based embodied agents; τ -Bench (Yao et al., 2024) compares database states for evaluation; concurrent work AgentRewardBench (Lù et al., 2025) builds a benchmark for reward models for web agents. Recently, there are observatory tools including Galileo (Galileo, 2025), Vertex AI Gen AI (Cloud, 2025), and Docent (Meng et al., 2025) which provide user interfaces to visualize agent failure modes. Generating intrinsic rewards have also been studied in the reinforcement learning community (Du et al., 2019; Pathak et al., 2017; Laskin et al., 2022) to encourage exploration, sub-task completion, or skill discovery. In contrast to these, AutoLibra is a pure data-driven task-agnostic method without predefined failure taxonomy for generating interpretable metrics for agents.

Learning from natural language and human feedback Researchers have been studying reinforcement learning with language feedback to provide a dense reward to agents (Goyal et al., 2019). Since LLM agents are even harder to train with sparse reward, there is substantial interest in training LLM agents from natural language feedback. Chen et al. (2024) propose an imitation learning method for learning from human feedback; Text2Reward (Xie et al., 2024) uses code generation to generate robot reward functions from open-ended human feedback; Chen et al. (2025) uses feedback to the improvement agent policy with prompting and then align the unprompted agent policy with the prompted one; Shi et al. (2024) propose a new model architecture to incorporate human feedback into policy learning. On the other hand, human non-open-ended feedback is also incorporated in training agents, including rating feedback (Nguyen et al., 2017), preference feedback (Christiano et al., 2017), demonstrative feedback (Shaikh et al., 2025). Unlike these papers, AutoLibra induces metrics from feedback from all annotated instances and generates metrics that are generalizable to different tasks and useful for both evaluation and agent fine-tuning.

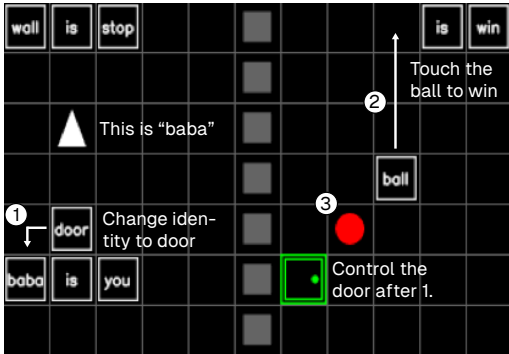


Figure 5: Example of Baba-Is-AI game.

Thematic analysis Thematic analysis is a powerful tool for qualitative study through coding and iterative creation of themes. Gauthier & Wallace (2022) provide computational tools to aid this process; Hong et al. (2022) and Gebreegziabher et al. (2023) explore human-AI collaboration in thematic analysis; LLoM (Lam et al., 2024), an automatic method for concept induction, closely aligns with and informs our approach. This paper completes the loop of concept induction by using the meta-evaluation step to optimize the induced metrics, and apply it to agent evaluation.

7 CONCLUSION AND FUTURE WORK

This work introduces AutoLibra, a new paradigm for agent evaluation, one of the first works to explore adaptable trajectory-derived evaluation heuristics, offering substantial advantages in agent training over traditional end-to-end evaluation. We find that this framework is generalizable to a diverse range of agent tasks, provides new insights into agent behaviors, and identifies strong optimization targets for agent improvement. There are a few directions for further extending and applying this framework. (1) **Behavior-centric evaluation** AutoLibra leads a *paradigm shift* from end-to-end agent evaluation (analogous to “integration tests” in software development) to evaluation with granular metrics that measure agents’ concrete behaviors (analogous to “unit tests”). Future work can study whether this process can be improved through better human-AI collaboration. (2) **Sub-trajectory feedback from humans** In AutoLibra, we label each trajectory with one piece of feedback, and ground it into the agents’ concrete behavior which is at the sub-trajectory level. In the future, researchers can let users directly give feedback for one or multiple steps in the trajectory, which should lead to better feedback grounding results. Similarly, user feedback can be collected during the interaction instead of after the agent has completed the tasks, which is a more user-friendly way to gather high quality feedback data. (3) **Wider exploration of agent improvement methods** In this paper, we only explored non-parametric for agent improvement to show the utility of AutoLibra. Future work can use AutoLibra to provide dense rewards for individual steps, and use reinforcement learning to train agents with these dense rewards.

8 THE BIGGER PICTURE

Humans learn not only from their own experience, but crucially from collective knowledge transmitted through social interaction (Tomasello et al., 1993). This capacity for social learning and teaching enables knowledge accumulation across generations, allowing us to build upon rather than reinvent skills and artifacts (Humphrey, 1976). At the core of this capability lies a distinctive form of intelligence that sets humans apart from species lacking cumulative culture: social intelligence. A fundamental question emerges: how can we leverage this social intelligence to enable AI agents to learn from humans and potentially teach them in similar ways?

Current training paradigms for language agents predominantly focus on behavior cloning or reinforcement learning from self-generated experience. However, behavior cloning has inherent limitations for skill acquisition. First, it requires teachers or demonstrators to operate in the same environment as the learning agent, constraining the scalability of knowledge transfer. Second, agents learning from one or a few demonstrations may develop misunderstandings about what constitutes appropriate behavior. In such cases, explicit verbal feedback from teachers becomes crucial for establishing the boundaries of acceptable behaviors and clarifying underlying principles that cannot be easily inferred from demonstrations alone.

AutoLibra offers a computational approach to address these limitations by incorporating the verbal feedback that humans naturally exchange in daily interactions to systematically improve agent behavior. Looking forward, the broader vision is to deploy AI agents in real-world settings where they can learn from diverse human feedback at scale. This approach could enable agents to acquire skills from the collective experience of all users, forming both general competencies and specialized skill sets at *personal* and *organizational* levels, mirroring how human communities accumulate and share knowledge.

Going one step further, such agents could serve as intermediaries for accelerating skill and culture transmission between humans themselves—distilling expertise from proficient users into interpretable metrics and actionable feedback that can guide novices, thereby compressing traditional learning curves and democratizing access to specialized knowledge.

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APPENDIX

CONTENT OF APPENDIX

1. AutoLibra Ladder Methodology

- A Illustration of AutoLibra Method
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2. Baba-is-ai

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- E Experiment Results
- F Metric Scores
- G Metric Examples
- H Prompts
- I Qualitative Observations of Agent Performance

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- J Rules and Environment Details
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- N Prompts
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4. WebVoyager

- P NNetNav-Live Induced Metrics

A ILLUSTRATION OF AUTO LIBRA METHOD

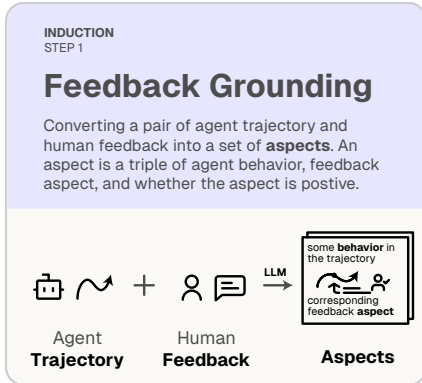


Figure 6: Feedback Grounding

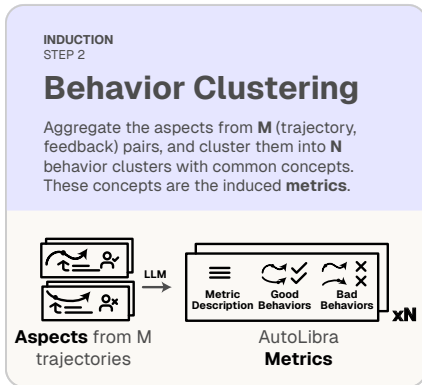


Figure 7: Behavior Clustering

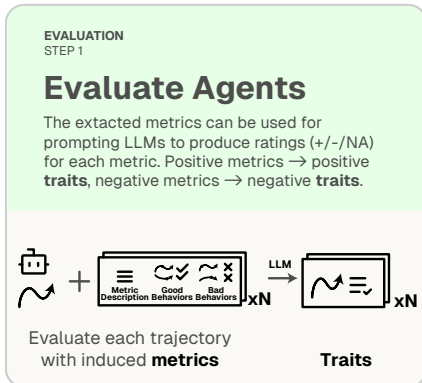


Figure 8: Evaluation with induced metrics

B ALGORITHM OF AUTO LIBRA LADDER EXPERIMENT

C AUTO LIBRA LADDER EXPERIMENT SETUP

This section describes the test configuration used during AutoLibra Ladder experiments, as described in 5.

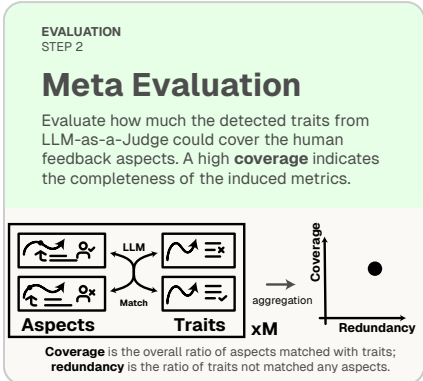


Figure 9: Meta evaluation

Algorithm 1 Pseudocode for iterative agent improvement with AutoLibra

```

1: for  $i$  in range( $n\_iters$ ) do
2:   for  $task$  in  $selected\_tasks$  do
3:      $traj_i, eval\_score_i += agent.play(task, prompt)$ 
4:      $annotations_i += editor.annotate(traj_i)$ 
5:   end for
6:    $metrics_i = AutoLibra.extract\_metrics(traj_i, annotations_i)$ 
7:    $traj\_scores_i = AutoLibra.llm\_eval(metrics_i, traj_i)$ 
8:    $curr\_scores = eval\_score_i$ 
9:   while  $curr\_scores \leq eval\_score_i$  do
10:     $prompt = updated\_prompt_k$ 
11:    for  $task$  in  $selected\_tasks$  do
12:       $\_, curr\_scores = agent.play(task, prompt)$ 
13:    end for
14:   end while
15: end for

```

For each environment experiment, one unmodified agent is used as a baseline for comparison (*Iteration 0*), and three complete iterations of iterative agent improvement with AutoLibra are performed (*Iterations 1-3*), for a total of four iterations. Six representative tasks for baba-is-ai are used in to induce metrics within the AutoLibra pipeline, with the remaining 34 tasks held out for evaluation. The AutoLibra Ladder pipeline is evaluated on the baba-is-ai and MiniHack environments; any changes to the agent code, the environment score, trajectory performance, and other metrics are recorded at the end of each iteration. GPT-4o-241120 OpenAI et al. (2024) is used as the agent model in all experiments; the human-in-the-loop configuration of the AutoLibra pipeline is used.

D BABA-IS-AI RULES AND ENVIRONMENT CONFIGURATION

This section discusses the rules and implementation details of Baba is AI, the task environment used in experiments in Section 4. Baba is AI is derived from Baba is You, a grid-based puzzle video game, and was originally implemented as part of the BALROG Paglieri et al. (2024) agent benchmark.

Baba Is You is a puzzle game where the player controls a character that can navigate and modify the rules of the game by pushing blocks containing words such as 'you', 'is', 'key', that, when combined, define the game's rules.

The game field consists of a rectangular 4-connected grid with a number of objects, rules blocks, and obstacles present.

Words (represented as rule blocks) can be combined to form sentences that define the properties of objects, rules, and obstacles in the game, with rules becoming active when a full sequence of rule blocks are joined in a 3-block line horizontally or vertically.

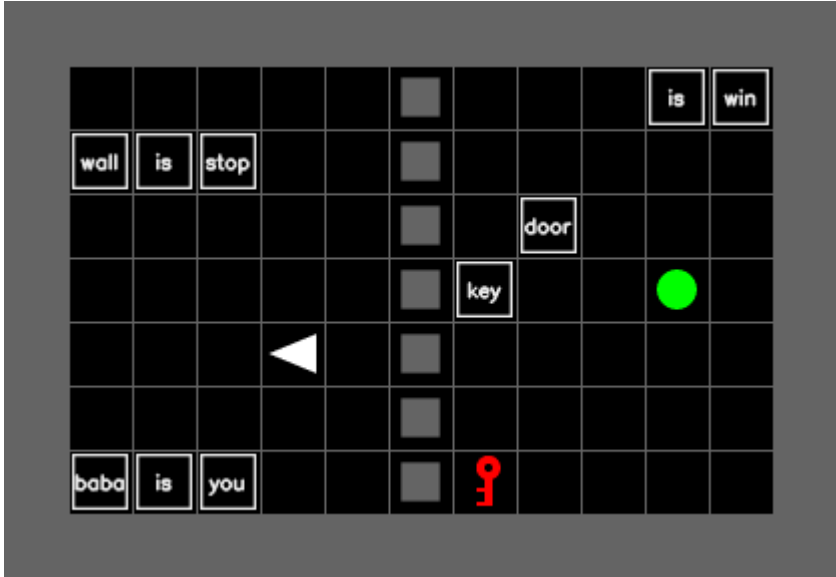


Figure 10: Example of the baba-is-ai environment. In this task (*two_room-break_stop-make_win-distr_obj-irrelevant_rule*), the agent has to break the "wall is stop" rule by pushing either 'wall', 'is', or 'stop' out of alignment with the other blocks, and must then push the "key" rule block next to "is win" at (9, 1) to assemble the win rule, then touch the key at (7, 7) to win. Pushing the "door" rule block would be a mistake, as no door object is present.

Active rules are built in the form [`<subject> <verb> <object>`], where the subject and object are the names of objects in the game, and the verb is one of the following: "is", "has", "can", or "not".

The goal of the game is to reach a win condition, by manipulating the rules of the game to create new win conditions, modify the properties of objects, or change the behavior or identity of the player character.

The testing implementation we use is the baba-is-ai environment, a simplified version of Baba is You originally implemented within the BALROG agent benchmark Cloos et al. (2024); Paglieri et al. (2024). This implementation has several simplifications compared to the original game, including a smaller grid size, fewer objects, and a limited set of rules. The environment is designed to be easy to use and understand, while still providing a challenging testbed for evaluating the performance of reinforcement learning agents on agentic reasoning tasks.

A single baba-is-ai task is defined by an arbitrary rectangular grid where an exit condition must be reached, with several possible obstacles and rules preventing the player from reaching the exit. Intermediate goals to achieving the exit condition can be defined by the user, and the environment will generate a task that requires the agent to learn how to manipulate the rules of the game in order to reach the exit. These intermediate goals are referred to as "subtasks" within our paper, and include:

- **Goto-Win:** The agent must reach a specific location on the grid.
- **Make-Win:** The agent must create a new win condition by manipulating the rules of the game.
- **Break-Stop:** The agent must break or bypass a wall or obstacle in order to reach the exit.
- **Change-You:** The agent must change the identity of the player character in order to reach the exit, by modifying the "baba is you" rule.

These subtasks can be arbitrarily combined with distractor objects or rules, immovable game field walls, and each other to generate tasks of varying complexity and length; baba-is-ai implements 40 total unique tasks of gradually increasing difficulty.

The agent is provided observations in a text form, which includes the current state of the game field, the currently active rules, and relative locations of obstacles to the active player character in terms of

shortest Manhattan distance. This is done to make the environment compatible with purely text-based language models.

The agent is provided the space of possible actions it can take, which consist moving one space in one of the four cardinal directions (up, down, left, right), but is not given information about whether a given move will result in movement; it is thus free to move into immovable walls without effect, to push rule blocks into corners where they cannot be moved, or to make the task unsolvable by breaking the active "baba is you" rule without taking control of a new object; in this last instance, the environment automatically resets the task to a randomized beginning state for that task.

The environment is limited to 100 steps per task episode to avoid tasks being solved by random walks.

E BABA-IS-AI EXPERIMENT RESULTS

Iteration	0	1	2	3	Baseline
Babaisai Score GPT-4o	30%	40%	43%	55%	33%
Babaisai Score GPT-4o (Only Held-Out)	33%	40%	44%	53%	33%
Babaisai Score Claude 3.5 Sonnet	35%	40%	45%	55%	37%
Babaisai Score Claude 3.5 Sonnet (Only Held-Out)	38%	42%	47%	58%	33%
Average Env. Steps	79	63	60	51	-

Table 3: Baba-is-ai Scores and Average Environment Steps

F BABA-IS-AI METRIC SCORES










	Iteration	0	1	2	3
Win Condition Recognition		35.0%	55.0%	87.5%	87.5%
Rule Modification		0.0%	10.0%	37.5%	61.9%
Direct Navigation Efficiency		5.6%	22.5%	27.5%	37.5%
Context-Sensitive Decision Making		2.5%	27.5%	30.0%	37.5%
Win Rule Construction		0.0%	0.0%	0.0%	5.3%
Selective Interaction With Relevant Objects		35.0%	40.0%	45.0%	82.5%
Rule Manipulation and Execution		0.0%	12.5%	31.0%	35.5%
Subtask Coordination		2.5%	25.0%	27.5%	35.0%
Immovable Interaction		64.9%	69.7%	69.7%	87.9%
Coverage		65.0%	83.0%	85.0%	92.0%
Redundancy		58.0%	59.0%	47.0%	59.0%

Table 4: Metric Performance for baba-is-ai AutoLibra Iterations 0–3, Across Full (40) Environment Tasks

G BABA-IS-AI METRIC EXAMPLES

Iteration 0: Context-Sensitive Decision Making**Explanation:**

This metric assesses the agent’s capacity for context-sensitive decision making. It evaluates whether the agent tailors its actions according to the immediate game conditions—balancing between direct navigation and rule modification. Positive behaviors in new environments will demonstrate an ability to determine when obstacles require intervention and when direct movement is sufficient, thereby optimizing overall efficiency.

Good Behaviors:

- Accurately gauges the game context by recognizing when obstacles are not an issue—such as when the win condition is already accessible—and refrains from unnecessary rule modifications.
- Selects focused, goal-oriented actions that align with observed win conditions, avoiding extraneous exploration.
- Adapts its strategy based on spatial layout and current rules, ensuring that its actions are timely and appropriate for the situation.

Bad Behaviors:

- Engages in excessive exploratory actions that do not contribute to reaching the win condition.
- Repeatedly takes ineffective actions (for example, persistently moving into walls) before finally switching strategy, indicating delayed context-sensitive decisions.
- Alters irrelevant rules or diverts attention from the active win condition when the situation does not demand it.
- Fails to adjust decision-making based on contextual cues, leading to uncoordinated or delayed progression toward the goal.

Iteration 1: Rule Modification for Obstacle Management**Explanation:**

This metric measures the agent’s competence in managing obstacles through rule modifications. It focuses on the agent’s ability to detect when a game rule (such as a blocking wall or an unchangeable character assignment) is hindering progress and to successfully alter that rule to create a viable path to victory. In novel scenarios, agents displaying positive behavior will apply targeted rule changes that directly open the path toward the win condition.

Good Behaviors:

- Proactively breaks the `'wall is stop'` rule when an obstacle blocks access to the win condition.
- Effectively modifies rules—such as replacing `'baba is you'` with `'key'`—to remove or bypass obstacles.

Bad Behaviors:

- Fails to modify critical rule blocks (for instance, not altering `'baba is you'` when required) that prevent access to the win condition.
- Does not interact with immovable obstacles like the `'wall is stop'` rule, neglecting available mechanisms to bypass them.
- Neglects to rearrange rule blocks to create or build necessary win conditions (e.g., `'door is win'`), leaving obstacles unaddressed.

Iteration 2: Subtask Coordination and Overall Task Planning

Explanation:

This metric assesses how well the agent coordinates multiple sub-tasks and plans its overall strategy. It rewards behaviors that demonstrate clear sequencing – from recognizing obstacles and manipulating rules to directly advancing toward the final objective. Failures in subtask coordination result in repetitive loops, ineffective transitions between actions, and an inability to achieve a meaningful win condition.

Good Behaviors:

- Final movement and approach towards 'ball' after removing the obstacle.
- Direct movement between objectives as opposed to unrelated exploration.
- Throughout the trajectory, the agent repeatedly chooses actions that reduce the distance to the door: moving left and down as needed.
- The trajectory demonstrates efficient movement towards the goal without unnecessary actions.
- The trajectory shows direct movement to the door without redundant backtracking or circular movement.
- Throughout the trajectory, the agent follows a direct and purposeful path towards its goal.

Bad Behaviors:

- The trajectory shows multiple iterations of upwards movement resulting in no significant progress.
- In the trajectory, actions such as repeated 'left' moves where no significant progress towards the goal is made.
- In over multiple steps, the agent moves unsuccessfully against immovable boundaries and objects.
- There are periods in the trajectory where the agent exhibits loops or repetitive movements without advancing its position strategically.
- Ultimately, the agent's efforts to form victory conditions do not result in a meaningful or achievable goal given the map's configuration.

Iteration 3: Interaction with Immovable Obstacles

Explanation:

This metric measures how the agent handles immovable obstacles. Positive behaviors show proper recognition and effective avoidance of fixed objects, whereas negative behaviors involve futile or incorrect push attempts that betray a lack of understanding of the environment's static features.

Good Behaviors:

- Recognizes that immovable walls or blocks should not be pushed and instead plans to bypass them.
- Avoids colliding with immovable objects by correctly assessing their fixed nature.
- Plans actions that account for static obstacles, ensuring safe navigation around them.

Bad Behaviors:

- Repeatedly tries to push into an immovable wall or rule block despite the known constraints.
- Interacts with stationary obstacles in ways that disregard their immovability, leading to ineffective progress.
- Executes push commands in the wrong direction on fixed objects, indicating a misunderstanding of obstacle dynamics.

H BABA-IS-AI PROMPTS

Iteration 0 Baba-is-ai Prompt

Baba Is You is a puzzle game where you can manipulate the rules of each level. The following are the possible actions you can take in the game, followed by a short description of each action:

- **idle**: wait for one step,
- **up**: take one step up,
- **right**: take one step to the right,
- **down**: take one step down,
- **left**: take one step to the left.

Tips:

- Examine the level carefully, noting all objects and text blocks present.
- Identify the current rules, which are formed by text blocks in the format "[Subject] IS [Property]" (e.g. "BABA IS YOU").
- Consider how you can change or create new rules by moving text blocks around.
- Remember that you can only move objects or text that are not defined as "STOP" or similar immovable properties.
- Your goal is usually to reach an object defined as "WIN", but this can be changed.
- Think creatively about how changing rules can alter the properties and behaviors of objects in unexpected ways.
- If stuck, try breaking apart existing rules or forming completely new ones.
- Sometimes the solution involves making yourself a different object or changing what counts as the win condition.

PLAY!

Current Observation:

Active rules:

- ball is win
- baba is you

Objects on the map:

- rule ball: 5 steps to the left and 1 step up
- rule is: 4 steps to the left and 1 step up
- rule win: 3 steps to the left and 1 step up
- ball: 5 steps to the left and 2 steps down
- rule baba: 5 steps to the left and 4 steps down
- rule is: 4 steps to the left and 4 steps down
- rule you: 3 steps to the left and 4 steps down

First, think about the best course of action. Then, you must choose exactly one of the listed actions and output it strictly in the following format:

```
<|ACTION|>YOUR_CHOSEN_ACTION<|END|>
```

Replace YOUR_CHOSEN_ACTION with the chosen action.

Iteration 1 Baba-is-ai Prompt

Baba Is You is a puzzle game where you can manipulate the rules of each level. The following are the possible actions you can take in the game, followed by a short description of each action:

- **idle**: wait for one step,
- **up**: take one step up,
- **right**: take one step to the right,
- **down**: take one step down,
- **left**: take one step to the left.

Additional Tips:

1. The game is won by identifying a win condition and making it true by placing the "object is win" rule blocks next to each other in line.
2. First, identify the win condition and where the object corresponding to the win condition is located.
3. If it is blocked, identify the rules that are blocking it and try to remove them, or circumvent them by changing the character you control by changing the "baba is you" rule.
4. If the path to the win condition is not blocked, travel directly to the win condition object without distractions.
5. If a "wall is stop" rule is bounded on two sides by walls, the blocks cannot be moved, and you must find another way to reach the win condition.
6. Ignore any objects not related to the win condition, as they are not necessary to complete the level.

Example:

If your observation is:

```
Active rules: ball is win wall is stop baba is you
Objects on the map: wall 5 steps to the right and 2 steps up
rule ball 8 steps to the right and 2 steps up
rule is 9 steps to the right and 2 steps up
rule win 10 steps to the right and 2 steps up
rule wall 1 step up
rule is 1 step to the right and 1 step up
rule stop 2 steps to the right and 1 step up
wall 5 steps to the right and 1 step up
rule door 10 steps to the right and 1 step up
wall 5 steps to the right
ball 6 steps to the right
wall 5 steps to the right and 1 step down
wall 5 steps to the right and 2 steps down
wall 5 steps to the right and 3 steps down
rule baba 4 steps down
rule is 1 step to the right and 4 steps down
rule you 2 steps to the right and 4 steps down
wall 5 steps to the right and 4 steps down
door 7 steps to the right and 4 steps down
```

You should reason that:

- The win condition is "ball is win," therefore you should reach the ball to win.
- The ball is blocked by a wall, so you should remove the "wall is stop" rule.
- The "wall is stop" rule is not bounded by walls, so you can move the blocks to remove the rule.
- The door is not necessary to reach the win condition, so you can ignore it.
- Once the "wall is stop" rule is removed, you can move directly to the ball to win.

PLAY!

Current Observation:

Active rules: baba is you

Objects on the map:

- rule `is`: 2 steps to the left and 3 steps up
- rule `win`: 1 step to the left and 3 steps up
- key: 2 steps to the right and 2 steps up
- rule `key`: 1 step to the right and 1 step up
- rule `baba`: 3 steps to the left and 2 steps down
- rule `is`: 2 steps to the left and 2 steps down
- rule `you`: 1 step to the left and 2 steps down
- ball: 2 steps down
- rule `ball`: 2 steps to the right and 2 steps down

First, think about the best course of action. Then, you must choose exactly one of the listed actions and output it strictly in the following format:

<|ACTION|>YOUR_CHOSEN_ACTION<|END|>

Iteration 2 Baba-is-ai Prompt

Baba Is You is a puzzle game where you can manipulate the rules of each level. The following are the possible actions you can take in the game, followed by a short description of each action:

- **idle**: wait for one step,
- **up**: take one step up,
- **right**: take one step to the right,
- **down**: take one step down,
- **left**: take one step to the left.

You solve the puzzle by identifying the type of sub-problem, and then applying the following blocks of solution steps:

1. If the win condition is not blocked and its rule is active, move to the win condition object.
2. If the win condition is blocked by a wall and "wall is stop" rule is active and not bounded by the map boundary:
 - (a) Move into the "wall is stop" blocks to remove the rule.
 - (b) Move to the win condition object.
3. If the win condition is blocked by a wall and "wall is stop" rule is active and bounded by the map boundary:
 - (a) Locate and move to an object rule block on your side of the wall.
 - (b) Push the object rule block towards the "baba is you" rule block by moving into it, and use this rule block to push the "baba" block out of the "baba is you" rule block.
4. If the win condition is not active:
 - (a) Locate the object rule block that can be pushed to the "is" rule block to activate the win condition.
 - (b) Push the object rule block to the "is" rule block, making sure they are adjacent.
 - (c) Move to the win condition object.
5. If the win condition object is not present:
 - (a) Locate an object rule block that can be pushed to the "is" rule block to create the win condition object.
 - (b) Push the object rule block to the "is" rule block, making sure they are adjacent.
 - (c) Move to the win condition object.

Example:

If your observation is:

```
Active rules: wall is stop baba is you
Objects on the map: wall 3 steps to the right and 3 step up
rule is 7 steps to the right and 3 step up
rule win 8 steps to the right and 3 step up
rule wall 2 step to the left and 2 step up
rule is 1 step to the left and 2 step up
rule stop 2 step up
wall 3 steps to the right and 2 step up
wall 3 steps to the right and 1 step up
key 4 steps to the right and 1 step up
wall 3 steps to the right
rule ball 7 steps to the right
wall 3 steps to the right and 1 step down
```

wall 3 steps to the right and 2 steps down
rule baba 2 step to the left and 3 steps down
rule is 1 step to the left and 3 steps down
rule you 3 steps down
wall 3 steps to the right and 3 steps down
ball 4 steps to the right and 3 steps down

You should plan your actions as follows:

1. The win condition is not active, so it needs to be built.
2. The win rule can be built by pushing the "ball" block on the other side of the wall next to the "is" block.
3. The "wall is stop" rule is blocking the path to the ball, so you should remove this rule first.
4. The "wall is stop" rule is not bounded by walls, so you can move the blocks to remove the rule.
 - Move 2 steps to the left and 2 steps up to reach the "wall is stop" rule, and push the "wall" block to remove the rule.
5. Once the "wall is stop" rule is removed, you can push the "ball" block to the "is" block to win.
 - Move 7 steps to the right, 3 steps down to reach the "ball" block.
 - Move 3 steps up to push the "ball" block to the "is" block.
6. Once you detect the "ball is win" rule as being active, you can move directly to the ball to win.

PLAY!

Current Observation:

Active rules: ball is win baba is you

Objects on the map:

- rule ball: 3 steps to the left and 3 steps up
- rule is: 2 steps to the left and 3 steps up
- rule win: 1 step to the left and 3 steps up
- ball: 3 steps to the left and 2 steps up
- key: 3 steps to the left and 1 step up
- rule baba: 3 steps to the left and 2 steps down
- rule is: 2 steps to the left and 2 steps down
- rule you: 1 step to the left and 2 steps down

First, think about the best course of action. Then, you must choose exactly one of the listed actions and output it strictly in the following format:

<|ACTION|>YOUR_CHOSEN_ACTION<|END|>

Replace YOUR_CHOSEN_ACTION with the chosen action.

Iteration 3 Baba-is-ai Prompt

Baba Is You is a puzzle game where you can manipulate the rules of each level. The following are the possible actions you can take in the game, followed by a short description of each action:

- **idle**: wait for one step,
- **up**: take one step up,
- **right**: take one step to the right,
- **down**: take one step down,
- **left**: take one step to the left.

You solve the puzzle by identifying the type of sub-problem, and then applying the following blocks of solution steps:

1. If the win condition is not blocked and its rule is active, move to the win condition object.
2. If the win condition is blocked by a wall and "wall is stop" rule is active and not bounded by the map boundary:
 - (a) Move into the "wall is stop" blocks to remove the rule.
 - (b) Move to the win condition object.
3. If the win condition is blocked by a wall and "wall is stop" rule is active and bounded by the map boundary:
 - (a) Locate and move to an object rule block on your side of the wall.
 - (b) Push the object rule block towards the "baba is you" rule block by moving into it, and use this rule block to push the "baba" block out of the "baba is you" rule block.
4. If the win condition is not active:
 - (a) Locate the object rule block that can be pushed to the "is" rule block to activate the win condition.
 - (b) Push the object rule block to the "is" rule block, making sure they are adjacent.
 - (c) Move to the win condition object.
5. If the win condition object is not present:
 - (a) Locate an object rule block that can be pushed to the "is" rule block to create the win condition object.
 - (b) Push the object rule block to the "is" rule block, making sure they are adjacent.
 - (c) Move to the win condition object.

Example:

If your observation is:

Active rules:

wall is stop
baba is you

Objects on the map:

rule wall at (1, 1)
rule is at (2, 1)
rule stop at (3, 1)
rule is at (7, 3)
rule win at (8, 3)
rule ball at (7, 0)
rule baba at (5, 6)
rule is at (6, 6)

rule you at (7, 6)
wall at (4, 0), (4, 1), (4, 2), (4, 3), (4, 4), (4, 5), (4, 6)
key at (5, 1)
ball at (5, 6)

Current position: (4, 3) in a grid of shape (1, 0) to (8, 6)

You should plan your actions as follows:

1. The win condition is not active, so it needs to be built.
2. The win rule can be built by pushing the ball block on the other side of the wall next to the is block.
3. The "wall is stop" rule is blocking the path to the ball, so you should remove this rule first.
4. The "wall is stop" rule is not bounded by walls, so you can move the blocks to remove the rule.
 - Move 2 steps to the left and 2 steps up to reach the "wall is stop" rule, and push the wall block to remove the rule.
5. Once the rule is removed, you can push the ball block to the is block.
 - Move 7 steps to the right and 3 steps down to reach the ball block.
 - Move 3 steps up to push the ball block to the is block.
6. Once you detect the ball is win rule is active, move directly to the ball to win.

PLAY!

Current Observation:

Active rules:

baba is you

Objects on the map:

- rule is: at (2, 1)
- rule win: at (3, 1)
- key: at (6, 2)
- rule key: at (3, 4)
- door: at (6, 5)
- rule baba: at (1, 6)
- rule is: at (2, 6)
- rule you: at (3, 6)
- rule door: at (6, 6)

Current position: (4, 3) in a grid of shape (1, 1) to (6, 6)

Rule block pushing physics explanation:

- Avoid moving into any non-wall rule block unless you are ready to interact with it.
- Do not push "wall is stop" blocks if the "wall is stop" rule is not currently active.

Steps to avoid unwanted interaction:

1. Read all rule block positions.
2. Read your current position and direction.

3. If a rule block is in your path, change direction by 90° (e.g., if going up, go left or right).
4. If a rule is on the wall of the grid, it can only be pushed parallel to that wall.

Example:

If you are at (3, 3) and a rule block is at (3, 4), you cannot push it up by first moving down. Instead, move to (2, 3) or (4, 3), then move down to (3, 6) to push it upward.

Strategic Planning:

First, think about your current goal based on the game state. If an active rule changes, your goal likely changes too.

Most Important Rule: If "wall is stop" is active, find a way to remove it or gain control of a different object before doing anything else.

Pushing Strategy:

- Always push blocks upward first (maximum 10 spaces), then push them left or right.
- Rule blocks are written in backticks. Objects are not. Only blocks can be pushed.
- Never interact directly with the `is` or `win` blocks.

Rule Construction Example:

If `win` is at (11, 1) and `is` is at (10, 1), place the object rule at (9, 1) to form a valid rule.

Coordinate System:

- Top-left is (1, 1), bottom-right is (x, y).
- Moving right increases x, moving down increases y.

Goal Planning Example:

Active rules:

- `wall is stop` — Must be broken under all circumstances!

Steps to achieve the goal:

1. Break "wall is stop" by moving into its blocks from below.
2. Build "ball is win" rule.
3. `ball` block is at (7, 4), `is` is at (8, 1). So:
 - `ball` needs to move 3 steps up, 1 step right.
 - Push from the left (1 step) and from below (3 steps).
4. If you're at (6, 4), move 1 step down and 1 step right to reach (7, 5), then push from below.
5. Move 3 steps up.

Then, you must choose exactly one of the listed actions and output it strictly in the following format:

<|ACTION|>YOUR_CHOSEN_ACTION<|END|>

I QUALITATIVE OBSERVATIONS OF BABA-IS-AI AGENT PERFORMANCE

The metrics induced by AutoLibra capture the behavior of the agent effectively, with coverage increasing from 65% at *Iteration 0* to 92% at *Iteration 3* and a low mean redundancy of 56%. Notably, earlier metrics were found to describe higher-level behaviors than later metrics, reflective of the more complex behaviors that the agent demonstrated in later iterations, as well as the compositionality of induced metrics. Code changes were selected to specifically target given metrics, and the agent’s performance on the targeted metric improved significantly in the iteration following the code change. This demonstrates the utility of AutoLibra for fine-grained agent improvement, as well as the human interpretability of the induced metrics.

The section below discusses iteration-by-iteration induced metrics, code changes directed by the metrics, and the results of these code changes on agent environment and trajectory performance.

Iteration 0 The agent behavior is stochastic and inconsistent, with no clear strategy or goal. Any progress in the environment is the consequence of a random walk. `Win Condition Recognition` 🔍🏆 was identified as a prerequisite to all other metrics induced in this iteration, as progress in the environment is impossible without recognizing the win condition, and was therefore targeted for improvement. Improvements took the form of few-shot prompting, by supplying an example of observations and the corresponding win condition and subtasks, and guidance on subtask-level planning, by mapping specific environmental observations to actions that would progress the agent towards the win condition. **Iteration 1** An increase in 🔍🏆 performance of 22% was observed between *Iteration 0* and *Iteration 1*, indicating that the code changes were effective in improving the agent’s ability to recognize the win condition. A slight but statistically insignificant increase was observed for the other metrics induced in *Iteration 0*, but the agent’s overall baba-is-ai environment score increased by 10%, indicating that 🔍🏆 was correctly identified by AutoLibra as a key bottleneck to the agent’s performance in the environment.

The agent now targets specific blocks and objects instead of moving randomly, but gets stuck in loops and on immovable objects, and is unable to consistently complete multi-step tasks.

Based on the metrics induced in *Iteration 1*, several changes to the agent code were implemented:

- Augmentation of existing subtask-level planning guidance with low-level position instructions, targeting improvement of `Rule Modification for Obstacle Management` 🖋️📖 and `Direct Navigation Efficiency` 🧑🎯
- Meta-prompting [Suzgun & Kalai \(2024\)](#) by providing subtask identification heuristic, targeting improvement of `Selective Interaction with Relevant Objects` 🖱️🔑 and `Context-Sensitive Decision Making` 🤔➡️
- Augmentation of single-shot example with movement instructions, targeting improvement of `Rule Manipulation` and `Execution` 🖋️📖

Iteration 2 Substantial improvements in 🔍🏆 were observed due to more detailed single-shot examples and reasoning templates, and the corresponding increase in other metrics supports idea that 🔍🏆 is a key bottleneck to the agent’s performance. We further observed a significant increase in 🖋️📖 and 🧑🎯, indicating that the changes targeting these metrics were effective in improving the agent’s reasoning performance and consequent avoidance of irrelevant objects. `Subtask Identification` 🧰💰 saw no significant improvement, as the agent still misunderstands map directions and confuses rule blocks with objects.

Qualitatively, the agent now recognizes when wall rules need to be broken and breaks them, but still cannot assemble rules to win, as it gets stuck on immovable blocks and walls and does not understand where rule blocks need to be placed to form a win condition.

Based on the metrics induced in *Iteration 2*, several changes to the agent code were implemented:

- Formatting observations as absolute position (as opposed to relative steps from the agent), and listing of immovable/movable blocks to improve Direct Navigation Efficiency 🧑🏻‍🚀🎯
- Chain-of-thought reasoning to assemble subtask completion agenda based on iteration-to-iteration observations, targeting improvement of Subtask Coordination and Overall Task Planning 📄✅
- Augmentation of single-shot example to few-shot example with reasoning templates, targeting improvement of Rule Manipulation and Execution 🧱📖
- Explicit instructions on navigation to avoid block collisions and assembly of rules, including movement templates, targeting improvement of Rule Manipulation and Execution 🧱📖 and Win Rule Construction 🔧🏆

Iteration 3 We observe a large increase in 🤔➡️ and 🧑🏻‍🚀🔑, indicating that the changes targeting these metrics were effective in improving the agent’s reasoning performance and consequent avoidance of irrelevant objects. 🧑🏻‍🚀🎯 saw further improvement, indicating that the use of absolute position and immovable/movable block listing was effective in improving the agent’s navigation efficiency. 🧱📖 saw a slight increase, indicating that the changes targeting this metric were effective in improving the agent’s ability to manipulate rules to achieve the win condition. 🔧🏆 saw its first improvement, indicating that more complex metrics are effectively targeted when the base performance and simpler metrics are improved.

Qualitatively, nearly every agent always understands when wall rules can be and cannot be broken, as well as when it’s not necessary to break the wall rule, covers nearly all tasks that involve going to win. The agent understands how to assemble win rules but still struggles with changing block direction and understanding that blocks get stuck against walls.

J MINIHACK RULES AND ENVIRONMENT CONFIGURATION

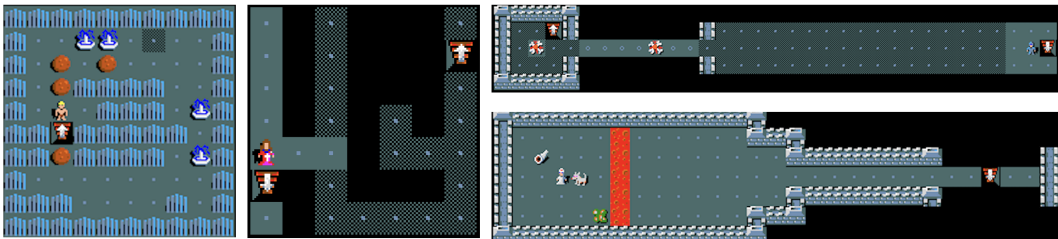


Figure 11: Overview of representative tasks used in MiniHack agent optimization process with AutoLibra. From left to right, up to down: (1) *Boxoban*, (2) *MazeWalk*, (3) *Corridor Fight*, and (4) *Quest*.

This section discusses the rules and implementation details of MiniHack, another task environment used in experiments in Section 4. Similarly to Baba is AI, MiniHack is derived from a grid-based puzzle video game (NetHack), and was originally implemented as part of the BALROG Paglieri et al. (2024) agent benchmark.

MiniHack is a grid navigation game expressed in text similar to baba-is-ai, consisting of a procedurally generated environment that requires the agent to navigate a space consisting of various agent roles, creatures, items, and tasks to reach a goal Samvelyan et al. (2021). Given its plasticity and abundant elements, MiniHack is more complex, challenging, and diversified than baba-is-ai; this is reflected in a lower success rate for agents on MiniHack versus Baba is AI, with a baseline agent task completion rate of 10% on MiniHack vs 33% on baba-is-ai Paglieri et al. (2024).

Similar to our experiments with baba-is-ai, the Ladder improvement process for MiniHack also follows the algorithm detailed in Appendix B. Two full iterations of agent improvement with AutoLibra were performed on MiniHack. Four representative tasks for MiniHack are used in iterative metric improvement, with the remainder held out for evaluation. The agent is evaluated on the MiniHack environment and any changes to the agent code at the beginning of each iteration, and the environment score, trajectory performance, and other metrics are recorded at the end of each iteration. GPT-4o-241120 is used as the agent model.

The four selected representative tasks each contain a unique subset of subtasks evaluating an agent’s capability. Figure 11 shows an example for each task, and from left to right, up to down, these maps respectively represent Boxoban, MazeWalk, Corridor Fight, and Quest.

Boxoban is a box-pushing puzzle game inspired by Sokoban, rendered within the MiniHack environment. To succeed in Boxoban, the agent needs to push the four boulders (orange balls) onto the four fountains (blue icons), and partial credit will be awarded for pushing some of the boulders onto the fountains. Boxoban tests the agent’s capability in strategic planning and rule-following.

MazeWalk is a game that requires the agent to explore unknown dark spaces to find the target exit staircase (the icon with a downward arrow). Two challenges for MazeWalk are fog of war – the agent initially lacks information about areas of the map it hasn’t visited, and must explore to discover the map and maze layout, and darkness – even if the agent has visited a block, the block will become ‘dark’ as the agent walks away and it passes out of view, retaining information about its layout but not any enemies or items present. Thus, MazeWalk tests the agent’s capability in map memory and strategic searching.

Corridor Fight is a game that requires the agent to explore an unknown dark corridor map to find the target exit staircase while engaging or avoiding giant rat enemies. Corridor Fight tests the agent’s capability in memory, space awareness, hazard awareness, and strategic combat.

Quest requires the agent to use a tool to help itself cross an otherwise impassable wall of lava, survive randomly generated monsters, and search for the target exit staircase. As the most subtask-rich and

randomized game, it tests the agent’s abilities to recognize and utilize tools, understand its role and special power, and strategically survive from monsters.

In all tasks, the agent is provided observations in a text form, which includes the current state of the game field, the currently active rules, and relative locations of obstacles to the active player character in terms of shortest Manhattan distance. This is done to make the environment compatible with purely text-based language models.

The environment is limited to 100 steps per task episode to avoid tasks being solved by random walks.

K MINIHACK EXPERIMENT RESULTS

Turn	0	1	2	Baseline
MiniHack Score GPT-4o	0%	12.5%	25%	10%
Average Env. Steps	85	91	88	-

Table 5: MiniHack Score and Average Environment Steps

L MINIHACK METRIC PERFORMANCE










	Iteration	0	1	2
Target Navigation Effectiveness		16.67%	8.33%	41.67%
Efficient Exploration and Map Memory Utilization		16.67%	0.00%	25.00%
Hazard Awareness and Equipment Utilization		0.00%	0.00%	0.00%
Boulder Manipulation Strategy		0.00%	0.00%	0.00%
Combat Engagement and Survival		8.33%	8.33%	25.00%
Role-Specific Ability Utilization		0.00%	0.00%	0.00%
Spatial Awareness and Interpretation		-	16.67%	58.33%
Object Pickup Efficiency		-	0.00%	0.00%
Giant Rats Encounter Handling		-	-	25.00%
Coverage		82.89%	81.82%	87.84%
Redundancy		61.11%	65.63%	71.30%

Table 6: Metric Performance for MiniHack AutoLibra Iterations 0–2

M MINI HACK METRIC EXAMPLES

Iteration 0: Target Navigation Effectiveness

Explanation:

This metric evaluates the agent’s ability to accurately identify and navigate toward key goal locations (e.g., the downward stairs). Positive behaviors show clear planning and directional focus, while negative examples reveal distractions or failures in goal-oriented movement.

Good Behaviors:

- Behavior: The agent decides to move south and reaches the downward stairs.
- Behavior: The agent’s reasoning shows it plans its action to reach the stairs.
- Behavior: From its reasoning, the agent appears to recognize the goal of locating the stairs downward.
- Behavior: From the trajectory and reasoning, the agent consistently aimed toward the general direction of its goal—the stairs down.

Bad Behaviors:

- Behavior: The repeated attempts to kick the goblin instead of progressing towards the stairs.
- Behavior: The agent repeatedly interacts with adjacent stairs up but does not visibly attempt to identify or locate downward stairs.
- Behavior: The agent explored the map but did not identify the downward stair in its trajectory.
- Behavior: Throughout the trajectory, the agent did not manage to locate the downward stairs, despite exploring various places in the environment.
- Behavior: The agent spends multiple actions traversing the map without making meaningful progress toward the downward stairs.
- Behavior: Performed in the sequence of actions where the agent explores but eventually doesn’t find the stairway downward, ending the session unsuccessfully.
- Behavior: During its navigation, the agent didn’t succeed in reaching the stairs down.

N MINIHACK PROMPTS

Iteration 0 MiniHack Prompt

You are an agent playing MiniHack. The following are the possible actions you can take in the game, followed by a short description of each action:

- **north**: move north,
- **east**: move east,
- **south**: move south,
- **west**: move west,
- **northeast**: move northeast,
- **southeast**: move southeast,
- **southwest**: move southwest,
- **northwest**: move northwest,
- **far north**: move far north,
- **far east**: move far east,
- **far south**: move far south,
- **far west**: move far west,
- **far northeast**: move far northeast,
- **far southeast**: move far southeast,
- **far southwest**: move far southwest,
- **far northwest**: move far northwest,
- **up**: go up the stairs,
- **down**: go down the stairs,
- **wait**: rest one move while doing nothing,
- **more**: display more of the message,
- **apply**: apply (use) a tool,
- **close**: close an adjacent door,
- **open**: open an adjacent door,
- **eat**: eat something,
- **force**: force a lock,
- **kick**: kick an enemy or a locked door or chest,
- **loot**: loot a box on the floor,
- **pickup**: pick up things at the current location if there are any,
- **pray**: pray to the gods for help,
- **puton**: put on an accessory,
- **quaff**: quaff (drink) something,
- **search**: search for hidden doors and passages,
- **zap**: zap a wand

For task which name consists "corridor": Your goal is to explore the level and reach the stairs down.

For task which name consists "quest": Your goal is to explore the level, fight monsters, and navigate rooms and mazes to ultimately reach the stairs down.

For task which name consists "boxoban": You are playing Boxoban, a box-pushing game inspired by Sokoban. Your goal is to push the boulders onto the fountains on the map. You can push the boulders by walking into them, as long as there are no obstacles behind them.

For task which name consists "mazewalk": Your goal is to explore the level and reach the stairs down.

Otherwise: Your goal is to get as far as possible in the game.

In a moment I will present a history of actions and observations from the game.

Tip: there is no point in outputting the same action over and over if nothing changes.

Additional Feedback (if provided): I will also present lists of positive and negative feedback based on your previous attempts on this task, use this information to change your strategy and improve your performance. Positive: positive Negative: negative

PLAY!

Iteration 1 MiniHack Prompt

You are an agent playing MiniHack. The following are the possible actions you can take in the game, followed by a short description of each action:

- **north:** move north,
- **east:** move east,
- **south:** move south,
- **west:** move west,
- **northeast:** move northeast,
- **southeast:** move southeast,
- **southwest:** move southwest,
- **northwest:** move northwest,
- **far north:** move far north,
- **far east:** move far east,
- **far south:** move far south,
- **far west:** move far west,
- **far northeast:** move far northeast,
- **far southeast:** move far southeast,
- **far southwest:** move far southwest,
- **far northwest:** move far northwest,
- **up:** go up the stairs,
- **down:** go down the stairs,
- **wait:** rest one move while doing nothing,
- **more:** display more of the message,
- **apply:** apply (use) a tool,
- **close:** close an adjacent door,
- **open:** open an adjacent door,
- **eat:** eat something,
- **force:** force a lock,
- **kick:** kick an enemy or a locked door or chest,
- **loot:** loot a box on the floor,
- **pickup:** pick up things at the current location if there are any,
- **pray:** pray to the gods for help,
- **puton:** put on an accessory,
- **quaff:** quaff (drink) something,
- **search:** search for hidden doors and passages,

- **zap**: zap a wand

For task name contains “corridor”:

Your goal is to explore the level and reach the stairs down.

Notes:

1. The target stairs down is always at the other room on the map, so you should prioritize exploring the other room.
2. Whenever you encounter a monster (giant rat) in a room, you should always try to run to the direction of the corridor.
3. Whenever you encounter a monster (giant rat) on the corridor, you should always try to kill the monster (giant rat).
4. Once you reach the second room on the map, you should explore the room fully to find the target stairs down, but whenever you encounter a monster (giant rat), you should always try to run to the direction of the corridor.

Example:

```

---
.<|
..@#
.|

```

For task name contains “quest”:

Your goal is to explore the level, fight monsters, and navigate rooms and mazes to ultimately reach the stairs down.

Notes:

1. You should never cross (lava) without necessary ability or equipment.
2. Always explore the area approachable (no need to cross the lava) well enough to find sufficient support. Below is an example:

Map Example:

```

-----
|@...}.....---
|. (...) .....F-
|.....}.....|
|.....}.....|
|.....}.....|
-----

```

3. You should always try to apply the tool you can get, even though you do not know the effect.
4. You should always try to apply your role’s ability, even though you do not know the effect.

For task name contains “boxoban”:

You are playing Boxoban, a box-pushing game inspired by Sokoban. Your goal is to push the boulders onto the fountains on the map. You can push the boulders by walking into them, as long as there are no obstacles behind them.

Notes: For this task, you should follow the below rules with priority from top to down:

1. You should remember the locations of the fountains in the beginning.
2. You should never push a boulder in a direction if in this direction, the next spot next to the boulder is not empty or is not the fountain.
3. You should never push a boulder to any L-shaped wall configuration (two adjacent walls).

Example (dead corner):

```
#####
# \ . . . . ###
```

4. You should never push a boulder next to a wall unless, in the direction perpendicular to the line joining the boulder and its neighbor wall, there is at least one fountain left open such that between this fountain and the boulder all spots are empty.
5. You should never push a boulder if it is already on the fountain.
6. If a boulder and a fountain are on the same row or column, and all spots between this boulder and this fountain are empty, and the first spot next to the boulder on the opposite direction of which the fountain locates is empty, you should always push this boulder to the corresponding fountain.

Map Example (established path):

```
#####
# . . . . . < ##
# . # @ . { \ . ##
# . \ \ ## . # . #
# . . \ . . { . #
# . # . { . . . #
##### . { #
##### . . #
##### . . #
#####
```

Example (dead corner reminder):

```
#####
# \ . . . . ###
```

For task name contains “mazewalk”:

Your goal is to explore the level and reach the stairs down.

Notes: For this task, your action space will be limited to:

```
{ "north": "move north",
  "east": "move east",
  "south": "move south",
  "west": "move west" }
```

You will not choose any actions other than these four. Follow strictly:

1. If the block on your east is empty, move east.
2. If east is blocked and north is open, move north.
3. If east and north are both blocked, and west is open, move west.
4. If east, north, and west are blocked, move south.

Otherwise:

Your goal is to get as far as possible in the game.

In a moment I will present a history of actions and observations from the game.

Tip: there is no point in outputting the same action over and over if anything changes.

PLAY!

Iteration 2 MiniHack Prompt

You are an agent playing MiniHack. The following are the possible actions you can take in the game:

- **north**: move north,
- **east**: move east,
- **south**: move south,
- **west**: move west,
- **northeast**: move northeast,
- **southeast**: move southeast,
- **southwest**: move southwest,
- **northwest**: move northwest,
- **far north**: move far north,
- **far east**: move far east,
- **far south**: move far south,
- **far west**: move far west,
- **far northeast**: move far northeast,
- **far southeast**: move far southeast,
- **far southwest**: move far southwest,
- **far northwest**: move far northwest,
- **up**: go up the stairs,
- **down**: go down the stairs,
- **wait**: rest one move while doing nothing,
- **more**: display more of the message,
- **apply**: apply (use) a tool,
- **close**: close an adjacent door,
- **open**: open an adjacent door,
- **eat**: eat something,
- **force**: force a lock,
- **kick**: kick an enemy or a locked door or chest,
- **loot**: loot a box on the floor,
- **pickup**: pick up things at the current location if there are any,
- **pray**: pray to the gods for help,
- **puton**: put on an accessory,
- **quaff**: quaff (drink) something,
- **search**: search for hidden doors and passages,
- **zap**: zap a wand

For task name contains “corridor”:

Your goal: Your goal is to explore the level and reach the stairs down.

Notes:

Most important notice before you start: "." in the map means room, so if your current space is marked by "." you are in the room. In the map, "#" means corridor. You should never misrecognize the type of location you are currently at as this is crucial for your game. Always be certain about your current location before you decide an action.

You should permanently treat "<" the same as "."

1. The target stairs down is always at the other room on the map, so you should prioritize exploring the other room. Remember, the goal spot is always at the far east of the map.
2. Whenever you haven't moved onto the corridor ("#") yet, find one "#" as soon as possible and move onto it.

Example:

```

----
.<|
..@#
.|

```

Example:

```

-----
|..<|
|@...
|...|
-----

```

- Whenever you encounter a monster (giant rat) in a room, you should always try to run to the direction of the corridor. As soon as you reach the second block on the corridor, you should stop running away after moving west for a max of 3 steps and start fighting the rat. Fight until there are no rats on your adjacent spots.

Example:

```

-----
...|      |r...%
|...#####@r...
|<..|      |r...
-----

```

You should only fight the rat when there is exactly one rat adjacent (in the 8 surrounding spots).

- Whenever you encounter a monster (giant rat) on the corridor, you should always try to kill the monster immediately. Never retreat back into the room.

Example:

```

-----
|...|
|...#####@r.
|..<|
-----

```

Example:

```

-----
|...|
|...@r#####.
|..<|
-----

```

- Once you reach the second room on the map, you should explore the room fully to find the target stairs down, but whenever you encounter a monster, you should always try to run to the direction of the corridor. Once in the second room, never return to the corridor or first room unless actively fleeing a monster.

Example:

```

-----
|...|      |.....
|<.%#####. ....@..
|...|      |.....
-----

```

- In case you return to the first room (where you can see "<"), immediately find the corridor "#" again and go east as much as possible.

For task name contains "quest":

Your goal: Your goal is to explore the level, fight monsters, and navigate rooms and mazes to ultimately reach the stairs down.

Notes:

- You should never cross }(lava) without necessary ability or equipment.
- Always explore approachable areas (no need to cross the lava) well enough to find sufficient support. Below is an example:

Map Example:

```

-----
|@....}.....---
|. (...}.....F-
|.....}.....|
|.....}.....|
|.....}.....|
|.....}.....|
-----

```

- You should always try to apply the tool you can get, even if you do not know its effect.
- You should always try to apply your role's ability, even if you do not know its effect.

For task name contains "boxoban":

Your goal: You are playing Boxoban, a box-pushing game inspired by Sokoban. Your goal is to push the boulders onto the fountains on the map. You can push the boulders by walking into them, as long as there are no obstacles behind them.

Notes: For this task, follow these rules in priority order:

- Remember the locations of the fountains at the start.
- Never push a boulder if the next spot is not empty or not a fountain.
- Never push a boulder into an L-shaped wall configuration (two adjacent walls).

Example (dead corner):

```

#####
# \ . . . . ###

```

Visual Deadlock Examples (NEVER DO THESE):

Case 1: Before Push:

```

#####
#####
#<#####
#.#####
#.#####
#.{.#####
#@.\`#####
#\{.\`{.###
#.....###
#####

```

Action: Push South After Push:

```

#####
#####
#<#####
#.#####

```


Example 2 – Dead Corner: Before:

```
#####  
#####  
#<#####  
#.#####  
#.#####  
#..{.#####  
#@.``#####  
#\{.\{.###  
#.....###  
#####
```

After pushing south:

```
#####  
#####  
#<#####  
#.#####  
#.#####  
#..{.#####  
#..``#####  
#@{.\{.###  
#\.....###  
#####
```

Example 3 – Dead Corner: Before:

```
#####  
###...{\#  
#.#\....#  
#.@.##.<#  
#.\`..##.#  
##...{##.#  
#####.#  
#####...{#  
#####...#  
#####
```

After pushing north:

```
#####  
###...{\#  
#.#\....#  
#...##.<#  
#.@\`..##.#  
##\`..{##.#  
#####.#  
#####...{#  
#####...#  
#####
```

Example 4 – Dead Corner: Before:

```
#####  
###...{\#  
#..{\`....#  
#.{.##.<#  
#.\`..##.#  
##.@\`..##.#  
#####.#  
#####...{#  
#####...#  
#####
```

After pushing east:

```
#####  
###...{\`#  
#..{\`....#  
#.{.#.#.<#  
#.\`...##.#  
##.@`###.#  
#####  
###...{#  
#####  
#####
```

Terminal State Check: Remember all fountain locations initially. After each push, if a fountain spot “” is covered by a boulder, mark that spot terminated.

Example 1 – Termination: Before:

```
#####  
###...{\`#  
#..#\`....#  
#.{.#.#.<#  
#.\`...##.#  
##@..{##.#  
#####  
###...{#  
#####  
#####
```

After pushing north:

```
#####  
###...{\`#  
#..#\`....#  
#.\`.#.#.<#  
#.@`...##.#  
##...{##.#  
#####  
###...{#  
#####  
#####
```

Example 2 – Termination: Before:

```
#####  
###...{\`#  
#..{\`@...#  
#...#.#.<#  
#.\`...##.#  
##...{##.#  
#####  
###...{#  
#####  
#####
```

After pushing west:

```
#####  
###...{\`#  
#..\`@....#  
#...#.#.<#  
#.\`...##.#  
##...{##.#
```

```
#####.#
#####...{#
#####...#
#####
```

4. You should never push a boulder next to a wall unless, in the perpendicular direction there remains an open fountain with all intermediate spots empty. 5. You should never push a boulder if it is already on a fountain. 6. If a boulder and a fountain are aligned in the same row or column, all intermediate spots empty, and the spot behind the boulder (opposite the fountain) is empty, push toward the fountain.

Map Example (established path):

```
#####
#.....<##
#.#@.{\##
#.\`##.#.#
#.\`...{.#
#.#{....#
#####.#
#####...#
#####...#
#####
```

7. Always explore to create more paths. 8. If a boulder is in a dead corner initially, do not waste steps pushing it.

Example (dead corner reminder):

```
#####
#\.....###
```

Below are two quick dead-corner examples:

Example 1:

```
#####
####...{\#
#.#\@...# <-- Boulder in dead corner
#{.#.#.<#
#.\`...##.#
#...{##.#
#####.#
#####...{#
#####...#
#####
```

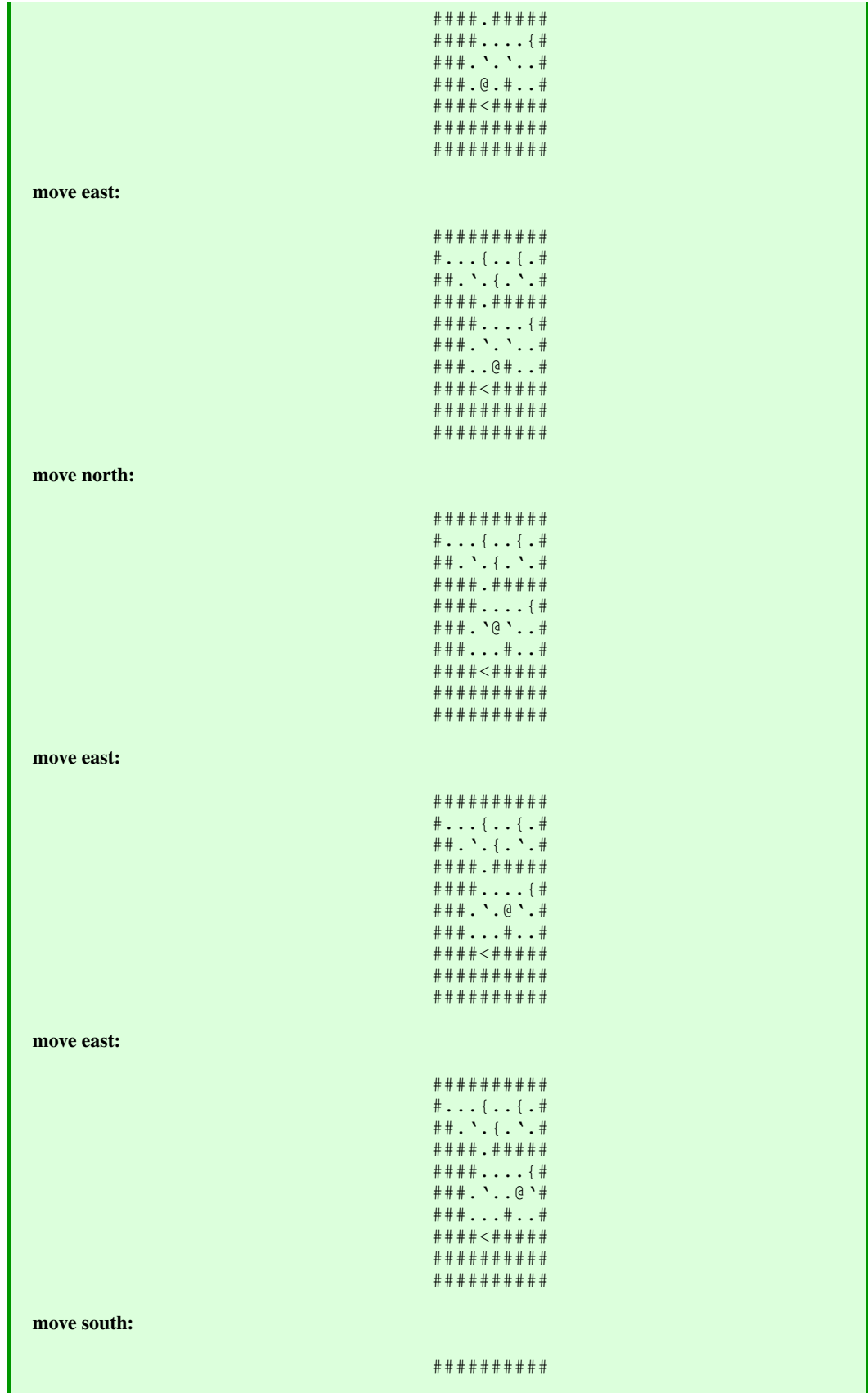
Example 2:

```
#####
#####
#<#####
#.######
#.######
#..{.#####
#.\`#####
#@{.\`{.###
#\.....### <-- Boulder in dead corner
```

Finally, a successful trajectory:

Example 1 – Beginning:

```
#####
#...{..{.#
#.\`{.\`.#
```



```
#...{...{.#
##.\{.\.#
###.#####
###...{.#
###.\...`#
###...#@.#
###<#####
#####
#####

move east:

#####
#...{...{.#
##.\{.\.#
###.#####
###...{.# <----target this fountain
###.\...`#
###...#@.#
###<#####
#####
#####

move north:

#####
#...{...{.#
##.\{.\.#
###.#####
###...`# <----boulder now on fountain
###.\...@.#
###...#...#
###<#####
#####
#####

move west:

#####
#...{...{.#
##.\{.\.#
###.#####
###...`#
###.\...@.#
###...#...#
###<#####
#####
#####

move west:

#####
#...{...{.#
##.\{.\.#
###.#####
###...`#
###.\...@.#
###...#...#
###<#####
#####
#####

move west:
```



```
#####  
#...{...{.#  
##.\`{.\`.#  
#####@#####  
#####...`#  
###.....#  
###...#...#  
####<#####  
#####  
#####
```

move north:

```
#####  
#...`...{.#  
##.`@{.\`.#  
#####.#####  
#####...`#  
###.....#  
###...#...#  
####<#####  
#####  
#####
```

move east:

```
#####  
#...`...{.#  
##.`@.\`.#  
#####.#####  
#####...`#  
###.....#  
###...#...#  
####<#####  
#####  
#####
```

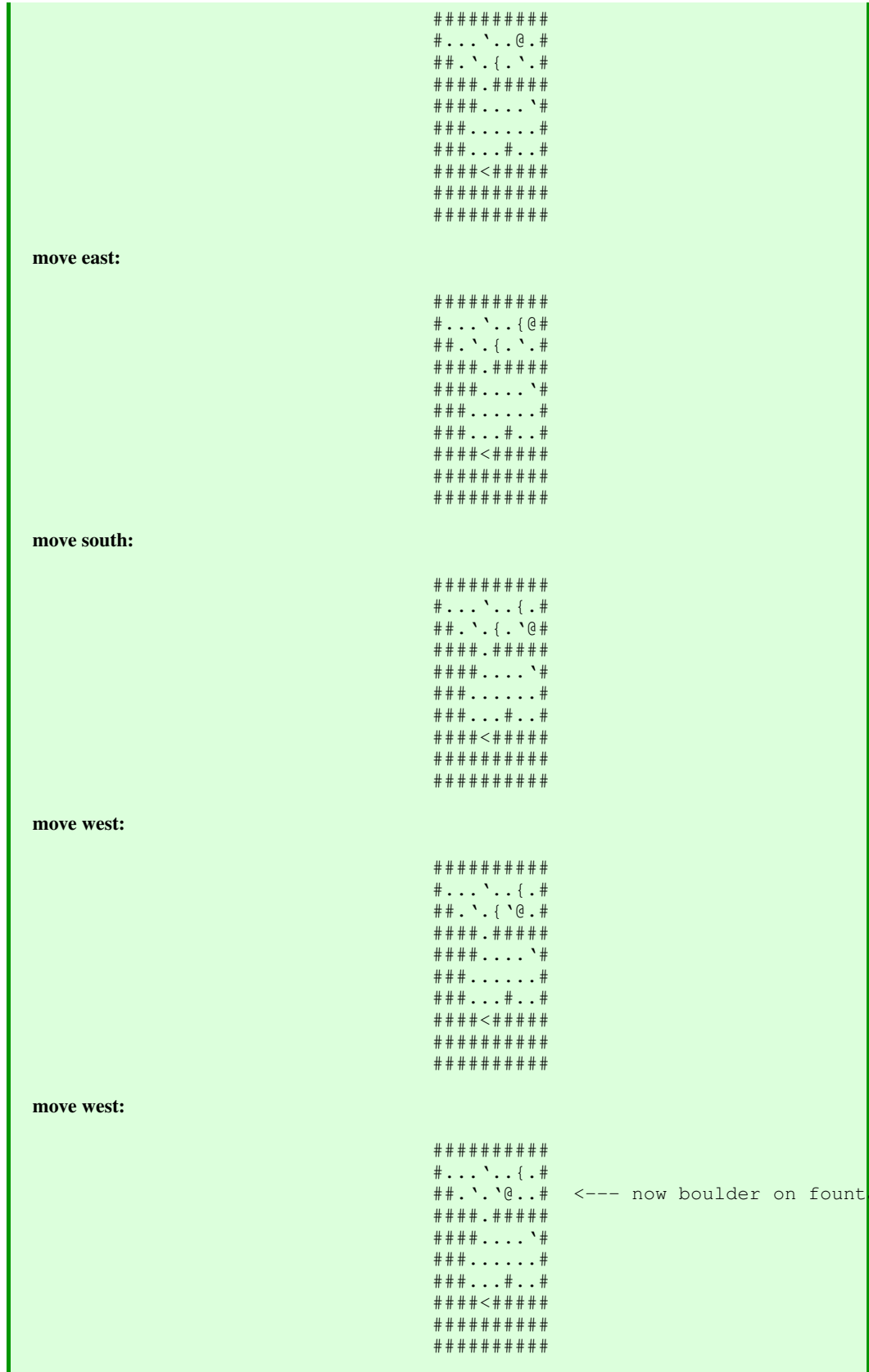
move north:

```
#####  
#...`@.{.#  
##.`{.\`.#  
#####.#####  
#####...`#  
###.....#  
###...#...#  
####<#####  
#####  
#####
```

move east:

```
#####  
#...`.@{.#  
##.`{.\`.#  
#####.#####  
#####...`#  
###.....#  
###...#...#  
####<#####  
#####  
#####
```

move east:



Now we have successfully pushed three boulders to the fountains.

For task name contains “mazewalk”:

Your goal: Your goal is to explore the level and reach the stairs down.

Notes: For this task, your action space is limited to:

```
{ "north": "move north",  
  "east": "move east",  
  "south": "move south",  
  "west": "move west" }
```

You must only choose these four directions:

1. If the block on your east is empty, move east.
2. If east is blocked and north is open, move north.
3. If east and north are both blocked, and west is open, move west.
4. If east, north, and west are blocked, move south.

Absolute Wall-Following Protocol:

Core Principle: “Follow priority order, probe dark directions ONLY when they’re current priority.”

Movement Validation:

- Priority rotation ONLY occurs AFTER SUCCESSFUL MOVEMENT.
- Wall collisions preserve current priority order.

1. Initialization: CURRENT_PRIORITY = [EAST, NORTH, WEST, SOUTH]; permanent_walls = {}. Move east until first wall.
2. At each position, check directions in CURRENT_PRIORITY:
 - If visible (“.” or “<”), move immediately and rotate per rules.
 - If dark, attempt move:
 - Success: continue protocol.
 - Wall collision: mark permanent_walls, skip direction, continue.
3. Rotation rules:
 - (a) 1st priority move: rotate clockwise (e.g. ENWS → SENW).
 - (b) 2nd priority: no rotation.
 - (c) 3rd priority: rotate counter-clockwise (ENWS → NWSE).
 - (d) 4th priority: reverse (swap 1↔3, 2↔4).
4. Terminal Condition: immediately go to stairs down (“>”) when visible; never treat “<” specially.

Walkthrough Example:

Initial: [E,N,W,S]

1. Move E until wall. 2. At start: E (wall) → N (open) → move north (no rotation). 3. Next: E (open) → move east (rotate to SENW).

Otherwise:

Your goal: Your goal is to get as far as possible in the game.

In a moment I will present a history of actions and observations from the game.

Tip: there is no point in outputting the same action over and over if nothing changes.

PLAY!















	Turn	Description
	0	Target Navigation Effectiveness
	0	Efficient Exploration and Map Memory Utilization
	0	Hazard Awareness and Equipment Utilization
	0	Boulder Manipulation Strategy
	0	Combat Engagement and Survival
	0	Role-Specific Ability Utilization
	1	Spatial Awareness and Interpretation
	1	Object Pickup Efficiency
	2	Giant Rats Encounter Handling




Table 7: Metrics and Turn of Induction for MiniHack

O QUALITATIVE OBSERVATIONS OF MINIHACK AGENT PERFORMANCE

The induced metrics and the agent’s per-task performance are shown in Table 7 and Table 6, respectively. A substantial improvement in the agent’s task completion performance is observed from *Iteration 1* to *Iteration 2*, with the agent achieving both a higher environment score and trajectory performance on the held-out tasks compared to the baseline agent. Specifically, the agent’s performance on metrics increased correspondingly to code changes, like  improving from 16.67% to 41.67%, demonstrating the utility of AutoLibra for fine-grained agent improvement. This is discussed in more detail in the following sections.

O.1 EXTRACTED METRICS AND IMPROVEMENTS

The metrics induced by AutoLibra (Table 7) capture the behavior of the agent through all iterations, with coverage of 83% at *Iteration 0* to 88% at *Iteration 2*. Due to the diversity of tasks, metrics pertain to one or two tasks, matching the expectation that AutoLibra should generate fine-grained metrics. Notably, the metrics generated at *Iteration 0* are nearly comprehensive as they demonstrate good coverage of all four MiniHack tasks, while the later metrics were found to specifically describe detailed behaviors for targeting one task each. Code changes were selected to specifically target improvements in given metrics, and as seen in Table 6, the agent’s performance on the targeted metric improved significantly in the iteration following the code change. This demonstrates the utility of AutoLibra for fine-grained agent improvement, as well as the human interpretability of the induced metrics. On the other hand, some metrics remain unchanged over iterations. The unchanged metrics are , , , and . These metrics are all tightly related to Boxoban or Quest environments. As these two environments contain high level of randomness, interactions with system, and sophisticated planning, our prompt and example based guidance do not provide obvious improvements. This result also indicates that simply coding might not be sufficient if the gap between the agent’s capability and the task’s complexity is too significant.

Iteration 0 The agent’s behavior is stochastic and repetitive, with no utilization of memory, planning, and goal awareness. Although the agent has reasoning before taking action, the decided action shows no correlation with the goal or the environment. Target Navigation Effectiveness  was identified as the core metric that evaluates the performance of all tasks except Boxoban. As all three other tasks require the agent to explore the target exit stairs,  serves as the fundamental test of the agent’s goal awareness for these tasks. Since Boxoban has a different winning condition, Boulder Manipulation Strategy  induced in this iteration targets describing the overall goal awareness for the agent in Boxoban environment. The remaining four metrics each cover two to three tasks on a more detailed level.

Based on the metrics induced in *Iteration 0*, several changes to the agent code were implemented:

- Augmentation of subtask-level behavioral restriction guidance with the single-shot example, targeting improvement of Boulder Manipulation Strategy 🗿👤, Combat Engagement and Survival ✂️❤️, and Hazard Awareness and Equipment Utilization ⚠️🔪.
- Meta-prompting by providing subtask instructions targeting improvement of Role-Specific Ability Utilization 🧑🏫🧠.
- Augmentation of subtask-level winning strategy with few-shot example, targeting improvement of Target Navigation Effectiveness 🏹🏆 and Efficient Exploration and Map Memory Utilization 🗺️🧠.

Iteration 1 The changes made after *Iteration 0* did not yield substantial improvements in agent task completion performance, but behavior changes matching the metrics were observed and insights on prompt improvements were obtained. A decrease in 🏹🏆 performance of 8.3% was observed between *Iteration 0* and *Iteration 1*, indicating that the code changes confuse the agent which reduces their capability of goal recognition, and the same reduction is also observed for 🗺️🧠. Three causes of these reductions are recognized. Firstly, the overly simplified strategy for MazeWalk provides no positive intuitions for the agent when loops exist in the map. Secondly, the seemingly straightforward behavioral restrictions with examples do not appear sufficient enough for the agent to avoid false action as the agent failed to comprehend the map thorough enough. Thirdly, the randomness of Quest is so high that existing guidance fails to cover new randomly generated situations. Based on *Iteration 1*'s result, MazeWalk and Corridor Fight both appear solvable given a more optimal strategy, and Quest and Boxoban, given their high randomness and complexity, do not appear easily solvable, so providing more examples seem to be the only direction of improvement. Moreover, two new metrics are induced, one focusing on Corridor Fight and the other focusing on Quest.

Based on the metrics induced in *Iteration 1*, new changes are listed below:

- Augmentation of existing subtask-level advanced strategy with step-by-step decision-making instructions and few-shot examples, targeting improvement of Target Navigation Effectiveness 🏹🏆 and Efficient Exploration and Map Memory Utilization 🗺️🧠.
- Augmentation of existing subtask-level strategy with corner cases handling guidance and few-shot examples, targeting improvement of Combat Engagement and Survival ✂️❤️, Hazard Awareness and Equipment Utilization ⚠️🔪, and Spatial Awareness and Interpretation 🧑🏫🗺️.
- Augmentation of existing few-shot examples with a full trajectory of the complete winning task, targeting improvement of Boulder Manipulation Strategy 🗿👤.
- Meta-prompting by providing more in-depth subtask instructions, targeting improvement of Role-Specific Ability Utilization 🧑🏫🧠 and Object Pickup Efficiency ✂️🔪.

Iteration 2 We observe a significant increase in 🏹🏆 and 🗺️🧠 indicating the code changes successfully improve agent's ability in goal awareness and goal reaching efficiency. Based on task-level observation, the agent succeeded in most MazeWalk and Corridor Fight tasks. The large increase in ✂️❤️ and 🧑🏫🗺️ shows the agent's strong performance in the Corridor Fight task. More specifically, the agent now demonstrates both the capability of choosing optimal action based on its current location and the capability of strategically handling dangerous enemies—giant rats—in an emergency. The new induced metric also further proves the agent's rat-handling ability. For instance, when the agent encounters multiple rats at the same time, it will immediately retreat to the middle of the single-way corridor to engage rats in combat individually. By doing so, the agent can easily beat rats one by one and navigate to the goal without danger. However, as all the remaining metrics show no improvements, we also observe the agent's poor performance on Boxoban and Quest. This result shows that our current targeting improvement strategy of adding abundant few-shot examples does not seem effective given the gap between the agent's reasoning ability and the high randomness and complexity of Boxoban and Quest. For example, despite more than ten examples of pushing a boulder to a dead corner, a prohibited behavior has been presented, the agent will still randomly push a boulder to the L-shaped dead corner formed by two walls which causes this boulder to become immovable.

0.2 HELD-OUT TASK PERFORMANCE

For the held-out tasks, the agent task completion rate improved from *Iteration 0* to *Iteration 2*, with scores from 0% to 25%. This result further proves that the improvements realized by AutoLibra are generalizable to unseen tasks. However, some failed cases also provide valuable insights into prospective future iterations. For instance,

the complete set of Corridor tasks consists of scenarios where the target downstairs may be located west of the agent’s starting point, unlike Corridor Fight, where the target always lies to the east. Consequently, an instruction that rigidly directs the agent to explore only eastward fails to generalize to the broader Corridor tasks. This outcome underscores the importance of crafting instructions that are specific yet flexible: they should provide sufficiently detailed, high-level strategies without relying on overly prescriptive, task-specific steps. By focusing on generalizable principles rather than rigid directions, the agent is better equipped to adapt to a wider range of scenarios while still benefiting from structured guidance. The agent’s performance on the held-out tasks is shown in Table 5.

P NNETHAV-LIVE INDUCED METRICS

It.	Metric
0	Navigation Accuracy
0	Search Term Accuracy
0	Information Extraction Details
0	Task Goal Achievement
0	Trajectory Efficiency
0	Barrier Avoidance
0	Navigation Loop Resolution
1	Subtask Coordination
1	UI Interaction Accuracy
2	Map Search Efficiency
2	Wish Cart Accuracy
3	News and Financial Information Retrieval

Table 8: Metrics for WebVoyager.