Scaling Environments for LLM Agents in the Era of Learning from Interaction: A Survey

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Abstract

LLM-based agents can autonomously accomplish complex tasks across various domains. However, to further cultivate capabilities such as adaptive behavior and long-term decision-making, training on static datasets built from human-level knowledge is insufficient. These datasets are costly to construct and lack both dynamism and realism. A growing consensus is that agents should instead interact directly with environments and learn from experience through reinforcement learning. We formalize this iterative process as the Generation–Execution–Feedback (GEF) loop, where environments generate tasks to challenge agents, return observations in response to agents' actions during task execution, and provide evaluative feedback on rollouts for subsequent learning. Under this paradigm, environments function as indispensable producers of experiential data, highlighting the need to scale them toward greater complexity, realism, and interactivity. In this survey, we systematically review representative methods for environment scaling from a pioneering environment-centric perspective and organize them along the stages of the GEF loop, namely task generation, task execution, and feedback. We further analyze benchmarks, implementation strategies, and applications, consolidating fragmented advances and outlining future research directions for agent intelligence.[1]

1 Introduction

The rapid progress of large language models (LLMs) has catalyzed a transformative shift in artificial intelligence, precipitating a surge of research on LLM-based agents [Luo et al., 2025a, Xi et al., 2025]. Such agents inherit strong reasoning and task-decomposition capabilities from their base models and, when augmented with modules for tool use and memory, can execute actions, interact with real or simulated environments, accumulate experience over time, and progressively improve their own behavior. This design has achieved remarkable progress across diverse domains, including automated coding [Qwen Team, 2025, Anthropic, 2025], interactive web navigation [OpenAI, 2025a, He et al., 2025], tool use [Zhang et al., 2025a, Anthropic, 2024], and deep research [Tongyi DeepResearch Team, 2025, OpenAI, 2025b, Google DeepMind, 2024].

However, as agent capabilities continue to evolve, it is infeasible to attain intelligence beyond the human-level merely by supervised fine-tuning (SFT) pretrained models on static datasets [Huang et al., 2025a, Su et al., 2025a, Zhao et al., 2025]. Such datasets are typically manually annotated or

[1]We provide a GitHub repository with real-time updates on this topic: `https://github.com/lukahhcm/Awesome_Scaling_Environments`.

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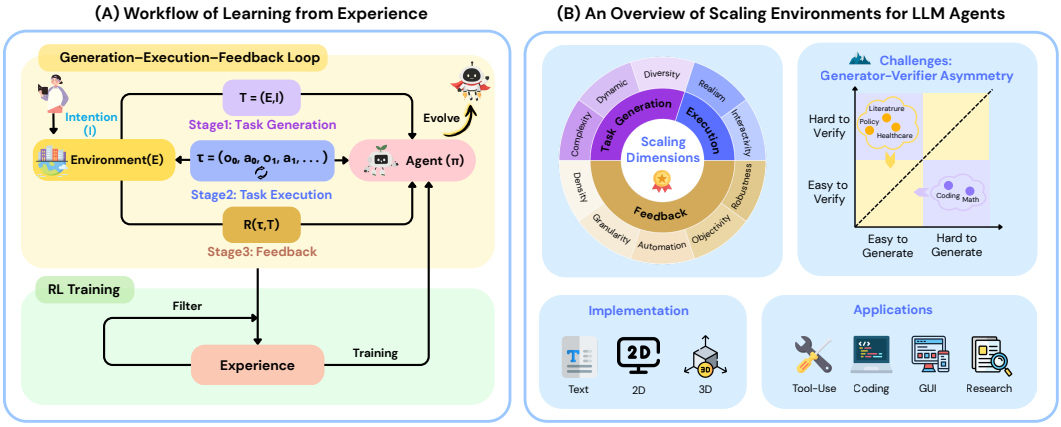

Figure 1: (A) Experience arises from the Generation–Execution–Feedback (GEF) loop, where environments generate tasks, agents execute them, and environments evaluate and filter useful experience for RL training. (B) Overview of environment scaling: a GEF-aligned taxonomy of environment-scaling methods, alongside implementation, applications, and the unique challenge of Generator–Verifier asymmetry.

extracted under human oversight; they are intrinsically limited to human-level knowledge, costly and labor-intensive to produce at scale, and often lack realism and adaptability. By contrast, reinforcement learning provides a more aligned training paradigm [Tao et al., 2024, Zhang et al., 2025b]: agents explore and interact with the environment, accumulate experience, and acquire new knowledge and skills. We formalize this interactive process as the Generation–Execution–Feedback (GEF) loop, illustrated in Figure 1 (A). In each iteration, the environment first generates diverse tasks, then the agent executes them within the environment, producing action–observation trajectories. The environment subsequently evaluates these rollouts and retains useful experience for subsequent training. Repeated iterations progressively refine the policy and expand the agent's capabilities. Notably, unlike prior work [Gao et al., 2025], we adopt a broad view of the environment: everything external to the current agent, including the state space, the executable action space, the design of feedback for interaction and evaluation, and the activities of users and other agents, is considered part of it. In this setting, the environment is no longer a mere container for agents' activities; it has become an active producer of experiential data, underscoring the growing need for scaling environments to create a more complex, realistic, and richly interactive world [CAMEL-AI, 2025].

Recent research has embraced this trend of scaling the environment from different perspectives. For instance, systems like AgentGen [Hu et al., 2025a], AgentGym [Xi et al., 2024], and GEM [Liu et al., 2025a] devise heterogeneous environments to increase the diversity of the generated tasks. R-Zero [Huang et al., 2025a] proposes a challenger–solver framework that autonomously generates increasingly difficult tasks. RandomWorld [Sullivan et al., 2025] scales up the interactivity by procedural generation of diverse tools for agents to access. ARE [Andrews et al., 2025] develops an event-driven environment that supports asynchronous interactions between the environment and agents, scaling up the environmental dynamics that conform to realistic settings. However, a systematic analysis that connects these research directions remains absent.

Therefore, we first comprehensively investigate current environment scaling methods and propose a unified taxonomy aligned with the stages of the GEF loop, adopting a pioneering environment-centric perspective. In the **task generation** stage, we categorize scaling methods into *static complexity*, *dynamic complexity*, and *diversity* scaling, which together characterize an environment's ability to generate challenging, adaptive, and diverse tasks continuously. In the **task execution** stage, we highlight interactivity and realism, since these properties determine the richness and fidelity of the interaction data from which agents learn. In the **feedback** stage, we categorize the scaling of evaluative signals along five aspects: *density*, *granularity*, *automation*, *objectivity*, and *robustness*, clarifying how environments evaluate and guide agent behavior. Beyond these three stages, we also analyze the evaluation benchmarks for environments and their implementation frameworks, highlight key applications, and outline future research directions. Figure 1 (B) presents a high-level overview

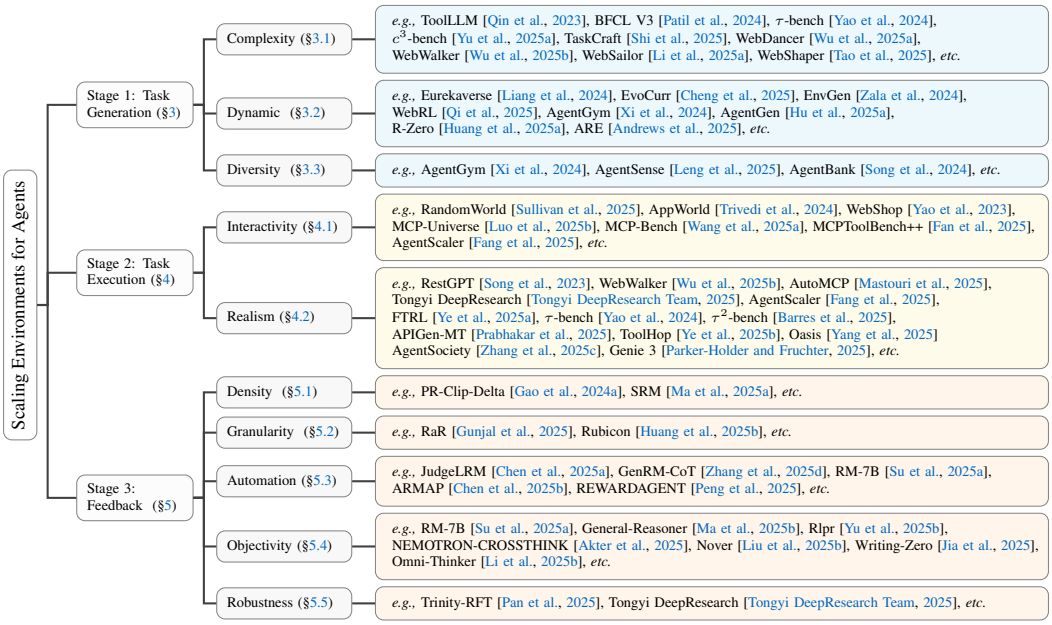

Figure 2: GEF-aligned taxonomy of environment scaling with dimensions for *Task Generation*, *Task Execution*, and *Feedback*. Representative works are illustrated as leaves on the branches.

of the taxonomy and its supporting branches, and Figure 2 summarizes representative works across the three stages. Building on these perspectives, our survey provides an organized framework for systematically understanding environment scaling and underscores its central role in the pursuit of agent intelligence.

The survey is organized as follows. We first introduce the background and conceptual framework in §2. We then categorize representative environment-scaling methods along the three stages of the GEF loop: task generation (§3), task execution (§4), and feedback (§5). Next, we discuss evaluation benchmarks(§A) and implementation frameworks (§6), as well as key applications (§B). Finally, we outline emerging research directions (§7).

2 Overview

In this section, we will discuss the background of environment scaling and the conceptual framework of the proposed paradigm.

2.1 Background

Scaling Laws for LLM Agents Just as large language models exhibit predictable performance scaling with increases in the number of parameters, the volume of training data, and the compute budget, agent systems likewise display scaling regularities along three axes: (i) expanding the agent population and identifying properties that emerge as interactions increase; (ii) increasing environmental complexity and assessing how realistic, dynamic settings shape learning and adaptation; and (iii) extending the horizons of evolution and memory to study how agents generalize and improve through accumulated experience [CAMEL-AI, 2025]. While most existing surveys on LLM agents adopt an agent-centric view [Luo et al., 2025a, Xi et al., 2025, Yehudai et al., 2025, Gao et al., 2025], covering topics from multi-agent interaction [Qian et al., 2024, Tran et al., 2025] to self-evolution [Gao et al., 2025, Tao et al., 2024], environment scaling remains underexplored and has not been systematically organized, despite its central role in experience formation through the Generation–Execution–Feedback (GEF) loop. In this work, we take an environment-centric perspective on scaling environments and examine how dynamic, richly interactive, high-fidelity worlds can accelerate agent development and evolution.

Generator-Verifier Asymmetry A fundamental characteristic in many real-world tasks is the inherent *Generator–Verifier Asymmetry* [Wei, 2025], namely the mismatch between the intelligence required for generator, which generates (§3) or executes (§4) tasks, and that required for verifier, which provides feedback (§5). These two kinds of intelligence naturally form two axes critical to next-generation Agentic AI, as illustrated in Figure 1(B). From this perspective, scaling up environments essentially corresponds to scaling intelligence along the x-axis and the y-axis. Current progress in RL largely exploits the regime on the easy-to-verify side of this asymmetry. These **Easy-to-Verify, Hard-to-Generate Domains** include fields such as mathematics and programming [Wei et al., 2025, Jimenez et al., 2023, Phan et al., 2025]. For these domains, generating and solving a continual stream of high-quality, non-trivial tasks is challenging. In contrast, verification is objective and computationally inexpensive (e.g., via unit tests or exact match on mathematical results). This enables weak-to-strong supervision, where a simple verifier can provide accurate feedback to train a much stronger agent for solving hard tasks. On the contrary, the **Hard-to-Verify, Easy-to-Generate Domains** include areas such as creative writing, policy-making, or healthcare [Lin et al., 2024a, Arora et al., 2025]. For these easy-to-propose, open-ended tasks, verification is subjective, requires substantial expert judgment, or unfolds over long horizons, making high-quality feedback scarce and expensive. This bottleneck, corresponding to the upper-left region of coordinate system, poses more difficulty in modeling the environment, and rendering environment scaling more challenging yet offering greater potential for advancing agent capabilities. Notably, the asymmetry also presents an opportunity: if the generator's stronger intelligence can be systematically leveraged to strengthen the verifier, so that it can supervise an even stronger generator, then such asymmetric property can be exploited to drive agents' self-evolution [Huang et al., 2025a, Hong et al., 2025, Lu et al., 2025a, Chen et al., 2025c, Wang et al., 2025b].

2.2 Conceptual Framework

Following the formalization by Gao et al. [2025], we model the environment E as a partially observable Markov decision process (POMDP). At the beginning of each episode, the environment generates a task $T = (E, I)$, where $I \in \mathcal{I}$ represents user intention drawn from intention space $\mathcal{I}$. The agent π interacts with the environment over horizon $T \in \mathbb{N}$, producing an interleaved observation–action trajectory $\tau = (o_0, a_0, o_1, a_1, \ldots, o_T) \in (\mathcal{O} \times \mathcal{A})^{T+1}$, where $\mathcal{O}$ and $\mathcal{A}$ denote the observation and action spaces respectively. The environment then evaluates performance and provides feedback $r \in \mathbb{R}^k$, which may take the form of step-level signals $r_{\text{step}}^{(t)} = R_{\text{step}}(s_t, a_t, T) \in \mathbb{R}$ for $t \in \{0, \ldots, T\}$, where $s_t \in \mathcal{S}$ denotes the state of the environment at step t, trajectory-level signals $r_{\text{traj}} = R_{\text{traj}}(\tau, T) \in \mathbb{R}^m$, or a combination of both $r = f(r_{\text{step}}^{(0:T)}, r_{\text{traj}})$ where $f : \mathbb{R}^{T+1} \times \mathbb{R}^m \to \mathbb{R}^k$. These signals need not be limited to sparse scalar rewards but can encode structured or adaptive assessments reflecting correctness, efficiency, reasoning depth, or long-term outcomes. This Generation-Execution-Feedback (GEF) Loop $\mathcal{L} = (T_{\text{gen}}, \text{Exec}, \text{Eval}) : \mathcal{I} \to \mathcal{T} \times (\mathcal{O} \times \mathcal{A})^* \times \mathbb{R}^k$, which encompasses task generation, task execution, and feedback, defines the essential mechanics of environments. Repeated iterations drive the accumulation of experience and the progressive evolution of the agent π.

3 Stage 1: Task Generation

In the task generation stage, the environment is required to propose challenging tasks to push the agent's capabilities forward. Scaling at this stage therefore targets three facets of the task supply: increasing difficulty, introducing dynamics, and expanding diversity. Accordingly, we organize representative approaches into three directions—*complexity scaling*, *dynamic scaling*, and *diversity scaling*—and illustrate them with a case study in Figure 3. For clarity, in *complexity scaling*, we only consider the intrinsic difficulty of a task (i.e., static complexity). We group the temporal evolution of task difficulty (dynamic complexity) together with changes in the environment itself under the *dynamic scaling* subsection.

3.1 Complexity Scaling

Static complexity increases a task's inherent structural intricacy, moving beyond single-step commands to challenges defined by dependencies, logical flows, and hierarchical relationships. A typical example is LLM tool use, from early single-step tasks to multi-turn, multi-step scenarios, where

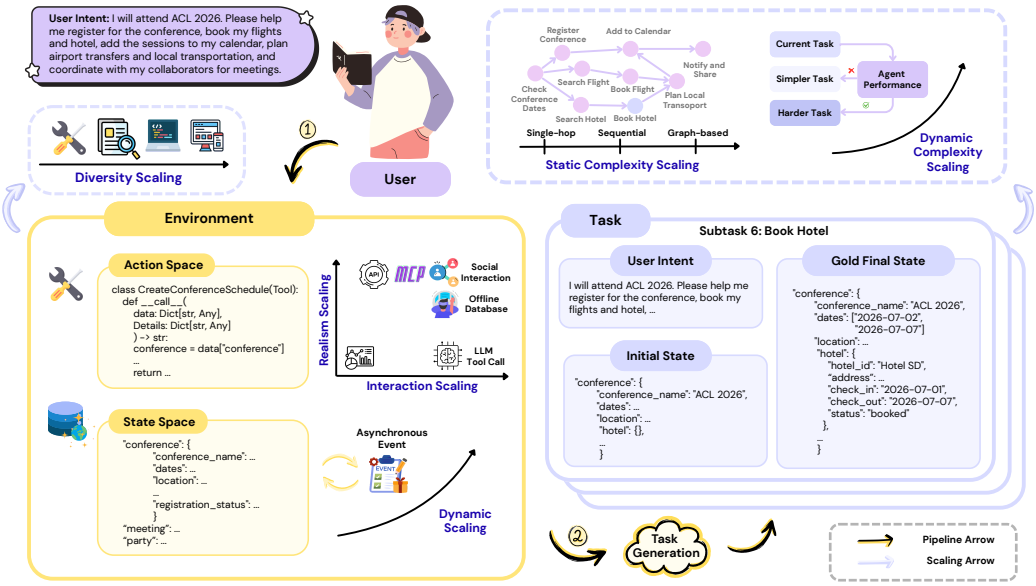

Figure 3: Illustration of environment scaling in the **task generation** and **task execution** stages, using the example of conference scheduling. Given a user intent, the environment produces a set of tasks for the agent to complete. Scaling in the task generation stage covers *complexity scaling*, *dynamic scaling*, and *diversity scaling*, while in the task execution stage scaling encompasses *interactivity scaling* and *realism scaling*.

complexity scales up as the number of turns and steps increases [Qin et al., 2023, Patil et al., 2024, Yao et al., 2024, Yu et al., 2025a]. More sophisticated tasks exhibit hierarchical or compositional structure, decomposing high-level objectives into nested sub-goals and thereby testing compositional generalization, namely an agent's ability to solve novel problems by recombining known skills [Shao et al., 2023]. TaskCraft [Shi et al., 2025] operationalizes this by expanding tasks both in depth (longer sequences of tool executions) and in width (multiple sub-goals per objective), enhancing hierarchical reasoning. At the highest level, conditional and graph-based tasks involve non-linear structures with branching logic, where planning must adapt dynamically to intermediate outcomes. Recent efforts in information-seeking agents extend linear sequences to complex graph-based information chains [Wu et al., 2025a, Tao et al., 2025, Li et al., 2025a, Wu et al., 2025b], and multi-agent settings further amplify this complexity, as optimal plans become contingent on the actions of other agents, producing intrinsically interdependent, graph-structured challenges.

3.2 Dynamic Scaling

Task Difficulty Dynamics Scaling dynamic complexity is critical for encouraging robust agent generalization, as it establishes non-stationary learning targets and distinct action and state spaces, which can be adjusted either according to predetermined schedules or in reaction to agent performance. A common strategy is performance-driven scheduling, where difficulty is regulated by the success rate (SR), as in Eurekaverse [Liang et al., 2024]. Other approaches target newly acquired or weaker skills, as in EvoCurr [Cheng et al., 2025] and EnvGen [Zala et al., 2024]. AgentGen's BI-EVAL mechanism [Hu et al., 2025a] introduces bidirectional variation, adjusting complexity upward or downward to match agent capability, in contrast to earlier methods that mostly increased difficulty [Xu et al., 2025, Luo et al., 2025c]. Beyond these, WebRL [Qi et al., 2025] implements self-adjusting curricula across complex web settings, and AgentGym [Xi et al., 2024] generalizes performance-adaptive scheduling to diverse benchmarks. R-Zero [Huang et al., 2025a] formalizes a challenger–solver paradigm in which a challenger proposes near-boundary tasks based on the solver's uncertainty, and the solver improves by training on filtered task sets, yielding iterative and targeted curricula.

Environmental Dynamics The Meta Agents Research Environments (ARE) platform [Andrews et al., 2025] pushes this paradigm further by introducing a more realistic form of dynamic complexity: an asynchronous environment that evolves independently of the agent. By decoupling the agent and environment clocks, ARE allows the simulated world state to change continuously with random or scheduled events, even while the agent is reasoning, shifting the challenge from solving discrete, static tasks to maintaining continuous, proactive engagement.

3.3 Diversity Scaling

Scaling the diversity of tasks and environments is essential for developing robust and generalizable LLM agents. While regulating task-level diversity helps maintain balanced curricula and avoid redundancy [Hu et al., 2025a, Huang et al., 2025a], an equally critical dimension is at the environment level, where exposing agents to a wide spectrum of scenarios mitigates overfitting and enhances adaptability to novel situations. Frameworks such as AgentGen [Hu et al., 2025a] and AgentGym [Xi et al., 2024] synthesize a wide range of heterogeneous settings, enriching the contextual and structural variety of training signals. Beyond these, AgentSense [Leng et al., 2025] generates diverse virtual sensor data by simulating varied human personas and routines, while AgentBank [Song et al., 2024] shows that fine-tuning on tens of thousands of heterogeneous interaction trajectories markedly improves generalization. Collectively, these approaches demonstrate that diversity across tasks and environments is fundamental to cultivating LLM agents that are adaptive and broadly capable.

4 Stage 2: Task Execution

In the task execution stage, after the agent takes an action, it receives an observation from the environment. Consequently, whether the agent can interact with the environment in real time (*interactivity*) and whether the returned observations are consistent with real-world scenarios (*realism*) are both critical to the quality of the resulting experience. Accordingly, we organize environment scaling in this stage into two directions: *interactivity scaling* and *realism scaling*, as shown next to the action space in Figure 3.

4.1 Interactivity Scaling

While early datasets [Liu et al., 2024a, Qin et al., 2023] primarily provided static interaction trajectories for training, recent methods [Zhang, 2025, Tang et al., 2024, Wang et al., 2024, Yao et al., 2023, Trivedi et al., 2024, Sullivan et al., 2025] allow agents to call a diverse set of real-world APIs or leverage auxiliary models as hierarchical tools via function calling or executable code generation. Standardized protocols such as the Model Context Protocol (MCP) [Anthropic, 2024, Luo et al., 2025b, Wang et al., 2025a, Fan et al., 2025] present tools, resources, and prompts through a unified interface, further improving controllability and efficiency. Complementary to MCP, another direction constructs offline environments from real-world data, sidestepping the high cost and brittleness of live API calls [Tongyi DeepResearch Team, 2025, Fang et al., 2025, Ye et al., 2025a, Yao et al., 2024, Barres et al., 2025, Prabhakar et al., 2025, Ye et al., 2025b]. This approach enables more efficient interaction while preserving realism, as the database originates from the real world. Taken together, these scaling methods enable agents to interact effectively with their environments and accumulate meaningful experiences.

4.2 Realism Scaling

To ensure that large language model (LLM) agents can generalize effectively to complex, real-world scenarios, the training data collected from these environments should reflect higher levels of realism.

Tool-Use Realism In tool-use environments, earlier works have utilized fine-tuned LLMs to generate the results of tool calls [Qin et al., 2023, Lu et al., 2025b, Sun et al., 2025]. However, more recent approaches have advanced by incorporating real-world APIs [Song et al., 2023, Wu et al., 2025b, Mastouri et al., 2025] or executing tasks within offline real-world databases as simulations [Tongyi DeepResearch Team, 2025, Fang et al., 2025, Ye et al., 2025a, Yao et al., 2024, Barres et al., 2025, Prabhakar et al., 2025, Ye et al., 2025b]. These methods help mitigate hallucinations and enhance consistency during the collection of experiential data. Specifically, Tongyi DeepResearch Team

[2025] constructs a simulated environment using an offline Wikipedia database and a custom tool suite, enabling the generation of knowledge-intensive tasks that provide rich, realistic learning signals in a cost-effective and controllable manner. Beyond traditional tool-use scenarios, which typically rely on text-based interactions, the emerging paradigm of *thinking with images* advocates for the use of visual information as a dynamic, manipulable workspace for intermediate reasoning, bridging the semantic gap between perception and symbolic thought [Su et al., 2025b]. Genie 3 [Parker-Holder and Fruchter, 2025] further focuses on simulating physical environments in immersive 3D scenes. It preserves realistic physical properties, ensures long-term consistency, and supports real-time interactivity, offering a robust framework for training agents in dynamic, physically grounded settings.

Multi-Agent Realism In multi-agent settings where agents may coordinate or compete with each other [Tran et al., 2025, Qian et al., 2024, Li et al., 2024, Zhang et al., 2024, Kim et al., 2024], the scalability of realism has received growing attention. In such scenarios, each agent's behavior naturally becomes part of the environment for others, and as the number of agents increases, these interactions give rise to emergent social and economic phenomena such as information diffusion, opinion polarization, and herding effects [Yang et al., 2025, Zhang et al., 2025c]. To address these challenges, Yang et al. [2025] leverage real-world social media data stored in a relational database to simulate interactive environments, enabling more realistic modeling of social dynamics. Meanwhile, Zhang et al. [2025c] move beyond earlier frameworks [Li et al., 2023, Gao et al., 2024b] that enforce execution order through message-passing SOPs by adopting the MQTT communication protocol to enable asynchronous decision-making among autonomous agents, more closely approximating real-world processes. Similarly, ARE [Andrews et al., 2025] decouples agent and environment clocks so that the world state evolves asynchronously, and it supports simulating other agents' activities by treating them as independent events in the environment's event stream. These environments make it possible to simulate real-world societal processes and to collect more realistic experiential data.

5 Stage 3: Feedback

In the feedback stage, the environment assesses the trajectories collected during task execution and generates feedback signals for subsequent RL training. Scaling at this stage focuses on how feedback is provided, including its frequency and richness (*density* and *granularity*), its level of automation (*automation*), as well as how objectively and reliably it is delivered (*objectivity* and *robustness*). Accordingly, we categorize representative approaches along five dimensions: *density scaling*, *granularity scaling*, *automation scaling*, *objectivity scaling*, and *robustness scaling*, which are illustrated in Figure 4.

5.1 Density Scaling

The first aspect is the density of feedback, which refers to how frequently the environment provides evaluative signals. Early environments offered sparse, outcome-based rewards that only indicated the final success or failure of a trajectory. While such trajectory-level signals can yield stable training dynamics in reasoning-intensive tasks such as mathematics or code generation [Jiang et al., 2025, Da et al., 2025, Qian et al., 2025], they suffer from credit assignment challenges. The overall success or failure cannot be easily attributed to intermediate actions. To mitigate this issue, recent studies have investigated step-level rewards derived from intermediate actions, providing denser supervision and detailed guidance for agents to learn. However, the effectiveness and underlying mechanisms of such step-level feedback remain insufficiently understood. Gao et al. [2024a] shows that naively combining step-level reward and outcome reward may degrade the agent's performance due to reward hacking. In this situation, trivial actions accumulate high rewards and lead to repetitive reasoning behavior. They mitigate this problem through threshold clipping and training with reward differences between adjacent steps. Similarly, Ma et al. [2025a] demonstrates that step-level reward models effectively capture the logical coherence of mathematical reasoning yet are unreliable for natural language tasks, highlighting both the promise and the limitations of denser feedback signals.

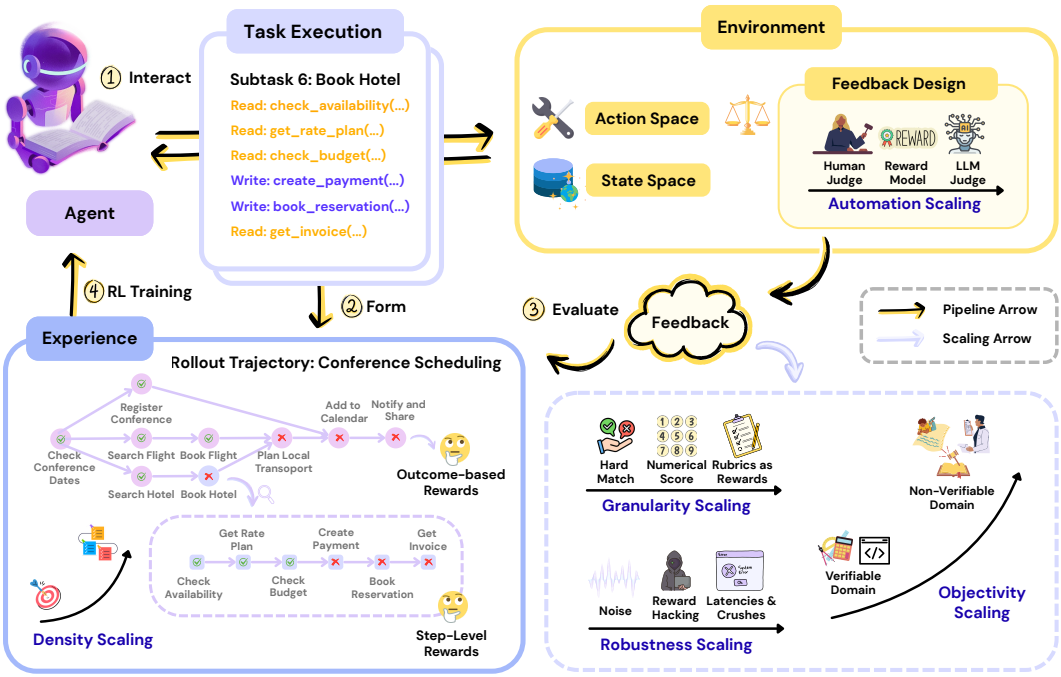

Figure 4: Illustration of environment scaling in the **feedback** stage using a conference-scheduling example. The agent first executes tasks in the environment and produces action–observation trajectories. The environment then evaluates these trajectories and returns feedback, yielding the experience used to train the agent. Scaling in the feedback stage covers *density*, *granularity*, *automation*, *objectivity*, and *robustness*.

5.2 Granularity Scaling

Granularity scaling captures how detailed the evaluative feedback of task performance is. Coarse-grained evaluation only focuses on end-to-end success and emphasizes the final outcome [Jin et al., 2025, Li et al., 2025c], whereas fine-grained evaluation decomposes agents' performance into structured components and provides richer feedback for error attribution and more targeted improvement. Moving beyond a single scalar reward, fine-grained schemes are often operationalized as multi-dimensional feedback, such as a set of scores across criteria that offers more informative guidance [Huang et al., 2025c]. Some work employs manually designed, rule-based rewards to improve different aspects such as correctness, format and efficiency [Qian et al., 2025, Song et al., 2025, Wang et al., 2025c, Zhang et al., 2025e]. Based on this idea, the Rubrics as Rewards (RaR) framework [Gunjal et al., 2025, Huang et al., 2025b] transforms checklist-based rubrics into structured, multi-criteria reward signals, thereby improving the alignment with human preferences and ensuring more consistent performance across diverse evaluation standards.

5.3 Automation Scaling

Automation scaling refers to the transition in feedback from human-provided supervision to AI-generated evaluation. Reinforcement Learning from Human Feedback (RLHF) encompasses a broad class of frameworks aimed at aligning LLMs with human preferences [Sheng et al., 2025, Hu et al., 2025b, Christiano et al., 2017]. While effective, these methods depend heavily on human annotators, making feedback slow, costly, and difficult to scale. To automate feedback and reduce reliance on labor-intensive preference labeling, a growing body of work replaces human evaluators with capable LLMs acting as automated judges, forming the paradigm of Reinforcement Learning from AI Feedback (RLAIF) [Zhang et al., 2025d, Su et al., 2025a, Chen et al., 2025a, Lee et al., 2024, Bai et al., 2022]. Pioneer works such as REWARDAGENT [Peng et al., 2025] employ a Verification Agent to assess both the factual correctness of responses and their adherence to instructions, integrating these evaluations with base human feedback to effectively guide training. In contrast, ARMAP [Chen et al.,

2025b] innovatively bypasses the need for a stronger LLM-as-judge by using LLM-generated positive and negative trajectories to train a classification model, thereby creating an automated and effective reward mechanism. By embedding such automated evaluation within the environment, agents are able to acquire higher-order capabilities progressively without continuous human supervision. However, this paradigm also amplifies risks such as propagating biases from the LLM judge and reward hacking, where agents exploit the reward model in ways that diverge from intended goals, potentially leading to model collapse. This presents a critical trade-off between scalability and safety, underscoring the need for research into robust mitigation strategies.

5.4 Objectivity Scaling

Scaling objectivity is about increasing the extent to which environmental feedback is grounded in verifiable truth, moving from subjective, preference-based, or generative evaluations to strictly objective signals. Objective feedback exemplified by Reinforcement Learning with Verifiable Rewards (RLVR) has demonstrated efficacy and is extensively utilized in structured domains, such as mathematics and programming, where solutions can be objectively validated [Shao et al., 2024, DeepSeek-AI et al., 2025]. Nonetheless, numerous real-world tasks, like writing and medical consultation, are open-ended and often lack objectively verifiable ground truth, making verification much harder. To mitigate this deficiency, recent studies have expanded RLVR to non-verifiable domains [Andrews et al., 2025, Ma et al., 2025b, Akter et al., 2025, Su et al., 2025a, Yu et al., 2025b, Liu et al., 2025b]. For instance, Writing-Zero [Jia et al., 2025] tackles the creative writing tasks by training a pairwise generative reward model, therefore transforming subjective assessments into reliable, verifiable reward signals. Li et al. [2025b] proposes Omni-Thinker, which combines rule-based verifiable rewards with generative preference signals from an LLM-as-a-judge, forming a unified multi-task RL training loop. ARE's verifier [Andrews et al., 2025] instantiates RLVR by taking the minimal correct sequence of write operations as ground truth, combining hard checks (exact parameter matches) and soft checks (LLM-based semantic judgments) under strict causal ordering. This work demonstrates the feasibility of structured verifiable rewards in open-ended environments.

5.5 Robustness Scaling

Feedback robustness requires the environment to provide stable and reliable reward signals. However, it is common for environmental instabilities (e.g., delays, crashes, corrupted tool outputs) to undermine feedback reliability and degrade the training process. To scale robustness **at the reward level**, some approaches mitigate the effects of noise by generating soft, probabilistic rewards with generative verifiers [Lin et al., 2024b, Su et al., 2025a]. For the reward-hacking problem, where agents tend to develop undesirable behaviors to maximize reward without achieving the intended goals, some studies propose frameworks such as MONA [Farquhar et al., 2025] to evaluate the future utility of actions via an overseer, constraining unstable behaviors while preserving explainability. **At the interaction level**, in order to solve challenges related to environmental failures, Trinity-RFT [Pan et al., 2025] proposes asynchronous inference and retry mechanisms, while Tongyi DeepResearch Team [2025] improves robustness by constructing a fast and deterministic interaction environment, employing caching, retrying failed calls, and switching to similar providers to prevent corrupted trajectories. Looking ahead, future reward design should prioritize both efficacy and the prevention of reward hacking via tricky patterns. Also, attention should also be paid to system-level robustness maintenance.

6 Implementation Frameworks

There exist diverse implementations of simulated environments that vary in modality and complexity. **Visual environments** include both two-dimensional and three-dimensional settings. In 2D, grid-based designs offer symbolic or pixel-level tasks, exemplified by MiniGrid [Chevalier-Boisvert et al., 2023] and the Atari-focused ALE [Bellemare et al., 2013]. Extensions such as Kinetix [Matthews et al., 2024] add physics-based interactions, while WebArena [Zhou et al., 2023], Mind2Web [Deng et al., 2023], and VisualWebArena [Koh et al., 2024a] bring agents into realistic web domains. Building on this line, ARE [Andrews et al., 2025] provides a mobile-style web environment with interconnected apps and tools, combining time control and a structured verifier for scalable evaluation. In 3D, environments emphasize embodied interaction with realistic physics and visual perception.

General-purpose simulators such as Habitat [Savva et al., 2019] and ThreeDWorld [Gan et al., 2020] support navigation and manipulation, while domain-specific worlds like MineRL [Guss et al., 2019] and MineDojo [Fan et al., 2022] exploit the flexibility of Minecraft. Household benchmarks such as ALFRED [Shridhar et al., 2020a] and EmbodiedQA [Das et al., 2018] further evaluate grounding of language in photo-realistic 3D spaces, requiring agents to follow instructions, answer questions, or perform multi-step tasks. **Text-based environments** instead emphasize reasoning and decision-making from natural language descriptions. TextWorld [Côté et al., 2018] provides a framework for procedurally generating text games with goal-driven challenges. Reddit-RL-simulator [He et al., 2016, Chan and King, 2018] implements an RL environment for iteratively tracking and recommending popular discussion threads on Reddit. ALFWorld [Shridhar et al., 2020b] adapts ALFRED tasks into textual form, and JerichoAgentBench [Liu et al., 2023] extends the Jericho suite [Hausknecht et al., 2020] with annotated benchmarks and concrete objectives. Such text environments stress the agent's ability to infer latent dynamics under partial observability, making them a natural testbed for language-based decision-making.

7 Future Directions

Co-Evolution via Embedded External Tools As task complexity increases, feedback mechanisms must scale in tandem to avoid sparse, noisy, or misaligned learning signals. Future environments can achieve this by embedding external tools such as verifiers, simulators, compilers, or executable systems directly into the learning loop. These tools co-evolve with task generation, providing structured, verifiable feedback and enabling agents to interact with increasingly sophisticated challenges. By integrating embedded tools with automated evaluators such as LLM-based formative signals, environments can better support multi-step, open-ended, and creative problem solving, while also helping to mitigate the Generator–Verifier Asymmetry.

Scaling Through Generator–Verifier Synergy Future environments can encourage strong generators to decompose solutions from complex problems into intermediate solutions from smaller subproblems that are tractable for weak verifiers or environments with scarce feedback. This enables scalable supervision even in domains such as creative cultural production and policy-making where holistic verification is difficult. Conversely, weak generators can provide diverse candidate solutions that are filtered, ranked, or refined by stronger Verifiers equipped with richer evaluative capabilities. By embedding such co-evolutionary dynamics into the environment design, Generator–Verifier asymmetry can shift into a catalyst for continuous self-improvement.

Open-Ended, Multi-Agent Environments Future environments can scale to support large-scale multi-agent interactions, emergent social dynamics, and economic- or organizational-level simulations, providing rich contexts for studying both collaborative and non-cooperative behaviors. In particular, scaling to massively multi-cultural multi-lingual settings requires scaling environment construction for agents to navigate the subtle semantics of concepts and values that vary across different societies, not only in the textual but also in the multi-modal domain [Koh et al., 2024b, Huang et al., 2025d]. By exposing agents to these open-ended, interactive scenarios, such environments foster generalization and strategic planning, equipping LLM agents to better handle complex, real-world challenges beyond isolated task execution.

8 Conclusion

The era of experience places environments at the core of LLM agent development, positioning them as active producers of experiential data and underscoring the growing need for scaling environments to create a more complex, realistic, and richly interactive world. From a pioneering environment-centric perspective, our survey proposes a unified taxonomy that organizes representative work across the GEF loop (task generation, task execution, and feedback), together with evaluation, implementation, and applications. We also surface key challenges for advancing agent intelligence, including the asymmetry between generators and verifiers and the construction of more open, large-scale multi-agent environments, thereby shedding light on future agentic work.

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A Evaluation Benchmarks

Direct evaluation of environments remains underexplored, with most research relying on indirect metrics. For example, works such as TaskCraft [Shi et al., 2025] and AgentScaler [Fang et al., 2025] assess environments by training agents through the resulting trajectories of environment–agent interactions, where strong agent performance indirectly reflects environmental quality. While some direct evaluation has emerged, it has largely been confined to symbolic or text-based settings. Bytesized32 [Wang et al., 2023] introduces task-specific text games and evaluates them using automated metrics on fidelity, validity, specification adherence, and winnability, bridging code generation and cognitive modeling. Text2World [Hu et al., 2025c] further benchmarks symbolic world model generation, employing structural similarity for overall evaluation while also using component-wise F1 scores to capture finer-grained aspects such as action dynamics. Recent work has begun to extend direct evaluation to video-based domains. VidOSC [Xue et al., 2024] examines open-world dynamics, WorldScore [Duan et al., 2025] proposes a unified framework for evaluating world generation, and WorldPrediction [Chen et al., 2025d] targets high-level visual reasoning, focusing on long-horizon program planning and semantic-temporal abstraction. Despite these advances, comprehensive and general-purpose evaluation protocols remain scarce, highlighting the need for broader, domain-agnostic methodologies to rigorously and directly assess environment quality beyond agent-centric performance metrics.

B Applications

Recent progress in agentic systems, typically built on state-of-the-art LLM families such as GPT [OpenAI, 2025a], Claude [Anthropic, 2025], Gemini [Team et al., 2024], LLaMA [Touvron et al., 2023], and Qwen [Bai et al., 2023], is increasingly driven by interactions with dynamic and multifaceted environments. **Tool-use environments** expose APIs and function calls as structured action spaces, and many LLMs now natively support function invocation, thereby extending reasoning with external tools [OpenAI, 2023, Anthropic, 2024, Song et al., 2023, Wu et al., 2025b, Mastouri et al., 2025, Luo et al., 2025b, Wang et al., 2025a, Fan et al., 2025]. **Coding environments** leverage repositories, test frameworks, and IDE integration to support long-horizon programming. Within these settings, systems such as Qwen3-Coder [Qwen Team, 2024] and Claude 4 [Anthropic, 2025] demonstrate reliability in code editing and debugging, and ReTool [Feng et al., 2025] integrates code-interpreter execution into the reasoning loop, enabling agents to exhibit code self-correction and adaptive tool selection. **Web navigation environments** build on HTML/DOM structures to support tasks such as browsing, form filling, and transactions. AutoWebGLM [Lai et al., 2024] illustrates how simplified webpage representations can enhance navigation efficiency, while open-source agents such as AgenticSeek [Fosowl, 2024] and Auto-GPT [Significant-Gravitas, 2023] showcase how browser-control environments enable general-purpose task execution on the web. **GUI agent environments** extend these capabilities to graphical user interfaces on desktops and mobile devices [Qin et al., 2025, Wang et al., 2025d, Ye et al., 2025c, Lu et al., 2025c, Liu et al., 2024b, Sun et al., 2022, Huang et al., 2025e]. Beyond these, more comprehensive platforms [Wang et al., 2025e, Xie et al., 2024, OpenAI, 2025] integrate terminals, operating systems, applications, and APIs to provide more interactive, open-ended, and real-world computer-use environments. **Deep research environments** require both long-context reasoning and robust retrieval. Systems such as Gemini1.5Pro [Google DeepMind, 2024] and OpenAI's deep research agents [OpenAI, 2025b] show that extended context windows enable sustained analysis, while effective retrieval pipelines mitigate distraction and context dilution. Across these domains, environments transform general LLM capacities into agent skills by defining action spaces, providing feedback, and maintaining state continuity.