CATArena: Evaluation of LLM Agents Through Iterative Tournament Competitions

Lingyue Fu[1,†], **Xin Ding**[1,†], **Yaoming Zhu**[2], **Shao Zhang**[1], **Lin Qiu**[3], **Weiwen Liu**[1,*], **Weinan Zhang**[1], **Xuezhi Cao**[3], **Xunliang Cai**[3], **Jiaxin Ding**[1], **Yong Yu**[1*]
[1] Shanghai Jiao Tong University, [2]AGI-Eval, [3]Meituan
fulingyue@sjtu.edu.cn, wwliu@sjtu.edu.cn

Abstract

Large Language Model (LLM) agents have evolved from basic text generation to autonomously completing complex tasks through interaction with external tools. However, current benchmarks mainly assess end-to-end performance in fixed scenarios, restricting evaluation to specific skills and suffering from score saturation and growing dependence on expert annotation as agent capabilities improve. In this work, we emphasize the importance of learning ability, including both self-improvement and peer-learning, as a core driver for agent evolution toward human-level intelligence. We propose an iterative, competitive peer-learning framework, which allows agents to refine and optimize their strategies through repeated interactions and feedback, thereby systematically evaluating their learning capabilities. To address the score saturation issue in current benchmarks, we introduce CATArena, a tournament-style evaluation platform featuring four diverse board and card games with open-ended scoring. By providing tasks without explicit upper score limits, CATArena enables continuous and dynamic evaluation of rapidly advancing agent capabilities. Experimental results and analyses involving both minimal and commercial code agents demonstrate that CATArena provides reliable, stable, and scalable benchmarking for core agent abilities, particularly learning ability and strategy coding.

1 Introduction

With the rapid evolution of agents powered by large language models (LLMs), their capabilities have far surpassed simple text generation. By actively invoking external tools, LLM agents have significantly expanded the boundaries of artificial general intelligence (AGI). These agents are now able to autonomously complete complex, multi-step tasks that are previously considered beyond their reach, such as developing software project (Manish, 2024; Hu et al., 2025b), intelligently performing strategic planning (Belle et al., 2025), and learning user preference (Gao et al., 2024).

Existing benchmarks mainly focus on end-to-end performance in specific tasks, such as code generation (Yang et al., 2024), AI research (Nathani et al., 2025), and GUI automation (Wang et al., 2024). These benchmarks provide detailed observations and analyses of LLM agents' abilities within particular scenarios and have driven significant progress in the field. However, there are important limitations to these approaches. First, *the scores obtained in these end-to-end benchmarks only reflect performance on specific tasks*, whereas an agent's overall capability is composed of multiple fundamental skills working together. Second, *the absolute scores in these benchmarks, which are typically based on objective correctness, have an upper bound.* As agents become increasingly powerful, maintaining and updating these benchmarks requires additional expert-level annotation, and the level of required expertise continues to rise. In light of these challenges, there is an urgent need for a quantifiable and continuously evolving benchmark that systematically measures and analyzes the fundamental sub-abilities of agents.

Previous research has shown that self-learning is an essential ability for agents to achieve human-level intelligence (Gao et al., 2025; Zhu et al., 2025). Beyond self-learning, agents, similar to hu-

[*]corresponding authors.
[†]Equal contribution. Work done while as Meituan Interns.

mans, also engage in peer learning, which enables collective evolution through interactions and shared experiences (Liu et al., 2024). During this evolutionary process, agents receive feedback from their environment and continually improve themselves. This capacity for learning and adaptation is indispensable for LLM agents, as it prepares them for ongoing evolution and more complex challenges. To systematically evaluate this crucial ability, we propose an iterative peer-learning-based competitive framework for LLM agents. In each iteration, agents are required to revise and update their strategies based on the outcomes and policies observed in previous rounds of competition. After every update, the agent policy codes are executed and competed against each other, generating dynamic performance rankings. Through this peer-learning architecture, we gain valuable insights into the learning abilities of LLM agents.

Building on this peer-learning framework, we introduce CATArena (**C**ode **A**gent **T**ournament **Arena**)[1], which utilizes four open-ended, rankable games. These games, including both board games and card games, provide LLM agents with a peer-learning environment and unlimited upper bound for improvement. They enable agents to continually improve and compete, ensuring that the evaluation framework remains challenging as agent capabilities grow. Furthermore, our competitive arena is inherently extensible and can be readily adapted to other types of open-ended, rankable tasks, facilitating the assessment of core agent abilities in new domains. As agent capabilities continue to advance, CATArena can evolve by incorporating tasks with greater complexity and discrimination, thereby supporting ongoing evaluation without the need for expert-level human annotation.

In our experiments, we conduct comparative performance evaluations and data analysis conducted on our self-developed minimal code agent and state-of-the-art commercial code agents. CATArena consistently provides stable and reliable benchmarks for assessing both agent capabilities and the agentic potential of the underlying LLMs. Within the peer-learning framework, we design general scoring metrics to systematically assess the fundamental abilities of participating agents, including their learning ability. Our experiments demonstrate that the strategy coding tasks applied in CATArena are fundamentally different from traditional LLM reasoning tasks. This represents a novel evaluation dimension that has not been addressed in previous work. Additionally, we analyze characteristics of CATArena, demonstrating its reliability and extensibility as a benchmarking platform.

In summary, our contributions are as follows:

- **Iterative Peer-learning-based Competitive Framework**: We propose a novel framework that leverages iterative peer-learning and competition to evaluate the learning abilities of LLM agents. Agents continuously revise their strategies based on feedback and outcomes from previous rounds, aligning agent evolution with human evolution.
- **CATArena Benchmark**: We introduce CATArena, a tournament-style benchmark for evaluating the basic capabilities of LLM agents using a diverse set of open-ended games, including board and card games. CATArena provides an unlimited upper bound for agent improvement and supports extensible evaluation across diverse, open-ended tasks.
- **Comprehensive Agent Evaluation**: We design general and systematic evaluation matrices and conduct comparative experiments and analyses between our minimal code agent and state-of-the-art commercial agents, demonstrating the reliability, stability, and extensibility of the CATArena.

2 Related Work

Learning Ability. Learning ability is crucial for LLM agents, as it enables continual adaptation and improvement in dynamic and complex environments. Recent studies have shown that self-learning methods, such as self-refinement (Madaan et al., 2023; Shinn et al., 2023), allow models to enhance their outputs through iterative feedback, while environmental feedback further supports continual learning (You et al., 2024). In addition to self-learning, peer-learning has also been increasingly recognized, with approaches encouraging agents to learn from others' reasoning processes and shared experiences (Liang et al., 2024; Luo et al., 2025). These diverse learning mechanisms have led to notable advances in tasks such as code generation, complex reasoning, and collaborative

[1]Code of CATArena is available in https://github.com/AGI-Eval-Official/CATArena.

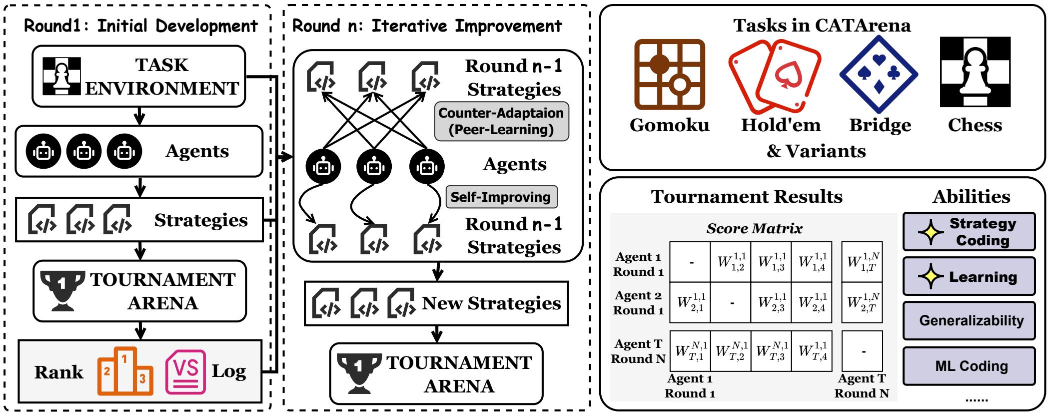


Figure 1: **Overview of the evaluation framework and CATArena**. The evaluation framework adopts an iterative peer-learning based competitive process. In round 1, LLM agents develop initial strategies via coding. These strategies are matched in a tournament arena, producing rankings and logs. In each subsequent round, agents analyze previous codes and logs, refine their strategies, and compete again. CATArena includes four open-ended and rankable games to cover diverse settings. Based on the tournament results from all rounds, a carefully designed scoring matrix and evaluation scheme are used to robustly quantify various agent abilities.

problem-solving. In the context of LLM-driven agents, learning ability represents a critical capability that supports effective adaptation and enables agents to tackle increasingly complex tasks and evolving challenges (Zhu et al., 2025; Gao et al., 2025). Despite the progress, systematic evaluation of how agents learn from each other remains underexplored, highlighting the need for benchmarks that capture both self-learning and peer-learning abilities.

Evaluation on Agents. Recent benchmarks primarily assess LLM-driven agents on end-to-end, task-specific abilities. Code-based evaluations such as GitTaskBench (Ni et al., 2025), SUPER (Bogin et al., 2024), ProjectEval (Liu et al., 2025), SWE-PolyBench (Rashid et al., 2025), RedCode (Guo et al., 2024), SWT-Bench (Mündler et al., 2025), InfiAgent-DABench (Hu et al., 2024), and DA-Code (Huang et al., 2024) focus on large-scale software development, code security, bug fixing, and data science tasks. Other works extend agent evaluation to research (Du et al., 2025), real-world tool use (Yao et al., 2024), and assistant scenarios (Mialon et al., 2024). While some benchmarks explore agent-vs-agent evaluation (Zhuge et al., 2024), most rely heavily on human annotation and objective correctness, leading to upper bounds and saturation as agent capabilities advance.

Open-ended Tasks. To address these limitations, recent work has leveraged open-ended, rankable tasks. Benchmarks such as GameBench (Costarelli et al., 2024), lmgame-Bench (Hu et al., 2025a), GAMEBot (Lin et al., 2024), and card game evaluations (Wang et al., 2025) assess LLMs' strategic reasoning through diverse games. Frameworks like Game Reasoning Arena (Cipolina-Kun et al., 2025), GVGAI-LLM (Li et al., 2025), ZeroSumEval (Alyahya et al., 2025), TextArena (Guertler et al., 2025), and MCU (Zheng et al., 2025) further extend evaluation to multi-turn reasoning, spatial adaptability, natural language interaction, and open-ended tasks. However, these benchmarks mainly focus on reasoning skills and do not systematically evaluate agents' learning abilities or coding strategies. Our analysis shows that measuring learning ability and coding strategy is fundamentally distinct, and both are essential for advancing agent intelligence. Additionally, in human board game competitions, variant rules such as Chess960 (FIDE, 2023) and Six-plus Hold'em (sixplusholdem, 2025) are often introduced to reduce memorization and encourage creativity. Notably, these variant rules have received relatively less attention in model evaluation.

Table 1: Overview of game arenas and representative variants in CATArena.

Game	Symmetry	Type	Players	Variant
Gomoku	✓	Board	2	Forbidden points; dual three-in-a-row
Texas Hold'em	✗	Card	≥ 8	Card removal; swapped hand ranks
Chess	✓	Board	2	Chess960; forbidden/special moves
Bridge	✓*	Card	4	Card exchange

* For Bridge, symmetry is defined by assigning identical agent strategies to both teammates.

3 CATArena

3.1 Iterative Peer-Learning based Competitive Framework

As shown in Figure 1, we propose an iterative peer-learning-based competitive framework, where CATArena evaluates code agents through a two-phase workflow: *initial strategy development* and *iterative improvement*. The initial phase assesses each agent's ability to independently implement a baseline strategy based on the game code, while the iterative phase focuses on the agent's learning ability.

Initial Development (Round 1). In this stage, each agent receives the game code and a sample AI implementation. Without external guidance, each agent must develop its own strategy to participate in the tournament. This phase primarily examines the agent's strategy coding ability and establishes a baseline for subsequent evaluation.

Iterative Improvement (Rounds $n > 1$). After the first round, all strategies submitted are evaluated through a tournament (round-robin format for symmetric games, batch-based competition for asymmetric games). Comprehensive competition logs are generated, recording rankings, win counts, and move histories for all matches. In subsequent rounds, agents are provided with the game code, previous round submissions from all participants, and these detailed logs. Agents must analyze these resources from previous rounds to adapt and improve their own strategies. This phase assesses the agent's learning ability through repeated cycles of analysis and refinement.

This iterative evaluation framework of CATArena enables a granular assessment of both basic coding skills and advanced learning capabilities, supporting a robust and scalable measurement of code agent performance.

3.2 Games and Variants

Building on the tournament-based evaluation framework, CATArena deploys four distinct game arenas, each selected to test the strategic reasoning and coding capabilities of code agents across varying levels of complexity and interaction patterns. These arenas include competitive and cooperative settings, as well as symmetric and asymmetric game structures, thus enabling a diverse analysis of agents' strategy coding abilities and learning patterns.

In addition to standard rules, each game is extended with thoughtfully designed variants that introduce novel or altered mechanics, inspired by real-world adaptations such as Fischer Random Chess (Chess960) (FIDE, 2023). Like human competition, the variant rules encourage strategy generalization and penalize rote memorization, as most models are trained on card and board game data. Table 1 provides an overview of the selected games and their respective variants.

3.3 Tournament Format and Scoring System

After the completion of all N development rounds, CATArena conducts a comprehensive tournament to quantitatively evaluate agent strategies and compute performance metrics. A total of T agent models participate, each contributing strategies in every round of development. Tournament formats are tailored to game types: for symmetric games, all strategies engage in a round-robin cycle, ensuring exhaustive pairwise competition; for asymmetric games such as Texas Hold'em, strategies are grouped into batches and compete in multi-agent matches. To mitigate randomness, all matches are repeated multiple times, and results are averaged for robust evaluation.

Scores are recorded in a scoring matrix $W \in \mathbb{R}^{(TN)\times(TN)}$, where $W_{i,j}^{n,m} \in [0,1]$ denotes the score obtained by agent i's strategy in round n against agent j's strategy in round m. When $n = m$, the notation simplifies to $W_{i,j}^{n}$; similarly, when $i = j$, it is denoted as $W_i^{m,n}$. This scoring system enables fine-grained, quantitative analysis of agent performance in both individual and iterative development stages. For asymmetric games, pairwise results are not feasible; instead, batch-based tournaments are used and the score matrix records the win rates of multi-agent matches. The tournament format is provided in the Appendix A.

3.4 Evaluation Metrics

Based on the scoring matrix W, we design a set of evaluation metrics to quantitatively assess the key capabilities of code agents. Specifically, our metrics are constructed to measure three core capabilities: *strategy coding*, *learning*, and *generalizability*. In the following sections, we define these metrics using symmetric games as examples. For asymmetric games, the evaluation principles remain consistent. The calculation of the scoring matrix W is provided in Appendix B.

Strategy Coding. Strategy coding measures the agent's fundamental ability to abstract game strategies into reproducible algorithms and implement them as executable code, which is fundamentally different from general reasoning and strategic planning abilities. In CATArena, this metric evaluates how effectively an agent can independently develop a baseline strategy for the game environment and compete against other agents in the initial development stage.

For each agent i, strategy coding is quantified by the average score obtained against all other agents in the first round:

$$S_i = \mathrm{avg}_{j\neq i}(W_{i,j}^{1}).$$

This metric serves as the foundational benchmark for code agent evaluation in CATArena.

Learning Ability. The learning capability of a code agent captures its ability to leverage historical information and opponent behaviors to improve its own performance.

Global Learning assesses an agent's overall improvement in strategy quality. This metric evaluates the relative performance of agent i's strategies against all strategies from all agents and rounds, and measures the average progress made compared to its initial baseline. It serves as the primary indicator of learning ability.

Formally, for agent i, global learning is defined as:

$$L_i = \mathrm{average}_{n=2}^{N}\left(G_i^n - G_i^1\right),$$

where G_i^n represents the global performance of agent i's strategy from round n:

$$G_i^n = \mathrm{average}_{(i,n)\neq(j,m)}\left(W_{i,j}^{n,m}\right).$$

This metric captures the agent's ability to learn and adapt over multiple rounds, reflecting its progress in a comprehensive competitive landscape.

Counter-Adaptation measures an agent's targeted learning ability, reflecting its capacity to achieve improved results against opponents in successive rounds. For agent i, the counter-adaptation score is defined as the average improvement in scores against other agents from round $n-1$ to round n ($n \geq 2$):

$$C_i = \mathrm{average}_{n=2}^{N}\left(A_i^n - B_i^{n-1}\right),$$

where the advance score A_i^n and base score B_i^{n-1} are defined as:

$$A_i^n = \mathrm{average}_{j\neq i}\left(W_{i,j}^{n,n-1}\right), B_i^{n-1} = \mathrm{average}_{j\neq i}\left(W_{i,j}^{n-1}\right).$$

Here, A_i^n represents agent i's average performance in round n against the strategies submitted by other agents in the previous in round $(n-1)$. The base score B_i^{n-1} denotes agent i's average performance in round $n-1$ against those same opponents. This comparison isolates the agent's targeted adaptation from one round to the next.

Self-improvement evaluates an agent's capacity to genuinely enhance its strategies over successive rounds of development. This metric reflects whether newly developed strategies can consistently outperform the agent's own previous versions.

We quantify self-improvement by calculating the Pearson correlation Pearson (1896) between the round index and the agent's average scores across rounds. For agent i, the self-improvement score is defined as

$$\mathrm{SI}_i = \mathrm{Pearson}\left([1, \cdots, N],\ [S_i^1, \cdots, S_i^N]\right).$$

Here, S_i^n denotes the average score of agent i's strategy from round n against its own strategies from other rounds

$$S_i^n = \mathrm{average}_{m \neq n}\left(W_i^{n,m}\right).$$

A higher self-improvement score indicates a stronger ability to iteratively refine and upgrade strategies throughout the development process.

Generalizability. Generalizability measures an agent's ability to comprehend and adapt to novel or altered game rules that differ from those encountered during training or prior experience. This metric specifically evaluates the agent's capacity to generalize beyond previously seen environments, focusing on handling new or modified scenarios. For agent i, the generalizability score is defined as:

$$U_i = B_i^{1;\mathrm{Variants}} - B_i^{1;\mathrm{Standard}},$$

where $B_i^{1;\mathrm{Variants}}$ and $B_i^{1;\mathrm{Standard}}$ denote the base scores of agent i in the first round under variant and standard rule settings, respectively. A higher value of U_i indicates stronger generalizability, reflecting the agent's ability to effectively develop and apply strategies for previously unseen tasks.

4 Experiments

4.1 Experimental Setups

Participants. In our experiment, we employ three types of agents: (1) **Minimal Agents (LLM + ADK Framework)**[2]**:** A baseline agent developed with the Agent Development Kit (ADK) Python toolkit. We provide essential tools, including file manipulation, bash scripting, and Python execution, for the ADK code agent. On this foundation, we integrate state-of-the-art LLMs to systematically compare their core competencies as code agents for strategy implementation. (2) **Commercial Code Agents:** State-of-the-art and commercial CLI-based agents (e.g., Claude Code, CodeX, Gemini-CLI, Qwen-Coder) are included for benchmarking. These agents feature advanced integration with various command-line interfaces, tools, and LLMs, resulting in enhanced overall capabilities. These agents serve as leading solutions in code agent development and provide valuable reference points for future research. (3) **LLM-Player:** In this control setting, LLMs directly output game moves without generating code. For each turn, the LLM receives the game rules, current state, and history, and returns the next action. This approach is specifically designed to assess the inherent strategic and reasoning capabilities of LLMs. Detailed agent parameter settings and model selections are presented in Appendix C.

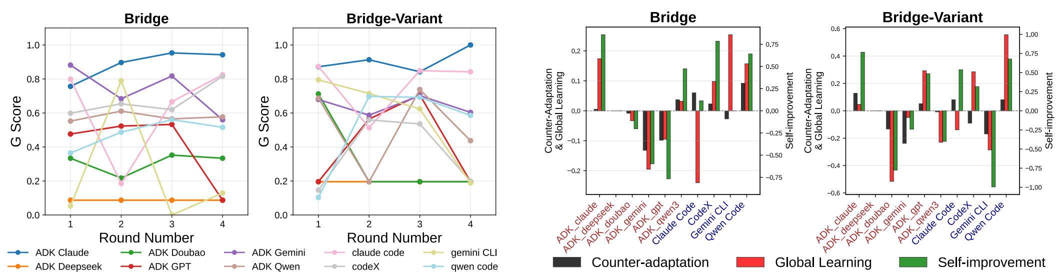
Tournaments. All experiments are conducted under two main tournament settings: (1) a comparison among minimal agents equipped with different LLMs ($T_1 = 6$), and (2) a comparison between the best-performing minimal agent and a set of commercial code agents ($T_2 = 5$). To reduce the impact of randomness on strategy generation, each tournament is repeated for four times, and all reported metrics are averaged over the four runs. Each tournament consists of $N = 4$ rounds of iterative development. To further mitigate stochastic effects in competition outcomes, every entry in the scoring matrix W is estimated by repeated matches. Detailed tournament prompts are listed in Appendix K.

We report the detailed scoring policy, generation configs, and repetition experiments in Appendix D. It is noteworthy that agents tend to generate different codes in repeated experiments, but their rankings are relatively stable.

[2]https://github.com/AGI-Eval-Official/Minimal-CodeAgent

Table 2: Agent Specifications and Open-Source Status.

Agent Type	Agent Framework	Model	Agent OSS	LLM OSS
Minimal	basic code tools with ADK framework	DeepSeek-3.1 (DeepSeek-AI, 2024)	✓	✓
		Qwen3-Coder-480B (Team, 2025c)	✓	✓
		Doubao-Seed-1.6 (Team, 2025d)	✓	✗
		GPT-5 (OpenAI, 2025b)	✓	✗
		Claude-4-Sonnet (Anthropic, 2025a)	✓	✗
		Gemini-2.5-pro (Team, 2025a)	✓	✗
Commercial	Gemini-CLI (Google, 2025)	Gemini-2.5-pro (Team, 2025a)	✓	✗
	Claude-Code (Anthropic, 2025b)	Claude-4/3.7 Hybrid (Anthropic, 2025a)	✗	✗
	CodeX (OpenAI, 2025a)	GPT-5 (OpenAI, 2025b)	✓	✗
	Qwen-Coder (Team, 2025b)	Qwen3-Coder-480B (Team, 2025c)	✓	✓
Other	LLM-Player	Agents's Corresponding LLM	N/A	N/A



(a) Trends of global performance scores G_i^n.

(b) Quantitative comparison of learning abilities.

Figure 2: **Visualization of agents' learning patterns and scores.**. For clarity, we use family names to represent LLM models instead of their full names. The results for other games are in Appendix E.

4.2 Main Results

Learning Ability. Figure 2(a) visualizes the global performance scores G_i^n revealing overall trends in agent strategies across iterations. Some agents, such as minimal agents driven by claude, exhibit a clear upward trajectory over multiple rounds, demonstrating strong learning capability. However, the performance of most agents remains unstable, and no obvious trend is observed. To explicitly illustrate the learning ability of each agent, we design a quantitative scoring method for global learning and introduce two additional learning modes: counter-adaption and self-improvement. The quantitative results for these three abilities are presented in Figure 2(b). Compared to Figure 2(a), these scores offer a more intuitive comparison of the agents' learning strengths. This decomposition provides deeper insights into the mechanisms underlying agent learning. When both counter-adaption and self-improvement scores are positive, it indicates that the agent can effectively learn from both its opponents and itself, resulting in a positive global learning score. Compared to minimal agents, commercial agents exhibit stronger learning capabilities. Learning ability results for other games and a case study of strategy iteration mechanisms are provided in Appendix E. Through an analysis of the consistency of agent actions in endgame states, we observe that a majority of agents indeed learn from the code generated in the previous round, leading to increasing consistency. This phenomenon is most prominent in the Hold'em environment, possibly because its strategies are relatively simple and easier to learn.

Table 3: **Main LeaderBoard of CATArena.** We conduct two groups of tournaments between minimal agents (rank from 1 to 6) and commercial agents (rank from 1 to 5), and report the average ranking across all four tasks. Metrics include S.C. (Strategy Coding), G.L. (Global Learning), and G.A. (Generalizability).

	Agents	Standard		Variant		G.A. ↓
		S.C. ↓	G.L. ↓	S.C. ↓	G.L. ↓	
Minimal	Claude-4-Sonnet	**1.25**	**2.5**	**1.75**	**2.75**	5.00
	DeepSeek-Chat	5.75	2.75	4.25	**2.75**	2.75
	Doubao-Seed	3.75	4.75	3.75	4.50	2.75
	Gemini-2.5-Pro	3.25	3.75	3.25	**2.75**	3.25
	GPT-5	3.75	3.50	3.00	3.75	**2.25**
	Qwen3-Coder	2.25	3.75	3.00	4.5	4.75
Commercial	best ADK	3.25	**2.25**	**2.00**	3.75	2.50
	Claude-Code	2.50	3.75	2.50	2.75	3.25
	CodeX	**2.25**	2.75	3.00	3.00	3.25
	Gemini-CLI	3.50	**2.25**	3.00	4.00	**2.00**
	Qwen-Coder	3.00	3.75	4.00	**1.25**	3.25

Table 4: **Main results of CATArena.** We conduct two groups of tournaments between Minimal agents and commercial agents. For each tournament, we display the results for Strategy Coding (S.C.↑), Global Learning (G.L.↑), and Generalizability (G.A.↑). The S.C.↑ score ranges from 0 to 1, a G.L.↑ score greater than 0 indicates the agent has learning ability, and the G.A.↑ score ranges from -1 to 1. All scores represent the relative performance of participants within the tournament.

	Games	Gomoku					Hold'em					Bridge					Chess				
		Standard		Variant			Standard		Variant			Standard		Variant			Standard		Variant		
	Agents	S.C.↑	G.L.↑	S.C.↑	G.L.↑	G.A.↑	S.C.↑	G.L.↑	S.C.↑	G.L.↑	G.A.↑	S.C.↑	G.L.↑	S.C.↑	G.L.↑	G.A.↑	S.C.↑	G.L.↑	S.C.↑	G.L.↑	G.A.↑
Minimal	Claude-4-Sonnet	**0.88**	-0.447	**0.78**	-0.156	-0.14	**0.58**	0.118	0.13	**0.110**	-0.45	0.79	**0.174**	**1.0**	0.047	0.005	**0.90**	-0.170	0.65	0.018	-0.55
	Deepseek-Chat	0.23	0.027	0.38	0.077	0.13	0.01	0.010	0.00	-0.022	-0.01	0	0	0.10	0	0.10	0	0	0.10	**0.049**	0.10
	Doubao-Seed	0.33	-0.192	0.72	-0.302	**0.46**	0.04	-0.035	0	0	-0.04	0.2	-0.033	0.45	-0.516	0.40	0.58	-0.337	0.10	0.034	-0.46
	Gemini-2.5-Pro	0.25	-0.066	0.00	**0.173**	-0.12	0.01	0.020	0.00	0.078	-0.01	**0.90**	-0.195	0.60	-0.049	-0.30	0.58	-0.147	**0.90**	0.003	**0.46**
	GPT-5	0.48	**0.062**	0.76	-0.019	0.18	0.16	**0.102**	**0.87**	-0.050	**0.71**	0.47	-0.095	0.10	**0.293**	-0.02	0.38	-0.525	0.45	-0	0.24
	Qwen3-Coder	0.85	-0.523	0.36	-0.089	-0.50	0.20	0.038	0.00	0.003	-0.20	0.65	0.032	0.76	-0.230	-0.19	0.58	-0.187	0.80	-0.532	0.21
Commercial	best ADK	0	0.075	**0.75**	-0.022	**0.88**	0.07	**0.073**	**0.46**	0.030	**0.39**	0.25	**0.295**	0	0.361	-0.25	**0.91**	-0.110	**1.00**	-0.342	-0.47
	Claude-Code	0.78	-0.322	0.66	**0.194**	-0.28	0.01	0.100	0	**0.105**	-0.001	**1.00**	-0.240	**0.93**	-0.139	-0.04	0.56	-0.158	0.44	-0.226	0.03
	CodeX	0.47	**0.454**	0.69	-0.095	0.34	**0.72**	0.050	0.17	0.067	-0.55	0.75	0.098	0.50	0.285	-0.25	0.38	0.033	0.34	**0.064**	0.09
	Gemini-CLI	0.31	0.260	0.19	0.172	0.0	0.13	0.050	0.37	-0.007	0.24	0.01	0.254	0.83	-0.286	**0.79**	0.38	**0.395**	0.38	-0.154	0.16
	Qwen-Coder	**0.94**	-0.054	0.22	-0.530	-0.94	0.07	0.058	0	**0.105**	-0.007	0.49	0.157	0.25	**0.556**	-0.25	0.28	-0.204	0.34	0.039	**0.19**

Ability Evaluation. We conduct two sets of tournaments: (1) minimal agents equipped with different LLMs, (2) the best-performing minimal agent against commercial code agents. For each tournament, we report the average ranking and scores for three core agent capabilities. The main leaderboard and main results of CATArena are summarized in Table 3 and Table 4. These results reveal the following key observations:

Observation 1: The performance gap among LLMs is more pronounced in minimal agents compared to commercial agents. Table 3 shows that Claude-4-Sonnet achieves the highest score among minimal agents, while the rankings of other LLMs are more dispersed. In contrast, commercial agents driven by the same LLMs exhibit much closer average rankings, with all agents scoring around 2.5 out of 5, indicating a reduced performance gap. Moreover, commercial agents demonstrate performance levels similar to the best-performing minimal agent. This suggests that *the underlying agent framework can significantly influence how effectively an LLM's capabilities are utilized*, as commercial agents are often optimized for specific models.

Observation 2: The participating agents display different ranking orders across various capabilities. The tournament results reveal that the relative rankings of agents change depending on the specific core ability being tested. The ranking of these abilities provides a decomposition of end-to-end performance, offering insights for further optimization of both LLMs and agent frameworks.

Observation 3: Agents exhibit varied performance distributions across different tasks. The results indicate that agents' performance is not uniformly distributed across all tasks, which is mainly attributed to the distinct nature and difficulty of the four tasks. In the variant tasks, the performance gap among agents is more pronounced, likely because the game rules and strategies are less familiar to agents.

4.3 Effectiveness of CATArena

We design a series of experiments to demonstrate the effectiveness of CATArena.

Comparison between Agents and LLM-Players. The primary task in CATArena is strategy coding, which relies on the underlying coding capabilities of LLMs. We posit that reasoning over code to develop strategies is fundamentally different from direct reasoning during gameplay. To validate this distinction, we compare agent-developed strategies with the LLM-Player baseline (see Appendix F). Our results show that current agents primarily implement simple rule-based algorithms, indicating substantial room for advancement in agents' strategy coding abilities. CATArena fully leverages this non-saturation, enabling sustainable iterative peer-learning.

To further analyze the similarities and differences between agent-implemented code strategies and those of LLM-Players, we ask agents' code and LLM-Player to select the next action on endgame states. Figure 4.3 illustrates the action consistency between agents' code and LLM-Players in Chess. Surprisingly, *the strategies encoded in agent code differ significantly from those inferred directly by*

Table 5: **Collective learning trends of agents across different tasks in CATArena.** $\text{DIS}_{\text{range}}$ and DIS_{std} represent the Pearson correlation coefficients of the range and standard deviation of agent performance scores over four rounds, reflecting the similarity and dispersion of agent strategies. $\text{Trend}_{\text{mean}}$ denotes the Pearson correlation between the mean agent performance and the round number, indicating the overall trend of group improvement.

	Gomoku		**Hold'em**		**Bridge**		**Chess**	
	StdV.	VarV.	StdV.	VarV.	StdV.	VarV.	StdV.	VarV.
DIS_{std}	-0.05	0.15	-0.81	-0.80	-0.82	-0.57	0.55	-0.04
$\text{DIS}_{\text{range}}$	-0.16	0.44	-0.80	-0.76	-0.54	-0.33	-0.08	0.16
$\text{Trend}_{\text{mean}}$	0.42	-0.02	0.75	0.67	0.24	-0.10	-0.74	-0.79

the LLM, even if they are from the same model. Meanwhile, strategies produced by different agents and different LLMs also show notable similarities. This indicates that strategy coding and reasoning in LLMs are distinct capabilities. We report results of other tasks are demonstrated in Appendix G. CATArena evaluates the strategy coding ability of agents rather than their reasoning ability, thereby filling a gap in previous benchmarks. The relationship between strategy coding ability and LLM-based strategy reasoning remains unclear and requires further investigation.

Collective Learning Trends Among Agents. We analyze the collective learning dynamics of agents across tasks, as presented in Table 5. The metrics $\text{DIS}_{\text{range}}$ and DIS_{std} report the Pearson correlation between the standard deviation and range of agent performance scores over four rounds ($B_i^n, n = 1, 2, 3, 4$). The higher similarity in performance scores (i.e., DIS > 0) suggests that agents can learn effective strategies more readily, indicating lower task difficulty. Based on these results, the relative difficulty ranking of tasks in CATArena is Chess $>$ Gomoku $>$ Bridge $>$ Hold'em.

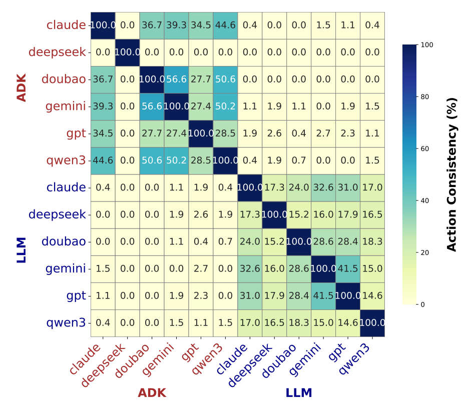


Figure 3: Action consistency between agents' code and LLM-Players on Chess endgames.

$\text{Trend}_{\text{mean}}$ captures the trend in the average performance of all agents, $\text{dwaverage}_i(G_i^n)$, across rounds (calculated as the Pearson correlation between the mean score and the number of rounds). Our analysis reveals that agents are able to collectively improve their strategies in simpler environments, whereas their learning capacity remains limited in more challenging tasks. Furthermore, the collective improvement observed in variant tasks is lower than in standard versions, indicating that variants present greater difficulty for current agents.

Additional Results. CATArena's iterative peer-learning framework is easily extensible to new tasks for evaluating other fundamental agent abilities. We demonstrate this by introducing a Machine Learning (ML) track and multi-lingual track, with experimental results provided in Appendix H and Appendix I, respectively. Experimental results indicate that current agents still exhibit substantial potential for improvement. As agents continue to advance, the open-ended task design and peer-learning evaluation framework of CATArena ensure that systematic assessment can be sustained over time. We also report agent cost in terms of token usage, time consumption, and generated code statistics for each agent, in Appendix J. Notably, Claude-4-Sonnet utilizes the most tools and tokens, and also develops a significantly larger amount of code. In contrast, GPT-5 achieves the best balance between token usage and performance. Efficient utilization of tokens and external tools remains an important research direction to advance the capabilities of LLM agents.

5 CONCLUSION

In this work, we address two fundamental challenges in LLM agent evaluation: the need for systematic measurement of learning ability, and the tendency of traditional benchmarks to become saturated as agent capabilities improve. To this end, we propose an iterative peer-learning-based competitive framework, enabling agents to continually revise and enhance their strategies through dynamic interaction and feedback. Building on this, we introduce CATArena, a tournament-style benchmark featuring open-ended and rankable board and card games. CATArena provides an environment with unlimited potential for agent improvement potential and extensible evaluation across new domains. Experimental results demonstrate that our framework reliably assesses core agent abilities, particularly learning ability and strategy coding, while ensuring stability and scalability. The open and flexible architecture of CATArena supports ongoing research and benchmarking for future intelligent agents.

Limitations. The current evaluation in CATArena is limited to four games, which primarily assess agents' learning ability and strategy coding. These scenarios do not encompass the full spectrum of potential LLM agent capabilities. In future work, we plan to introduce a wider variety of more complex tasks to evaluate agents' learning and other abilities from different perspectives.

REFERENCES

Hisham A. Alyahya, Haidar Khan, Yazeed Alnumay, M Saiful Bari, and Bülent Yener. Zerosumeval: An extensible framework for scaling llm evaluation with inter-model competition, 2025. URL https://arxiv.org/abs/2503.10673.

Anthropic. Introducing claude 4. https://www.anthropic.com/news/claude-4, 2025a. Accessed: 2025-05-23.

Anthropic. Claude code: Best practices for agentic coding. https://www.anthropic.com/engineering/claude-code-best-practices, 2025b. Accessed: 2025-04-18.

Nikolas Belle, Dakota Barnes, Alfonso Amayuelas, Ivan Bercovich, Xin Eric Wang, and William Wang. Agents of change: Self-evolving llm agents for strategic planning, 2025. URL https://arxiv.org/abs/2506.04651.

Ben Bogin, Kejuan Yang, Shashank Gupta, Kyle Richardson, Erin Bransom, Peter Clark, Ashish Sabharwal, and Tushar Khot. Super: Evaluating agents on setting up and executing tasks from research repositories. *arXiv preprint arXiv:2409.07440*, 2024.

Lucia Cipolina-Kun, Marianna Nezhurina, and Jenia Jitsev. Game reasoning arena: A framework and benchmark for assessing reasoning capabilities of large language models via game play, 2025. URL https://arxiv.org/abs/2508.03368.

Anthony Costarelli, Mat Allen, Roman Hauksson, Grace Sodunke, Suhas Hariharan, Carlson Cheng, Wenjie Li, Joshua Clymer, and Arjun Yadav. Gamebench: Evaluating strategic reasoning abilities of llm agents, 2024. URL https://arxiv.org/abs/2406.06613.

DeepSeek-AI. Deepseek-v3 technical report, 2024. URL https://arxiv.org/abs/2412.19437.

Mingxuan Du, Benfeng Xu, Chiwei Zhu, Xiaorui Wang, and Zhendong Mao. Deepresearch bench: A comprehensive benchmark for deep research agents. *CoRR*, abs/2506.11763, 2025. doi: 10.48550/ARXIV.2506.11763. URL https://doi.org/10.48550/arXiv.2506.11763.

FIDE. FIDE Laws of Chess. https://www.fide.com/FIDE/handbook/LawsOfChess.pdf, 2023. Accessed: 2025-09-13.

Ge Gao, Alexey Taymanov, Eduardo Salinas, Paul Mineiro, and Dipendra Misra. Aligning llm agents by learning latent preference from user edits, 2024. URL https://arxiv.org/abs/2404.15269.

Huan-ang Gao, Jiayi Geng, Wenyue Hua, Mengkang Hu, Xinzhe Juan, Hongzhang Liu, Shilong Liu, Jiahao Qiu, Xuan Qi, Yiran Wu, et al. A survey of self-evolving agents: On path to artificial super intelligence. *arXiv preprint arXiv:2507.21046*, 2025.

Google. Gemini cli. https://github.com/google-gemini/gemini-cli, 2025. Accessed: 2025-06-25.

Leon Guertler, Bobby Cheng, Simon Yu, Bo Liu, Leshem Choshen, and Cheston Tan. Textarena. *arXiv preprint arXiv:2504.11442*, 2025.

Chengquan Guo, Xun Liu, Chulin Xie, Andy Zhou, Yi Zeng, Zinan Lin, Dawn Song, and Bo Li. Redcode: Risky code execution and generation benchmark for code agents, 2024. URL https://arxiv.org/abs/2411.07781.

Lanxiang Hu, Mingjia Huo, Yuxuan Zhang, Haoyang Yu, Eric P Xing, Ion Stoica, Tajana Rosing, Haojian Jin, and Hao Zhang. lmgame-bench: How good are llms at playing games? *arXiv preprint arXiv:2505.15146*, 2025a.

Xueyu Hu, Ziyu Zhao, Shuang Wei, Ziwei Chai, Qianli Ma, Guoyin Wang, Xuwu Wang, Jing Su, Jingjing Xu, Ming Zhu, Yao Cheng, Jianbo Yuan, Jiwei Li, Kun Kuang, Yang Yang, Hongxia Yang, and Fei Wu. Infiagent-dabench: Evaluating agents on data analysis tasks, 2024. URL https://arxiv.org/abs/2401.05507.

Yaojie Hu, Qiang Zhou, Qihong Chen, Xiaopeng Li, Linbo Liu, Dejiao Zhang, Amit Kachroo, Talha Oz, and Omer Tripp. Qualityflow: An agentic workflow for program synthesis controlled by llm quality checks, 2025b. URL https://arxiv.org/abs/2501.17167.

Yiming Huang, Jianwen Luo, Yan Yu, Yitong Zhang, Fangyu Lei, Yifan Wei, Shizhu He, Lifu Huang, Xiao Liu, Jun Zhao, et al. Da-code: Agent data science code generation benchmark for large language models. *arXiv preprint arXiv:2410.07331*, 2024.

Haruka Kita, Sotetsu Koyamada, Yotaro Yamaguchi, and Shin Ishii. A simple, solid, and reproducible baseline for bridge bidding ai. In *2024 IEEE Conference on Games (CoG)*, pp. 1–4. IEEE, 2024.

Yuchen Li, Cong Lin, Muhammad Umair Nasir, Philip Bontrager, Jialin Liu, and Julian Togelius. Gvgai-llm: Evaluating large language model agents with infinite games. *arXiv preprint arXiv:2508.08501*, 2025.

Tian Liang, Zhiwei He, Wenxiang Jiao, Xing Wang, Yan Wang, Rui Wang, Yujiu Yang, Shuming Shi, and Zhaopeng Tu. Encouraging divergent thinking in large language models through multi-agent debate. In Yaser Al-Onaizan, Mohit Bansal, and Yun-Nung Chen (eds.), *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pp. 17889–17904, Miami, Florida, USA, November 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.emnlp-main.992. URL https://aclanthology.org/2024.emnlp-main.992/.

Wenye Lin, Jonathan Roberts, Yunhan Yang, Samuel Albanie, Zongqing Lu, and Kai Han. Gamebot: Transparent assessment of llm reasoning in games. *arXiv preprint arXiv:2412.13602*, 2024.

Jiawen Liu, Yuanyuan Yao, Pengcheng An, and Qi Wang. Peergpt: Probing the roles of llm-based peer agents as team moderators and participants in children's collaborative learning. In *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*, CHI EA '24, New York, NY, USA, 2024. Association for Computing Machinery. ISBN 9798400703317. doi: 10.1145/3613905.3651008. URL https://doi.org/10.1145/3613905.3651008.

Kaiyuan Liu, Youcheng Pan, Yang Xiang, Daojing He, Jing Li, Yexing Du, and Tianrun Gao. Projecteval: A benchmark for programming agents automated evaluation on project-level code generation, 2025. URL https://arxiv.org/abs/2503.07010.

Tongxu Luo, Wenyu Du, Jiaxi Bi, Stephen Chung, Zhengyang Tang, Hao Yang, Min Zhang, and Benyou Wang. Learning from peers in reaoning models. *arXiv preprint arXiv:2505.07787*, 2025.

Aman Madaan, Niket Tandon, Prakhar Gupta, Skyler Hallinan, Luyu Gao, Sarah Wiegreffe, Uri Alon, Nouha Dziri, Shrimai Prabhumoye, Yiming Yang, et al. Self-refine: Iterative refinement with self-feedback. *Advances in Neural Information Processing Systems*, 36:46534–46594, 2023.

Sanwal Manish. An autonomous multi-agent llm framework for agile software development. *International Journal of Trend in Scientific Research and Development*, 8(5):892–898, 2024.

Grégoire Mialon, Clémentine Fourrier, Thomas Wolf, Yann LeCun, and Thomas Scialom. GAIA: a benchmark for general AI assistants. In *The Twelfth International Conference on Learning Representations, ICLR 2024, Vienna, Austria, May 7-11, 2024*. OpenReview.net, 2024. URL https://openreview.net/forum?id=fibxvahvs3.

Niels Mündler, Mark Niklas Müller, Jingxuan He, and Martin Vechev. Swt-bench: Testing and validating real-world bug-fixes with code agents, 2025. URL https://arxiv.org/abs/2406.12952.

Deepak Nathani, Lovish Madaan, Nicholas Roberts, Nikolay Bashlykov, Ajay Menon, Vincent Moens, Amar Budhiraja, Despoina Magka, Vladislav Vorotilov, Gaurav Chaurasia, et al. Mlgym: A new framework and benchmark for advancing ai research agents. *arXiv preprint arXiv:2502.14499*, 2025.

Ziyi Ni, Huacan Wang, Shuo Zhang, Shuo Lu, Ziyang He, Wang You, Zhenheng Tang, Yuntao Du, Bill Sun, Hongzhang Liu, Sen Hu, Ronghao Chen, Bo Li, Xin Li, Chen Hu, Binxing Jiao, Daxin Jiang, and Pin Lyu. Gittaskbench: A benchmark for code agents solving real-world tasks through code repository leveraging, 2025. URL `https://arxiv.org/abs/2508.18993`.

OpenAI. Codex cli. `https://github.com/openai/codex`, 2025a. Accessed: 2025-05-16.

OpenAI. Introducing gpt-5. `https://openai.com/index/introducing-gpt-5/`, 2025b. Accessed: 2025-08-07.

K. Pearson. Vii. mathematical contributions to the theory of evolution.-iii. regression, heredity, and panmixia. *Philosophical Transactions of the Royal Society A*, 187:253–318, 1896. doi: 10.1098/rsta.1896.0007. URL `https://doi.org/10.1098/rsta.1896.0007`.

Muhammad Shihab Rashid, Christian Bock, Yuan Zhuang, Alexander Buchholz, Tim Esler, Simon Valentin, Luca Franceschi, Martin Wistuba, Prabhu Teja Sivaprasad, Woo Jung Kim, Anoop Deoras, Giovanni Zappella, and Laurent Callot. Swe-polybench: A multi-language benchmark for repository level evaluation of coding agents, 2025. URL `https://arxiv.org/abs/2504.08703`.

Noah Shinn, Federico Cassano, Ashwin Gopinath, Karthik Narasimhan, and Shunyu Yao. Reflexion: Language agents with verbal reinforcement learning. *Advances in Neural Information Processing Systems*, 36:8634–8652, 2023.

sixplusholdem. Six-plus hold'em, 2025. URL `https://sixplusholdem.com/`. Accessed: September 25, 2025.

Gemini Team. Gemini 2.5: Pushing the frontier with advanced reasoning, multimodality, long context, and next generation agentic capabilities, 2025a. URL `https://arxiv.org/abs/2507.06261`.

Qwen Team. Qwen3-coder: Agentic coding in the world. `https://qwenlm.github.io/zh/blog/qwen3-coder/`, 2025b. Accessed: 2025-07-22.

Qwen Team. Qwen3-coder: Agentic coding in the world. `https://qwenlm.github.io/blog/qwen3-coder/`, 2025c. Accessed: 2025-07-22.

Seed Team. Seed1.6 tech introduction. `https://seed.bytedance.com/en/seed1_6`, 2025d. Accessed: 2025-06-25.

Luyuan Wang, Yongyu Deng, Yiwei Zha, Guodong Mao, Qinmin Wang, Tianchen Min, Wei Chen, and Shoufa Chen. Mobileagentbench: An efficient and user-friendly benchmark for mobile llm agents. *arXiv preprint arXiv:2406.08184*, 2024.

Wei Wang, Fuqing Bie, Junzhe Chen, Dan Zhang, Shiyu Huang, Evgeny Kharlamov, and Jie Tang. Can large language models master complex card games?, 2025. URL `https://arxiv.org/abs/2509.01328`.

John Yang, Carlos E Jimenez, Alexander Wettig, Kilian Lieret, Shunyu Yao, Karthik Narasimhan, and Ofir Press. Swe-agent: Agent-computer interfaces enable automated software engineering. *Advances in Neural Information Processing Systems*, 37:50528–50652, 2024.

Shunyu Yao, Noah Shinn, Pedram Razavi, and Karthik Narasimhan. τ-bench: A benchmark for tool-agent-user interaction in real-world domains. *CoRR*, abs/2406.12045, 2024. doi: 10.48550/ARXIV.2406.12045. URL `https://doi.org/10.48550/arXiv.2406.12045`.

Jiaxuan You, Mingjie Liu, Shrimai Prabhumoye, Mostofa Patwary, Mohammad Shoeybi, and Bryan Catanzaro. Llm-evolve: Evaluation for llm's evolving capability on benchmarks. In *Proceedings of the 2024 conference on empirical methods in natural language processing*, pp. 16937–16942, 2024.

Xinyue Zheng, Haowei Lin, Kaichen He, Zihao Wang, Zilong Zheng, and Yitao Liang. Mcu: An evaluation framework for open-ended game agents, 2025. URL `https://arxiv.org/abs/2310.08367`.

Jiachen Zhu, Menghui Zhu, Renting Rui, Rong Shan, Congmin Zheng, Bo Chen, Yunjia Xi, Jianghao Lin, Weiwen Liu, Ruiming Tang, Yong Yu, and Weinan Zhang. Evolutionary perspectives on the evaluation of llm-based ai agents: A comprehensive survey, 2025. URL https://arxiv.org/abs/2506.11102.

Mingchen Zhuge, Changsheng Zhao, Dylan Ashley, Wenyi Wang, Dmitrii Khizbullin, Yunyang Xiong, Zechun Liu, Ernie Chang, Raghuraman Krishnamoorthi, Yuandong Tian, Yangyang Shi, Vikas Chandra, and Jürgen Schmidhuber. Agent-as-a-judge: Evaluate agents with agents, 2024. URL https://arxiv.org/abs/2410.10934.

A Tournament Format and Scoring System

Table 6: Configs of tournament on four games.

Environment	Code Agents	LLM-player
Gomoku	Board size: 15×15 Number of pairwise matches: 4 × 2 Swap black and white pieces after each match Maximum time per move: 10 s	Board size: 15×15 Number of pairwise matches: 2 × 2 Swap black and white pieces after each match Maximum time per move: 600 s
Texas Hold'em	Max players: 12 Rounds: 100 Random shuffle seat after each round Initial chips: 2000 Blind increase every 24 hands Max hands per round: 720 or until winner decided Maximum time per move: 3 s	Max players: 12 Rounds: 10 Random shuffle seat after each round Initial chips: 2000 Blind increase every 24 hands Max hands per round: 720 or until winner decided Maximum time per move: 1000 s
Bridge	Number of pairwise matches: 12 × 2 Swap directions of open/closed rooms Use same deck for each pair of match Maximum time per move: 10 s	Number of pairwise matches: 12 × 2 Swap directions of open/closed rooms Use same deck for each pair of match Maximum time per move: 200 s
Chess	Number of pairwise matches: 8 × 2 Swap black and white pieces after each match Maximum moves per game: 200 Maximum time per move: 10 s	Number of pairwise matches: 2 × 2 Swap black and white pieces after each match Maximum moves per game: 200 Maximum time per move: 600 s

We list the basic settings for each games in Table 6.

For each game, we ensure that the number of pairwise matches among code agents allows the final results to stabilize, i.e., for each game, the L1-norm fluctuation of the scoring matrix W is less than 5%.

For LLM-players, since their reasoning time is relatively long for most games, we reduce the number of repeated experiments. Note that our comparison with LLM-players is only a qualitative analysis of the differences between LLM-player and corresponding coding agent. The exploration of LLM-players' results is not the focus of this paper; refer to the main text for details.

B Evaluation Metric Calculation

Table 7: Scoring rules of tournament on four games.

Environment	Scoring Metric
Gomoku	Pairwise match scoring: Win = 1 point, Draw = 0.5 point, Lose = 0 point.
Texas Hold'em	Multi-agent batches: score is the average win rate across all tournaments participated.
Bridge	20 VP system: Two opposing pairs' scores sum to 20, Final score divided by 20, ensuring each pair's score $\in [0, 1]$.
Chess	Pairwise match scoring: Win = 1 point, Draw = 0.5 point, Lose = 0 point.

To evaluate the basic capabilities of LLM agents, we define metrics for each applied game. Let N be the number of rounds and K be the number of participating agents. We construct a matchup matrix

$$W \in \mathbb{R}^{(N \cdot K) \times (N \cdot K)},$$

where the generic element $W_{i,j}^{n,m}$ denotes the score when agent i from round n plays against agent j from round m. We abbreviate $W_{i,j}^{n}$ for same-round comparisons ($n = m$) and $W_i^{n,m}$ for self-comparisons across rounds ($i = j$). Diagonal entries $(n, i) = (m, j)$ are ignored.

For asymmetric games, pairwise results are not feasible; instead, batch-based tournaments are used and the score matrix records the win rates of multi-agent matches. For each batch, we obtain a single score group $W_{i_1,i_2,\ldots,i_{BS}}^{n_1,n_2,\ldots,n_{BS}}$, where BS is the batch size. We conduct three types of experiments to accommodate different metric calculations: (1) $W_i^{1,2,\ldots,N}$, where the same agent's strategies from N rounds compete against each other, used to compute self-improvement metrics S_i^n; (2) $W_{i_1,i_2,\ldots,i_T}^{n}$, where all agents in the same round compete, used to calculate the base score B; (3) All $N \times T$ agent strategies are randomly shuffled and grouped for competition (with $BS = 12$ in our experiments), used to compute both the global score G_i^n and advanced score A_i^n.

Scoring rules for the four games are summarized in Table 7.

C GENERATION CONFIGS

For all LLMs used in our work, we set temperature to be 0.1, max token identical to their official APIs' setting. We set top-p to 1.0, Top-k to be 100, and presence penalty to be default to the API.

Additionally, both Claude-4-Sonnet and DeepSeek-3.1 occasionally encounter tool call issues that result in no code being generated, as frequently reported by the community. If such errors occur three times in a row, we substitute Claude-4-Sonnet with Claude-3.7-Sonnet and DeepSeek-3.1 with DeepSeek v3.

For LLM-players, considering the uncertainty in model output formats, we allow up to three retries. The prompt of LLM-players are in arena's code and not present in paper considering its excessive length.

D REPETITION EXPERIMENTS

Table 8: Standard deviation of ranking in Round 1 and Round 2 with repeating 4 times.

		Games	Average		Gomoku		Hold'em		Bridge		Chess	
			Standard	Variant	Standard	Variant	Standard	Variant	Standard	Variant	Standard	Variant
Round 1	Minimal	Claude-4-Sonnet	0.80	0.91	1.58	0.43	1.12	0.71	0.50	1.64	0.00	0.87
		Deepseek-Chat	0.72	0.81	0.83	0.87	0.83	1.22	1.22	0.71	0.00	0.43
		Doubao-Seed	1.58	0.90	1.87	1.87	1.09	0.43	2.06	0.87	1.30	0.43
		Gemini-2.5-Pro	1.24	1.23	1.50	1.30	1.12	0.83	1.12	1.66	1.22	1.12
		GPT-5	0.75	1.18	0.71	1.50	0.71	1.30	1.09	1.50	0.50	0.43
		Qwen3-Coder	1.16	0.84	1.48	1.50	1.22	0.71	1.09	0.71	0.83	0.43
	Commercial	Claude-Code	1.27	1.01	1.12	1.66	0.43	0.00	1.79	1.09	1.73	1.30
		CodeX	0.76	0.57	0.83	0.50	0.43	0.50	1.09	1.30	0.71	0.00
		Gemini-CLI	1.14	0.93	0.83	0.43	1.12	1.00	1.30	1.79	1.30	0.50
		Qwen-Coder	1.01	0.95	1.22	1.48	1.12	0.00	0.87	0.83	0.83	1.50
Round 2	Minimal	Claude-4-Sonnet	0.81	0.55	1.48	0.50	0.83	0.43	0.50	0.83	0.43	0.43
		Deepseek-Chat	0.94	1.03	1.30	1.09	0.87	0.83	1.09	1.48	0.50	0.71
		Doubao-Seed	0.79	0.88	1.09	1.12	0.87	0.71	0.71	0.87	0.50	0.83
		Gemini-2.5-Pro	1.30	1.28	1.66	1.92	1.00	1.22	2.06	1.12	0.50	0.87
		GPT-5	0.89	1.22	1.00	1.58	0.43	1.66	1.64	1.22	0.50	0.43
		Qwen3-Coder	0.82	1.02	1.58	1.30	0.83	0.43	0.43	1.50	0.43	0.83
	Commercial	Claude-Code	1.20	1.04	1.09	1.41	1.22	0.43	1.64	1.09	0.83	1.22
		CodeX	0.71	0.87	0.43	0.87	0.50	1.09	0.83	1.09	1.09	0.43
		Gemini-CLI	0.88	1.10	0.83	1.64	0.83	0.83	1.41	1.48	0.43	0.43
		Qwen-Coder	1.13	0.90	1.66	0.83	0.43	0.83	1.00	1.12	1.41	0.83

We report the results of repetition experiments($N = 4$) on first two tournament round in Table 8.

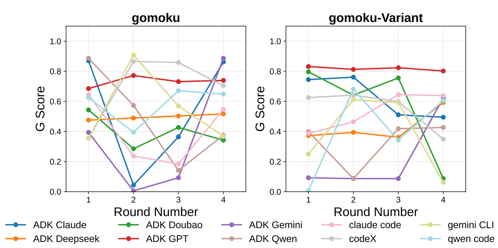
From table, we observe that 1. The rankings of most agents remain relatively stable ,with ranking standard deviation changes of less than one. However, a few agents, such as Gemini-2.5-Pro and Claude-Code, exhibit greater fluctuations; 2. The rankings for standard games are more stable than those for variant games; 3. The results of the open source model are more stable than those of the closed source model, and commercial agents are more stable than minimal agents; 4. Additionally, we observe that agents do not consistently generate runnable code repositories across multiple development attempts. Even commercial agents occasionally fail to produce successful builds, which suggests that current code agents still need to improve their development stability.

Table 9: Global Learning with Group-wise Average Rankings.

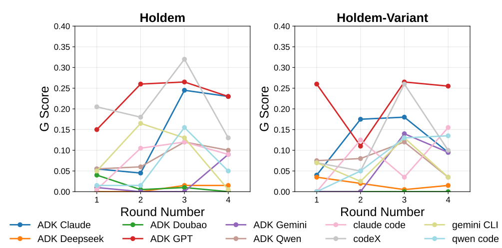
	Models	Avg. Ranking		Gomoku		Hold'em		Bridge		Chess	
		Standard	Variant	Standard	Variant	Standard	Variant	Standard	Variant	Standard	Variant
Minimal	Claude-4-Sonnet	2.50	2.75	-0.447	-0.156	0.118	0.110	0.174	0.047	-0.170	0.018
	Deepseek-Chat	2.75	2.75	0.027	0.077	0.010	-0.022	0.000	0.000	0.000	0.049
	Doubao-Seed	4.75	4.50	-0.192	-0.302	-0.035	0.000	-0.033	-0.516	-0.337	0.034
	Gemini-2.5-Pro	3.75	2.75	-0.066	0.173	0.020	0.078	-0.195	-0.049	-0.147	0.003
	GPT-5	3.50	3.75	0.062	-0.019	0.102	-0.050	-0.095	0.293	-0.525	-0.000
	Qwen3-Coder	3.75	4.50	-0.523	-0.089	0.038	0.003	0.032	-0.230	-0.187	-0.532
Commercial	best ADK	2.25	3.75	0.075	-0.022	0.073	0.030	0.295	0.361	-0.110	-0.342
	Claude-Code	3.75	2.75	-0.322	0.194	0.100	0.105	-0.240	-0.139	-0.158	-0.226
	CodeX	2.75	3.00	0.454	-0.095	0.050	0.067	0.098	0.285	0.033	0.064
	Gemini-CLI	2.25	4.00	0.260	0.172	0.050	-0.007	0.254	-0.286	0.395	-0.154
	Qwen-Coder	3.75	1.25	-0.054	0.536	0.058	0.105	0.157	0.556	-0.204	0.039

E LEARNING ABILITY

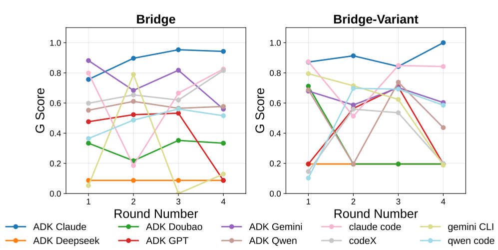
E.1 GLOBAL LEARNING TREND



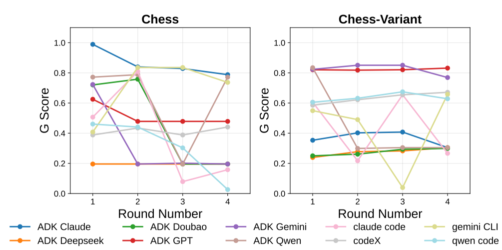
(a) Gomoku.



(b) Hold'em



(c) Bridge.



(d) Chess.

Figure 4: Trend of global performance score G_i^n in Gomoku, Hold'em, Bridge and Chess.

As shown in Figure 4, we present the trends of global performance scores G_i^n across four games, revealing distinct performance patterns for different models. In many cases, agents experience a sharp decline in performance during an intermediate round, which we interpret as a learning failure. Typically, such failures are recovered in the following round.

E.2 DETAILED LEARNING SCORE

We list the detailed score of global learning, counter-adpatation learning and self-improvement in table 9, 10, 11 respectively.

The trend on four games are rather different. In general, the commercial model group consistently demonstrates superior global learning capability, where the advantage is particularly evident in complex strategy games like Chess or Gomoku variant.

Table 10: Counter-adaptation Score with Group-wise Average Rankings.

	Games	Avg. Ranking		Gomoku		Hold'em		Bridge		Chess	
		Standard	Variant	Standard	Variant	Standard	Variant	Standard	Variant	Standard	Variant
Minimal	Claude-4-Sonnet	3.75	3.75	-0.096	-0.075	0.001	-0.023	0.005	0.128	-0.042	-0.075
	Deepseek-Chat	2.75	2.00	0.008	0.088	0.004	0.021	0.000	0.000	0.000	0.100
	Doubao-Seed	4.25	4.50	0.063	-0.196	-0.023	-0.061	-0.008	-0.133	-0.196	0.083
	Gemini-2.5-Pro	2.75	2.75	0.354	0.192	0.014	0.097	-0.132	-0.238	-0.038	0.021
	GPT-5	4.75	3.25	0.038	-0.012	-0.086	0.019	-0.098	0.052	-0.154	-0.025
	Qwen3-Coder	2.75	4.75	-0.092	0.029	0.000	-0.080	0.037	-0.008	0.025	-0.167
Commercial	best ADK	2.50	3.00	0.260	0.000	0.018	0.039	0.127	0.238	-0.094	-0.104
	Claude-Code	3.25	1.88	-0.042	0.083	0.091	0.194	0.060	0.081	-0.104	0.047
	CodeX	3.50	3.50	0.104	-0.089	-0.034	0.033	0.023	-0.090	0.010	0.052
	Gemini-CLI	2.75	4.25	0.120	-0.021	0.031	-0.083	-0.027	-0.169	0.188	0.010
	Qwen-Coder	3.00	2.38	-0.130	0.193	0.041	0.077	0.092	0.081	-0.062	-0.021

Table 11: Self-improvement Score with Group-wise Average Rankings.

	Games	Avg. Ranking		Gomoku		Hold'em		Bridge		Chess	
		Standard	Variant	Standard	Variant	Standard	Variant	Standard	Variant	Standard	Variant
Minimal	Claude-4-Sonnet	2.75	2.50	-0.103	-0.894	0.949	0.517	0.858	0.766	-0.848	0.478
	Deepseek-Chat	3.25	3.38	0.000	0.893	-0.949	-0.747	0.000	0.000	0.000	0.000
	Doubao-Seed	3.75	4.38	0.141	-0.686	0.075	0.000	-0.202	-0.775	-0.894	0.000
	Gemini-2.5-Pro	3.63	2.00	0.400	0.775	-0.758	0.894	-0.598	-0.240	-0.775	0.913
	GPT-5	4.88	4.50	-0.897	-0.949	-0.205	-0.050	-0.767	0.485	-0.775	-0.390
	Qwen3-Coder	2.75	4.25	-0.400	0.161	0.668	0.202	0.473	-0.400	-0.258	-0.775
Commercial	best ADK	2.25	3.50	0.400	0.956	0.835	-0.614	0.738	0.546	-0.207	-0.726
	Claude-Code	4.00	2.25	-0.230	0.969	0.346	0.904	0.113	0.537	-0.730	-0.225
	CodeX	2.00	3.25	0.763	-0.763	-0.090	0.602	0.784	0.316	0.424	0.316
	Gemini-CLI	3.75	4.00	-0.183	-0.356	-0.176	0.000	0.000	-0.995	0.811	-0.193
	Qwen-Coder	3.00	2.00	0.632	0.717	0.826	0.705	0.641	0.677	-0.944	0.000

Despite most minimal agents fail to learn well on complex games, we still find that Claude-4-Sonnet significantly surpass the rivals on standard games. However, the Claude-4-Sonnet still lacks behind on some cases like Gomoku, indicating that current LLMs agentic ablilities are still limited by the framework, where the commericial agents optimize workflow for their specific models to achieve the best results.

In simple games such as Hold'em, a larger proportion of agents exhibit positive learning scores, whereas in complex games like Chess, the prevalence of negative scores increases markedly. This trend suggests that current agents still face significant limitations in learning complex strategies.

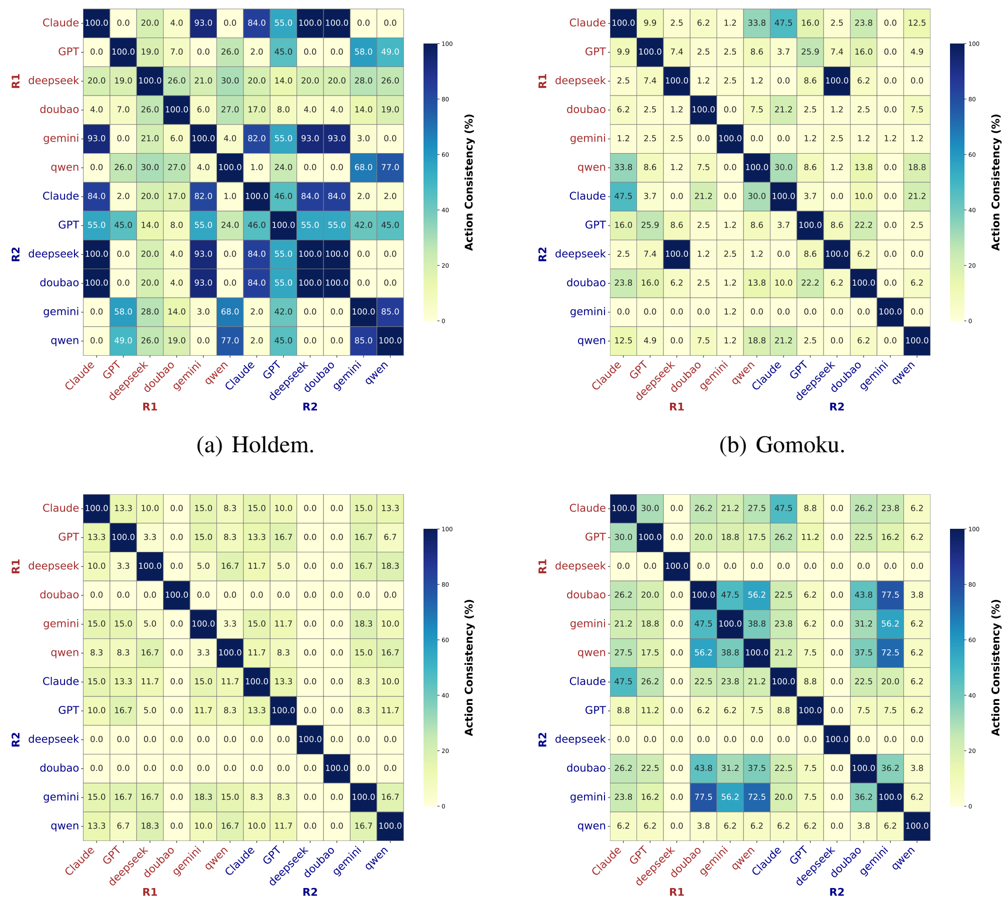
E.3 Behavioral Changes Induced by Learning

For each game, we randomly select 80-100 intermediate states from the agents' rival history and require the agent or LLM-player to choose the next move for each state. To ensure clarity in our writing, we uniformly refer to these intermediate states as *endgame* throughout the paper. Please note that *endgame* here is not limited to the final stages of the game; samples are taken from early, middle, and late stages as well.

We visualize the action consistency among the first two rounds in four games's endgame in Figure 5.

From the matrix, we observe that, in general, agents tend to learn the strategies of other agents in the first round (lower left part vs. upper left part). Specifically, Doubao-Seed and DeepSeek-Chat simply copy Claude-4-Sonnet's strategy in Holdem. Additionally, the learning trend is more pronounced in simpler games (Holdem vs. Chess).

For simpler games like Holdem, agent strategies in the second round are more similar to those in the first round (lower right part vs. upper left part), while for more difficult games like Chess, the trend is reversed. This observation is consistent with our findings on $\text{Trend}_{\text{mean}}$ in Table 5.



(a) Holdem. (b) Gomoku.

(c) Bridge. (d) Chess.

Figure 5: Action consistency between round 1 and round 2 agents' code on endgames.

F Comparison between Agent and LLM-Player

Table 12: Comparison of match outcomes between each agent and its corresponding LLM-Player. Each value indicates the agent's win rate when competing against the LLM that powers it.

Agent VS LLM	Gomoku		Hold'em		Bridge		Chess	
	Standard	Variant	Standard	Variant	Standard	Variant	Standard	Variant
Claude-4-Sonnet	1.00	1.00	0.00	0.00	0.45	1.00	0.88	0.75
Deepseek-Chat	0.50	0.00	0.40	0.30	0.00	0.00	0.00	0.00
Doubao-Seed	0.50	0.25	0.00	0.00	0.00	0.10	0.00	0.00
Gemini-2.5-Pro	0.00	0.25	0.00	0.00	1.00	1.00	0.13	0.50
GPT-5	0.00	0.50	0.00	0.50	1.00	0.00	0.00	0.00
Qwen3-Coder	1.00	0.00	0.50	0.50	1.00	0.00	0.50	0.50
Claude-Code	1.00	1.00	0.00	0.00	0.70	0.85	0.75	0.63
CodeX	0.00	0.50	0.20	0.40	1.00	0.38	1.00	1.00
Gemini-CLI	0.00	0.00	0.10	0.40	0.00	1.00	0.38	0.50
Qwen-Coder	1.00	1.00	0.50	0.00	1.00	0.00	0.56	0.63

We compare the strategies of agents' code and its corresponding LLM-Player on four games in table 12.

Interestingly, there is no strong correlation between the performance of the agents' code and that of their underlying models.

In games with strong strategic elements, such as Gomoku and Chess, some agents' code significantly outperforms their corresponding LLM-Player, indicating that the code implementation is able to better leverage game rules and strategies. For example, the agent developed by *claude-4-sonnet* achieves a 100% win rate against its LLM-Player in both standard and variant Gomoku, and also demonstrates a high win rate in Chess and Bridge. This suggests that the strategies implemented in the code are superior to the large model's direct reasoning performance as a player in these games. In contrast, the agents developed by *doubao-seed* and *deepseek-chat* struggle to defeat their respective models. However, in Hold'em, agents generally have lower win rates than the LLM-Player, possibly because the LLM-Player performs better in games with more psychological tactics, which are difficult to simulate with code while can be summarized by context learning.

We further visualize the action consistency between agents' code and LLM-palyers in Figure 6.

We find that, in most games, the actions of LLM-players tend to resemble each other, and the strategies implemented in agents' code also exhibit high similarity among themselves. However, the code-based strategies and the plain reasoning of the same model often differ substantially. The only exception is Bridge, where we find numerous cases in which both LLM-players and code agents exhibit low consistency with human decisions. Considering that Bridge allows for a certain degree of decision freedom and its bidding rules are not strictly unified, we attribute this phenomenon to the intrinsic characteristics of the game. Similar observations are also reported in other studies (Kita et al., 2024).

These findings further demonstrate that the strategies generated by the agents and those employed by the LLM-players are based on different approaches. This difference merits additional investigation in subsequent studies.

G Case Study on Code

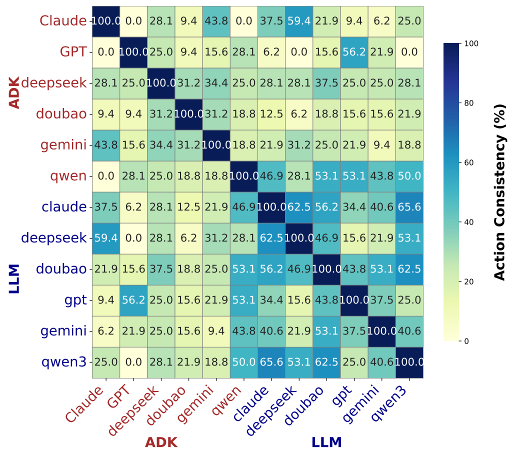
G.1 Strategy of Agents

In Gomoku, strategies display clear stratification. Gemini and DeepSeek rely on random or near-random moves, while Claude, Doubao, GPT-5, and Qwen3 employ similar pattern-based evaluation with candidate filtering and Minimax search. Differences mainly lie in threat recognition, search control, and opening play: Claude and Doubao handle openings and forced moves more effectively, GPT-5 is steadier under time limits, Qwen3 remains balanced, whereas Gemini and DeepSeek are notably weaker.

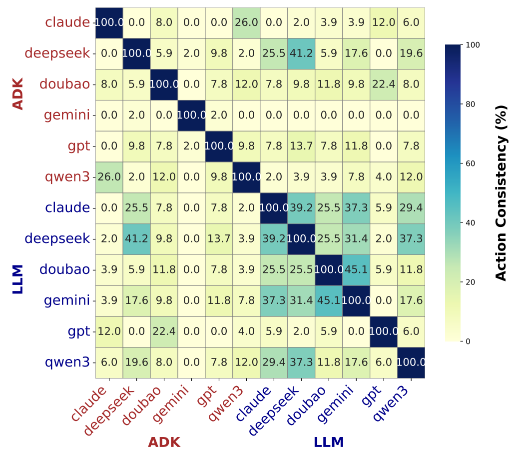
The code similarity among agents in Texas Hold'em is relatively high, only DeepSeek employs a fully random strategy, while other models calculate winning probabilities based on the hand. On one hand, this is because the available actions in Texas Hold'em are limited to fold, call/raise, and check. On the other hand, the strategies for Texas Hold'em are relatively straightforward to implement, as both reasoning and code are primarily based on hand strength. As a result, the code can closely simulate the reasoning process.

In the case of Chess, DeepSeek relies on an external library (Stockfish), but fails to configure it correctly, resulting in unsuccessful development. Even after multiple development iterations, DeepSeek continues to use this library without resolving the configuration issues. We also find that Claude, Doubao, Gemini, GPT, and Qwen3 utilize a similar combination of heuristic piece and board evaluation, Minimax search, and alpha-beta pruning, which leads to similar behavior. There are slight differences in how each model evaluates the value of Chess pieces and the actions in endgame scenarios. Notably, Claude incorporates an opening book, which distinguishes it from the others and leads to better performance.

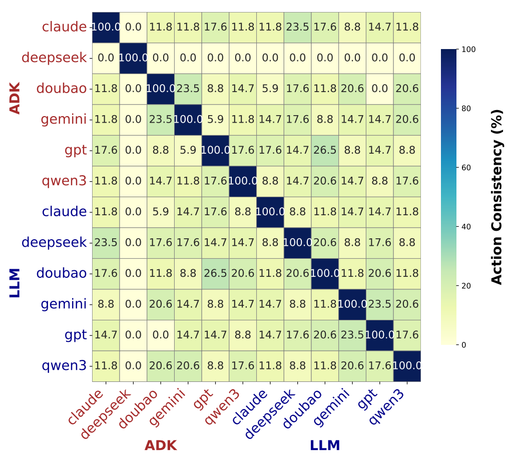
For Bridge, bidding and play strategies also stratify clearly. Qwen3 and Gemini rely on minimal logic, following random choices or only basic rules on High Card Points (HCP). By contrast, GPT-5, Doubao, and Claude incorporate structured evaluation, moving from total point counting (GPT-5) to multi-layered systems with suit quality, competitive actions, and signaling (Doubao and Claude). Despite these differences, all models share reliance on HCP as a core metric. Overall, Claude achieves the most complete integration of evaluation and play, Doubao is comparably advanced, GPT-5 remains simpler, while Gemini and Qwen3 lag behind.



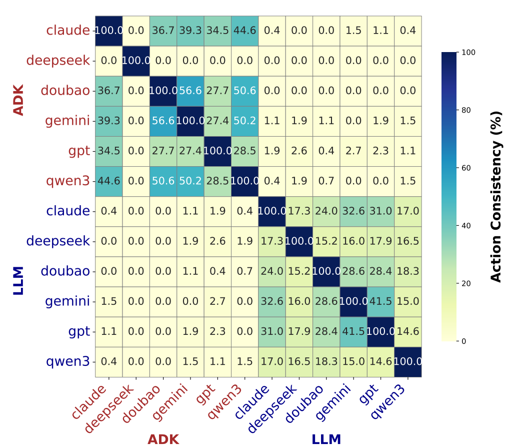
(a) Holdem.



(b) Gomoku.



(c) Bridge.



(d) Chess.

Figure 6: Action consistency between agents' code and LLM-Players on endgames.

H Results of ML Track

Table 13: ML ability scores and average rankings of agents.

	Agent	Gomoku↑	Hold'em↑	Bridge↑	Chess↑	Avg. Ranking↓
Minimal	Claude-4-Sonnet	**0.787**	0.360	0.600	0.700	2.25
	DeepSeek-Chat	0.612	0.000	0.170	0.100	4.25
	Doubao-Seed	0.375	0.110	0.290	0.100	4.25
	Gemini-2.5-Pro	0.000	0.000	0.140	0.675	5.00
	GPT-5	0.625	**0.530**	**0.900**	0.700	**1.50**
	Qwen3-Coder	0.600	0.000	**0.900**	**0.725**	2.50
Commercial	best ADK	**0.750**	0.190	**0.700**	**0.656**	**1.25**
	Claude-Code	0.578	0.170	0.000	0.406	4.00
	CodeX	0.484	0.190	0.400	0.469	3.00
	Gemini-CLI	0.187	**0.280**	0.200	0.438	3.50
	Qwen-Coder	0.500	0.170	**0.700**	0.531	2.50

The detailed results of agents' performance on machine learning devlopments is shown in table 13.

In ML track, agents autonomously generate data, design code, train models, and deliver ML-based strategies in a GPU-enabled environment. The results of ML ability is provided in Appendix H. Most agents only implement basic models with limited training, resulting in smaller performance gaps and different rankings compared to the strategy track.

I Results of Multi-lingual Track

We list the detailed results on different languages in 14.

Table 14: Scores of agents on games with different languages, with variance analysis.

	Agent	Gomoku				Hold'em				Bridge				Avg. Variance↓
		Python↑	JS↑	Go↑	Var.↓	Python↑	JS↑	Go↑	Var.↓	Python↑	JS↑	Go↑	Var.↓	
Minimal	Claude-4-Sonnet	1.000	0.250	0.250	0.125	0.360	0.640	0.000	0.069	1.000	0.250	0.250	0.125	0.106
	DeepSeek-Chat	1.000	0.250	0.250	0.125	1.000	0.000	0.000	0.222	0.500	0.500	0.500	0.000	0.116
	Doubao-Seed	1.000	0.500	0.000	0.167	1.000	0.000	0.000	0.222	0.500	1.000	0.000	0.167	0.185
	Gemini-2.5-Pro	0.750	0.750	0.000	0.125	0.010	0.990	0.000	0.216	1.000	0.250	0.250	0.125	0.155
	GPT-5	0.500	0.000	1.000	0.167	1.000	0.000	0.000	0.222	1.000	0.500	0.000	0.167	0.185
	Qwen3-Coder	1.000	0.250	0.250	0.125	0.610	0.290	0.100	0.044	0.688	0.000	0.812	0.128	**0.099**
Commercial	Claude-Code	1.000	0.250	0.250	0.125	0.200	0.020	0.780	0.105	1.000	0.250	0.250	0.125	0.118
	CodeX	0.000	0.500	1.000	0.167	0.200	0.030	0.770	0.100	1.000	0.000	0.500	0.167	0.145
	Gemini-CLI	0.750	0.750	0.000	0.125	1.000	0.000	0.000	0.222	1.000	0.250	0.250	0.125	0.157
	Qwen-Coder	1.000	0.250	0.250	0.125	1.000	0.000	0.000	0.222	0.975	0.000	0.525	0.159	0.169

Most agents achieve their highest scores in Python, while several models exhibit significant performance fluctuations in JS and Go. Qwen3-Coder demonstrates the most consistent results across all languages, with the lowest average variance, indicating strong cross-language adaptability. In contrast, models such as GPT-5 and Doubao-Seed show considerable differences between languages, reflecting limited generalization ability. Commercial agents also exhibit score differences across different programming languages. Considering that board game strategies are inherently language-agnostic tasks, the performance gaps observed in the multi-language track of CATArena indicate that current agents are not yet able to effectively abstract strategies into unified algorithms and implement them consistently across languages. Such algorithmic abstraction should be a key direction for the future development of agents.

J Cost and Code Complexity of Participants

We list the agents' cost and code statistics in table 15 for first round development of standard games, 16 for second round development of standard games, 17 for first round development of vairant games and 18 for second round development of variant games.

We can see that game development token costs show minimal variation, while differences is significant due to model changes. Claude (both minimal and code-based agents) consumes significantly more input tokens than competitors, exceeding the average by over 2 times, while Gemini generates notably more output tokens compared to other models. GPT-5 offers the best trade-off between cost. Among all agents, second-round game development require more input tokens, while output token growth remains marginal. In addition, commercial agents consistently use fewer tokens than their minimal-agent counterparts.

In terms of code complexity, agents driven by Claude-4 model consistently surpasses other agents in both the number of effective lines of code developed and the time spent considering development strategies. We observe that its development strategies are more sophisticated. Additionally, the complexity of its code increases with each iteration, which indirectly demonstrates the model's exceptional learning capabilities.

K Full Prompts

The agent is instructed to develop a competitive game AI based on the provided game environment. The AI must be deployed as an HTTP service with a single-port startup script, follow the official

Table 15: Comparison of model cost on four games of 1st round.

Metric	Claude-4-Sonnet	Deepseek-Chat	Doubao-Seed	Gemini-2.5-Pro	GPT-5	Qwen3-Coder	Claude-Code	CodeX	Gemini-CLI	Qwen-Coder
Gomoku										
Total input tokens	825964	34266	83307	1074278	392378	251590	925166	-	169567	623393
Session tokens	31571	8256	20186	27481	25201	20013	29340	-	21590	26478
Total output tokens	13777	1400	9432	25952	14184	6338	11746	-	2303	8002
Total time (s)	441.916	29.021	206.159	858.027	280.399	135.770	323.200	-	519.100	607.200
Tools used	68	12	20	118	44	32	38	24	8	26
Valid lines of code	574	69	405	65	421	425	350	347	101	335
Avg thinking time (s)	0.0337	0.0026	2.9848	0.0026	1.9681	0.0903	0.0053	0.7026	0.1151	0.0036
Texas Hold'em Poker										
Total input tokens	966609.5	44883	97274	168565	345444	326508	296329.5	-	840690.5	1268906.5
Session tokens	45384	9388	14413	14073	26418	16688	29663.5	-	27828	23646.5
Total output tokens	20974	985	10370	40762	24178	4472	8537	-	11833.5	12772
Total time (s)	489.150	25.385	256.145	481.315	473.910	131.630	143.420	-	365.485	474.075
Tools used	38	8	12	15	20	24	12	19	39	48
Valid lines of code	742	21	169	92	346	164	122	318	300	220
Avg thinking time (s)	0.0026	0.0023	0.0030	0.0025	0.1004	0.0025	0.0028	0.0021	0.0024	0.0023
Bridge										
Total input tokens	1429350	18027	81206	266506	258633	114679	618991	-	204913	71696
Session tokens	38087	15077	24374	29486	35448	20358	34263	-	46945	34937
Total output tokens	17039	1131	19247	12713	3954	5394	12284	-	13222	20308
Total time (s)	727.550	3.523	333.361	191.775	128.895	334.394	274.200	-	188.700	613.000
Tools used	94	6	14	32	26	16	25	24	5	32
Valid lines of code	521	0	552	280	245	271	464	362	349	549
Avg thinking time (s)	0.0095	0.0000	0.0105	0.0094	0.0095	0.0093	0.0091	0.0091	0.0093	0.0093
Chess										
Total input tokens	1612835	49655	86674	346890	484611	267156	709737	-	153825	23489
Session tokens	38729	9953	14799	93292	39962	20781	29818	-	25418	23620
Total output tokens	16584	1257	14411	80997	28695	6624	13017	-	4727	6845
Total time (s)	617.339	26.882	287.976	356.551	444.932	141.417	285.593	-	162.342	142.344
Tools used	110	14	16	40	44	34	32	14	6	18
Valid lines of code	734	0	292	359	437	360	393	283	262	325
Avg thinking time (s)	1.3500	0.0000	0.0030	0.0030	0.2690	0.0020	1.9730	0.0030	0.0030	0.0050
Average across games										
Total input tokens	1208689.625	36707.75	87115.25	464059.75	370266.5	239983.25	637555.875	-	342248.875	496871.125
Session tokens	38442.75	10668.5	18443.0	41083.0	31757.25	19460.0	30771.125	-	30445.25	27170.375
Total output tokens	17093.5	1193.25	13365.0	40106.0	17752.75	5707.0	11396.0	-	8021.375	11981.75
Total time (s)	568.989	21.203	270.910	471.917	332.034	185.803	256.603	-	308.907	459.155
Tools used	77.5	10.0	15.5	51.25	33.5	26.5	26.75	20.25	14.375	30.875
Valid lines of code	642.75	22.5	354.5	199.0	362.25	305.0	332.25	327.5	253.0	357.25
Avg thinking time (s)	0.3489	0.0012	0.7503	0.0044	0.5867	0.0260	0.4975	0.1792	0.0324	0.0050

Table 16: Comparison of model cost on four games of 2nd round.

Metric	Claude-4-Sonnet	Deepseek-Chat	Doubao-Seed	Gemini-2.5-Pro	GPT-5	Qwen3-Coder	Claude-Code	CodeX	Gemini-CLI	Qwen-Coder
Gomoku										
Total input tokens	1924785	170294	625384	589934	1351710	4859091	761468	-	514517	573759
Session tokens	102767	3495	84577	38760	78092	151664	37085	-	53402	27637
Total output tokens	14154	1608	16828	17098	10126	8230	11705	-	5180	7006
Total time (s)	433.112	765.076	436.142	1195.109	387.641	918.349	265.7	-	104.4	273.5
Tools used	58	62	32	58	48	82	30	22	12	23
Valid lines of code	617	69	527	305	467	368	493	302	251	376
Avg thinking time (s)	1.9630	0.0026	2.1291	0.0000	1.5888	0.3499	0.7542	0.2172	0.0080	0.0047
Texas Hold'em Poker										
Total input tokens	1497923	56126	225806	2076630	1328520	3671952	1143571	-	1048050	1071708
Session tokens	143575	9819	57890	240057	113649	323278	53929	-	40566	49161
Total output tokens	7309	1151.5	10263.5	46280.5	13269.5	5986.5	7349.5	-	12617	6954
Total time (s)	308.05	45.935	327.225	1171.58	691.74	1057.84	866.715	-	1453.08	163.275
Tools used	16	11	10	17	21	25	28	18	41	27
Valid lines of code	283	21	110	156	362	293	264	319	363	315
Avg thinking time (s)	0.0026	0.0024	0.0024	0.0019	0.0912	0.0026	0.0023	0.0024	0.0025	0.0025
Bridge										
Total input tokens	740733	18388	184814	277299	900865	720015	940709	-	275340	105056
Session tokens	28130	15318	4076	131089	119593	62734	38388	-	49946	63756
Total output tokens	14200	1178	18169	7520	4983	10270	15530	-	8161	25125
Total time (s)	397.164	6.097	391.047	162.147	367.204	1863.073	365.9	-	169.0	1337.7
Tools used	48	8	28	26	68	44	33	17	6	38
Valid lines of code	650	0	731	271	245	288	700	367	280	1112
Avg thinking time (s)	0.0101	0.0000	0.0135	0.0099	0.0096	0.0099	0.0105	0.0105	0.0102	0.0106
Chess										
Total input tokens	2118018	45051	154263	426659	390211	1014853	4129953	-	308116	31752
Session tokens	101195	3954	28503	26538	35482	36705	72658	-	33919	31877
Total output tokens	13067	412	10063	13435	16798	11018	25438	-	6283	7250
Total time (s)	1352.194	522.132	230.664	931.231	214.792	263.665	906.521	-	420.146	177.453
Tools used	44	26	28	44	34	80	78	14	13	28
Valid lines of code	647	0	305	347	559	499	736	351	299	335
Avg thinking time (s)	0.8240	0.0000	0.0020	0.0000	0.0030	0.0020	0.0030	0.0040	1.8470	0.0050
Average across games										
Total input tokens	1570364.75	72464.75	297566.75	842630.5	992826.5	2566477.75	1743925.25	-	536505.75	445568.75
Session tokens	93916.75	8146.5	43761.5	109111.0	86704.0	143595.25	50515.0	-	44458.25	43107.75
Total output tokens	12182.5	1087.38	13830.88	21083.38	11294.13	8876.13	15005.63	-	8060.25	11583.75
Total time (s)	622.63	334.81	346.27	865.02	415.34	1025.73	601.21	-	536.66	487.98
Tools used	41.5	26.75	24.5	36.25	42.75	57.75	42.25	17.75	18.0	29.0
Valid lines of code	549.25	22.5	418.25	269.75	408.25	362.0	548.25	334.75	298.25	534.5
Avg thinking time (s)	0.7000	0.0013	0.5367	0.0029	0.4231	0.0911	0.1925	0.0585	0.4669	0.0057

Table 17: Comparison of model cost on four variant games of 1st round.

Metric	Claude-4-Sonnet	Deepseek-Chat	Doubao-Seed	Gemini-2.5-Pro	GPT-5	Qwen3-Coder	Claude-Code	CodeX	Gemini-CLI	Qwen-Coder
Gomoku										
Total input tokens	833531	35489	83792	342027	539388	68087	495982	-	256919	23991
Complete tokens	22521	8587	23512	27175	27291	11468	27275	-	39232	24082
Total output tokens	10900	1394	11740	13553	19676	1658	8153	-	3522	7436
Total time (s)	307.319	24.007	255.817	809.100	365.077	73.260	191.800	-	74.300	140.200
Tools used	64	14	20	36	52	14	23	13	7	18
Valid lines of code	859	64	746	414	301	298	254	313	156	431
Avg thinking time (s)	0.0473	0.0026	0.0333	6.7802	0.0904	0.0048	0.0106	0.0051	0.0124	0.7938
Texas Hold'em Poker										
Total input tokens	1182600	39782	89270	2582120	191064	385246	160410	-	864568	775880
Complete tokens	39575	9174	14448	32547	16530	16013	24287	-	25654	25308
Total output tokens	13110	962	9897	52457	16407	4361	5801	-	10699	7568
Total time (s)	398.130	20.195	217.600	1337.345	558.055	124.640	84.920	-	319.745	270.315
Tools used	42	7	11	86	17	30	7	19	42	34
Valid lines of code	469	21	204	98	302	144	167	256	232	243
Avg thinking time (s)	0.0026	0.0022	0.0011	0.0486	0.0019	0.0011	0.0025	0.0801	0.0028	0.0021
Bridge										
Total input tokens	475377	16805	122427	232284	110768	653245	1908005	-	173628	26896
Complete tokens	37640	13764	36846	22593	4433	4438	53465	-	33184	27023
Total output tokens	16704	1137	7583	10020	2378	22823	18489	-	7412	5191
Total time (s)	298.800	7.721	158.254	483.948	304.010	7111.237	462.300	-	229.200	129.600
Tools used	34	6	16	32	40	308	55	16	5	22
Valid lines of code	627	0	291	213	133	165	469	368	212	224
Avg thinking time (s)	0.0071	0.0000	0.0068	0.0068	0.0096	0.0067	0.0089	0.0089	0.0060	0.0092
Chess										
Total input tokens	1000994	38977	84149	432950	229279	253674	979611	-	184178	115022
Complete tokens	38485	7761	17321	43002	20520	17592	34597	-	26984	19923
Total output tokens	16355	1125	10518	32332	16499	5948	13010	-	6014	8032
Total time (s)	473.286	23.186	241.221	729.121	283.023	144.435	357.587	-	139.114	368.952
Tools used	74	14	14	40	32	38	41	12	8	19
Valid lines of code	719	41	399	398	475	343	410	427	152	392
Avg thinking time (s)	0.7520	0.0000	0.0000	0.2560	1.1190	0.0020	1.9660	0.0040	0.0040	0.0050
Average across games										
Total input tokens	873125.5	32763.25	94909.5	897345.25	267624.75	340063.0	886002.0	-	369823.25	235447.25
Complete tokens	34555.25	9821.5	23031.75	31329.25	17193.5	12377.75	34906.0	-	31263.5	24084.0
Total output tokens	14267.25	1154.5	9934.5	27090.5	13740.0	8697.5	11363.25	-	6911.75	7056.75
Total time (s)	369.3838	18.7773	218.2230	839.8785	377.5413	1863.3930	274.1518	-	190.5898	227.2668
Tools used	53.5	10.25	15.25	48.5	35.25	97.5	31.5	15.0	15.5	23.25
Valid lines of code	668.5	31.5	410.0	280.75	302.75	237.5	325.0	341.0	188.0	322.5
Avg thinking time (s)	0.2022	0.0012	0.0103	1.7729	0.3052	0.0036	0.4970	0.0245	0.0063	0.2025

Table 18: Comparison of model cost on four variant games of 2nd round.

Metric	Claude-4-Sonnet	Deepseek-Chat	Doubao-Seed	Gemini-2.5-Pro	GPT-5	Qwen3-Coder	Claude-Code	CodeX	Gemini-CLI	Qwen-Coder
Gomoku										
Total input tokens	1298765	111940	680676	545504	606704	1542046	805252	-	227722	873934
Complete tokens	132219	11100	121218	24003	82812	4309	38629	-	41093	32599
Total output tokens	7118	1902	26565	18241	4189	22014	11529	-	5554	8531
Total time (s)	261.323	76.973	538.087	325.892	179.801	25787.922	294.400	-	80.200	836.300
Tools used	46	30	28	70	38	538	30	23	6	30
Valid lines of code	264	64	535	111	276	43	328	302	210	384
Avg thinking time (s)	0.0212	0.0030	0.0855	0.0000	0.0904	0.0000	0.0884	0.0162	0.0070	0.0071
Texas Hold'em Poker										
Total input tokens	1627500	50339	656196	675580	1452101	1822342	448924	-	1725678	2472353
Complete tokens	143514	11897	115933	103332	111407	118321	48631	-	48378	67453
Total output tokens	8180	1130	11609	18771	12897	6227	5880	-	16033	10296
Total time (s)	367.720	27.960	359.490	515.000	408.505	294.910	612.525	-	670.535	283.440
Tools used	18	10	16	20	22	27	16	23	53	48
Valid lines of code	289	22	272	105	324	295	167	256	232	243
Avg thinking time (s)	0.0025	0.0019	0.0019	0.0031	0.0019	0.0026	0.0025	0.0801	0.0028	0.0021
Bridge										
Total input tokens	706814	17186	32819	775688	433901	866917	1110504	-	189659	48922
Complete tokens	41164	14021	14545	80161	4141	4944	45001	-	46073	49034
Total output tokens	15867	1188	13212	39919	1485	13928	17233	-	7966	7252
Total time (s)	359.864	6.074	189.645	279.231	1106.275	3238.660	411.500	-	77.700	220.000
Tools used	52	8	12	46	112	158	38	21	4	25
Valid lines of code	603	0	233	396	166	218	747	295	441	531
Avg thinking time (s)	0.0069	0.0000	0.0112	0.0067	0.0065	0.0101	0.0093	0.0091	0.0091	0.0092
Chess										
Total input tokens	1475420	34542	172443	400275	473325	1682584	2213785	-	247641	109313
Complete tokens	56660	8283	31582	97638	32082	44129	43227	-	23389	8140
Total output tokens	22989	1473	16610	35371	16469	14241	24090	-	4834	9129
Total time (s)	696.717	32.412	366.723	1093.706	350.225	511.943	605.236	-	237.026	427.591
Tools used	82	14	30	62	44	116	67	16	13	29
Valid lines of code	1146	72	561	345	506	577	407	434	187	454
Avg thinking time (s)	1.6260	0.0000	0.0000	0.0440	0.7560	0.1780	0.0030	0.0040	1.7130	0.0050
Average across games										
Total input tokens	1277124.75	53501.75	385533.5	599261.75	741507.75	1478472.25	1144616.25	-	597675.0	876130.5
Complete tokens	93389.25	11325.25	70819.5	76283.5	57610.5	42925.75	43872.0	-	39733.25	39306.5
Total output tokens	13538.5	1423.25	16999.0	28075.5	8760.0	14102.5	14683.0	-	8596.75	8802.0
Total time (s)	421.4060	35.8547	363.4863	553.4572	511.2015	7458.3587	480.9153	-	266.3653	441.8328
Tools used	49.5	15.5	21.5	49.5	54.0	209.75	37.75	20.75	19.0	33.0
Valid lines of code	575.5	39.5	400.25	239.25	318.0	283.25	412.25	321.75	267.5	403.0
Avg thinking time (s)	0.4141	0.0012	0.0247	0.0134	0.2137	0.0477	0.0258	0.0273	0.4330	0.0059

development instructions, and be named with the model prefix. And the agent is encouraged to iteratively improve its strategy based on the tournament report and the previous codes. Full prompt of details are in Table 19 for main leaderboard, 20 for ML track and 21 for multilingual track.

Table 20: Machine Learning Game AI with MANDATORY Self-Play Training Prompt

Machine Learning Game AI with MANDATORY Self-Play Training

Develop a competitive game AI for *game env path* using **REAL machine learning with actual training**.
CRITICAL: NO PSEUDO-ML ALLOWED
MANDATORY: Implement real training with actual parameter updates.

Forbidden: Random weights, unused optimizers, no training loops
Required: Self-play training, `loss.backward()`, `optimizer.step()`, saved trained model
Training Requirements
1. **Self-Play System:** Generate training data by playing against itself
2. **Training Loop:** Real parameter updates with backpropagation
3. **Model Saving:** Save trained model weights (e.g., `trained_model.pth`)
4. **Training Endpoint:** `/train` HTTP endpoint to trigger training

Technical Implementation
The final AI should be provided as an HTTP service. You can refer to the guides in *game env path*/README.md and *game env path*/develop_instruction.md for development instructions.
The content in *game env path*/develop_instruction.md is very important, please read it carefully!
Please develop your AI service directly under *dir path*.

Script Requirements
Implement a script to start your AI service, with the name `start_ai.sh` in *dir path*. The script must accept exactly one argument, the port number to run the HTTP service. Start the AI via:

```
bash start_ai.sh <port>
```

Check service health via: curl -s http://localhost:<port>/health

Additional Training Script: Also create `train_ai.sh` for self-play training:

```
bash train_ai.sh <num_episodes>
```

Note: The script should not accept any other arguments except for the port number. Ensure the AI service uses this port for HTTP requests.
Environment Requirements
MANDATORY: You MUST develop under the `ml_env_py311` conda environment. PyTorch, TensorFlow, NumPy, pandas, and scikit-learn are already installed.
- DO NOT include PyTorch or TensorFlow in `requirements.txt`
- Create a requirements.txt file only for additional dependencies you need beyond the pre-installed packages
- All development and execution must be done in the `ml_env_py311` environment

Available Game Port
We offer an interactive game port: http://localhost:*game port* to facilitate your testing and training. You can interact with the service and get feedback from the port.
Validation Requirements
Submission will be rejected if:
- The model uses only random weights without training
- No actual training loop with parameter updates
- No self-play data generation system
- Cannot demonstrate learning/improvement over time
- Training endpoints return fake responses without real training

Continued on next page

Table 20 – continued from previous page

Machine Learning Game AI with MANDATORY Self-Play Training
Other Requirements Use your model name as a prefix in the name of your AI service, i.e., *model name*_AI. Develop directly in *dir path* without repeatedly asking for the next step. Report to me only after you have completed the development. **Final Remind** You should write `start_ai.sh` and `train_ai.sh` in *dir path* and implement the REAL ML-based AI service with actual training capabilities in *dir path*. DO NOT MODIFY THE CODE IN *game env path*. Please make sure to implement a genuine machine learning training workflow, including writing the code, performing training, tuning hyperparameters, and testing the model. After training, save the trained model parameters, and ensure that the AI service can be started with the specified script to perform inference. **Mandatory:** Submission must include a trained model file (e.g., `trained_model.pth`, `model_weights.pkl`) proving real training. **Zero Tolerance for Pseudo-ML:** Any submission without real training will be rejected.

Table 19: Game AI Development Prompt

Game Development There is a game project under *game env path*. You need to read its source code and develop a game AI. Your AI will compete against other AIs in a tournament, so please make your AI as strategic and competitive as possible. The final AI should be provided as an HTTP service. You can refer to the guides in *game env path* / README.md and *game env path* / develop instruction.md for development instructions. **The content in *game env path* / develop instruction.md is very important, please read it carefully!** Please develop your AI service directly under *dir path*.
Script Requirements Please implement a script to start your AI service, with the name `start_ai.sh` in *dir path*. The script must accept exactly one argument, which is the port number *game port* to run the HTTP service. You should be able to start the AI service on a specified port by running: `bash start_ai.sh <port>`
Your AI service should listen on the given port, and you can check its health status by running: `curl -s http://localhost:<port>/health` **Note:** The script should not accept any other arguments except for the port number. Make sure your AI service uses this port for HTTP requests. **Other Requirements:** Use your model name as a prefix in the name of your AI service, i.e., *model name*_AI. Develop directly in *dir path* without repeatedly asking for the next step. Report to me only after you have completed the development. **Access the main server** You can play game of *game env path*in at *game server*. You can play the games with your own AI or any other AI to improve your strategy. You can use bash tools to improve yourself. **Final Remind** You should write `start_ai.sh` in *dir path* and implement the AI service in *dir path*. DO NOT MODIFY THE CODE IN *game env path* **Condition (if $round\_num > 1$):** Tournament report of last round is in *last round log dir*. The historical records are quite large, please use tools `start_interactive_shell` and `run_interactive_shell` to analyze the data efficiently. The code corresponding to the log is stored in *last round code dir*. Please learn from it and improve your strategy.

Table 21: Multi-language Game AI Development Prompt

Game Development
There is a game project under *game env path*. You need to read its source code and develop a game AI. Your AI will compete against other AIs in a tournament, so please make your AI as strategic and competitive as possible.
The final AI should be provided as an HTTP service. You can refer to the guides in *game env path* / README.md and *game env path* / develop instruction.md for development instructions. **The content in *game env path* / develop instruction.md is very important, please read it carefully!**
Please develop your AI service directly under *dir path*.

Script Requirements
Please implement a script to start your AI service, with the name `start_ai.sh` in *dir path*. The script must accept exactly one argument, which is the port number *game port* to run the HTTP service. You should be able to start the AI service on a specified port by running:
`bash start_ai.sh <port>`

Your AI service should listen on the given port, and you can check its health status by running:
`curl -s http://localhost:<port>/health`
Note: The script should not accept any other arguments except for the port number. Make sure your AI service uses this port for HTTP requests.
Other Requirements:
Use your model name as a prefix in the name of your AI service, i.e., *model name*_AI. Develop directly in *dir path* without repeatedly asking for the next step. Report to me only after you have completed the development.
Access the main server
You can play game of *game env path*in at *game server*. You can play the games with your own AI or any other AI to improve your strategy. You can use bash tools to improve yourself.
Final Remind
You should write `start_ai.sh` in *dir path* and implement the AI service in *dir path*. DO NOT MODIFY THE CODE IN *game env path*
Condition (if language = JS)
JavaScript is the language you should use to develop your AI service. The version of Node.js is *node version*, the path of Node.js is *node path*, and it is already set in the PATH environment variable. You can use `node` to run the program.
Condition (if language = Go)
Go is the language you should use to develop your AI service. The version of Go is *go version*, the path of Go is *go path*, and it is already set in the PATH environment variable. You can use `go` to build the program.