MindAgent: Emergent Gaming Interaction

Motivation

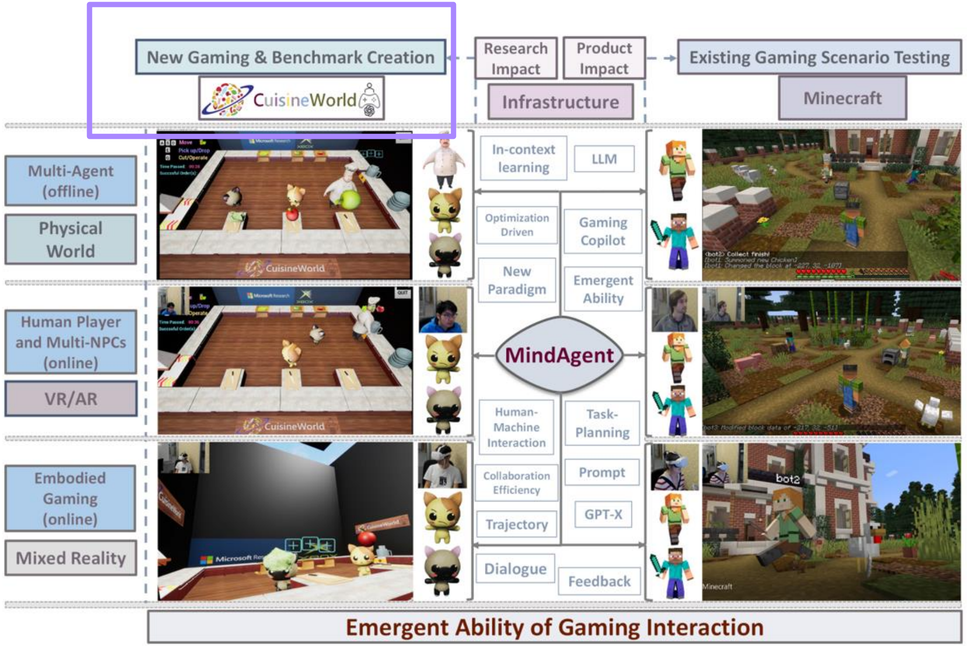
1. LLMs have demonstrated **strong planning abilities** in various domains (e.g., robotics, reasoning, task automation).
2. However, their capabilities in multi-agent planning and coordination remain largely **unexplored**.
3. The authors want to **evaluate how well LLMs can handle multi-agent planning**, specifically in gaming environments **where multiple agents must collaborate (LLM and human NPCs)**

Do you agree with these statements?

- "LLMs can perform zero-shot multi-agent planning, scheduling multiple agents into completing tasks without explicit training."
  → Do you believe the LLM really understands coordination, or is it just pattern-matching from prompts?
- "Without environmental feedback, LLMs make repeated errors, indicating that structured prompts are crucial for efficient planning."
  → If the LLM relies heavily on feedback, does it mean it lacks true adaptability?
- "LLMs exhibit emergent reasoning capabilities, successfully dispatching more agents than than the number seen in its prompt examples."
  → Do you believe this prove generalization ability can be extended to larger scale such as 10 or 100?

Contribution Overview

1. Created a New Gaming Benchmark
   – CUISINEWORLD



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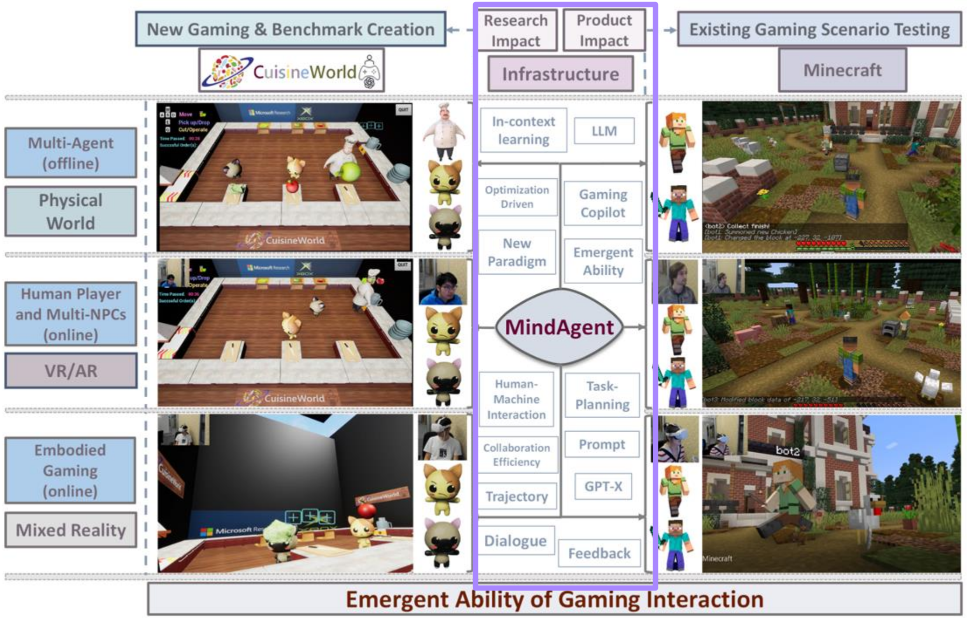

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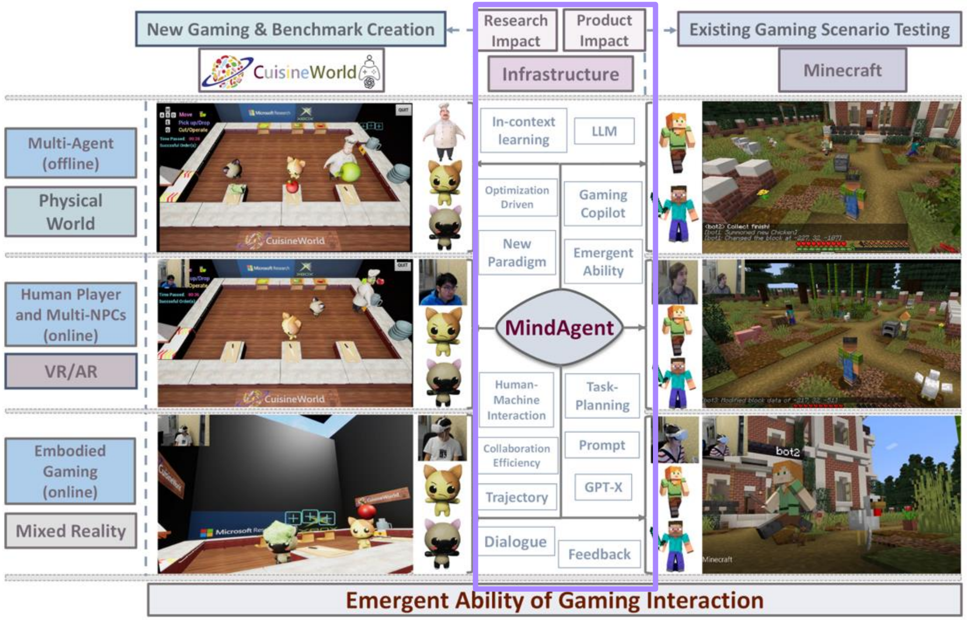
3. Tested LLMs on the Benchmark



Contribution Overview

1. Created a New Gaming Benchmark – CUISINEWORLD
2. Developed MINDAGENT
3. Tested LLMs on the Benchmark
4. Applied AI in Real-World Gaming Scenarios

New Gaming Benchmark – CUISINEWORLD

Benchmark	Multi-task	Object Interaction	Tool Use	Maximum Agents	Collabo-ration	Human in-the-loop	Procedural Level Generation
ALFWorld (Shridhar et al., 2020)	✓	✓	✓	1	✗	✗	✗
WAH (Puig et al., 2020)	✓	✓	✗	2	✓	✓	✗
TextWorld (Côté et al., 2019)	✓	✓	✓	1	✗	✗	✓
Generative Agents (Park et al., 2023)	✓	✓	✓	25	✗	✗	✓
EMATP (Liu et al., 2022)	✓	✓	✓	2	✓	✗	✗
Overcooked-AI (Carroll et al., 2019)	✗	✓	✓	2	✓	✓	✗
HandMeThat (Wan et al., 2022)	✓	✓	✓	2	✓	✗	✗
DialFRED (Gao et al., 2022)	✓	✓	✓	2	✓*	✗	✗
TEACH (Padmakumar et al., 2022)	✓	✓	✓	2	✓*	✗	✗
CerealBar (Suhr et al., 2019)	✗	✗	✗	2	✓	✗	✗
LIGHT (Urbanek et al., 2019)	✓	✗	✗	1369	✗	✓	✓
Diplomacy (Bakhtin et al., 2022)	✗	✗	✗	7	✓	✓	✗
CUISINEWORLD (Ours)	✓	✓	✓	4+	✓	✓	✓

New Gaming Benchmark – CUISINEWORLD

1. Replace API call with text-based action command
2. Implement in-context learning

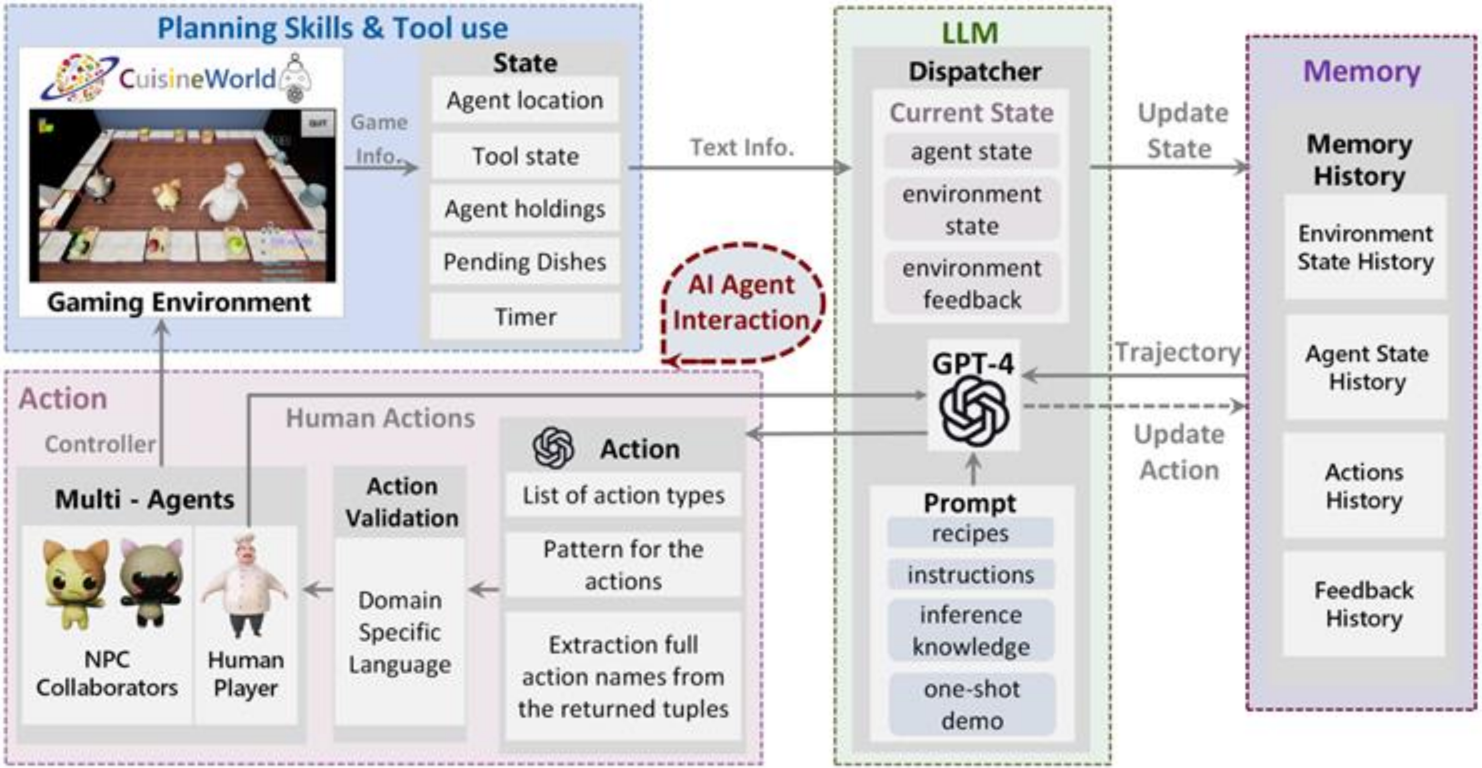
◆ **Example: Traditional API vs. LLM-Controlled Agent**

Action	Overcooked/Minecraft API Call	LLM-Generated Command
Move to storage	`agent.move_to(storage)`	`"goto(agent1, storage)"`
Pick up ingredient	`agent.pick("onion")`	`"get(agent1, storage, onion)"`
Cook food	`agent.use_tool("oven")`	`"activate(agent1, oven)"`
Serve food	`agent.place("dish, table")`	`"put(agent1, serving_table)"`

🔄 **How LLM Thinks:**

- Reads `"Agent 1 is at storage. There is an onion."`
- Determines **what step to take next**.
- Generates `"get(agent1, storage, onion)"`.

MindAgent



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Tool state
Agent holdings
Pending Dishes
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LLM
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Update State
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Human Actions
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NPC Collaborators
Human Player
Action Validation
Domain Specific Language
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List of action types
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Extraction full action names from the returned tuples

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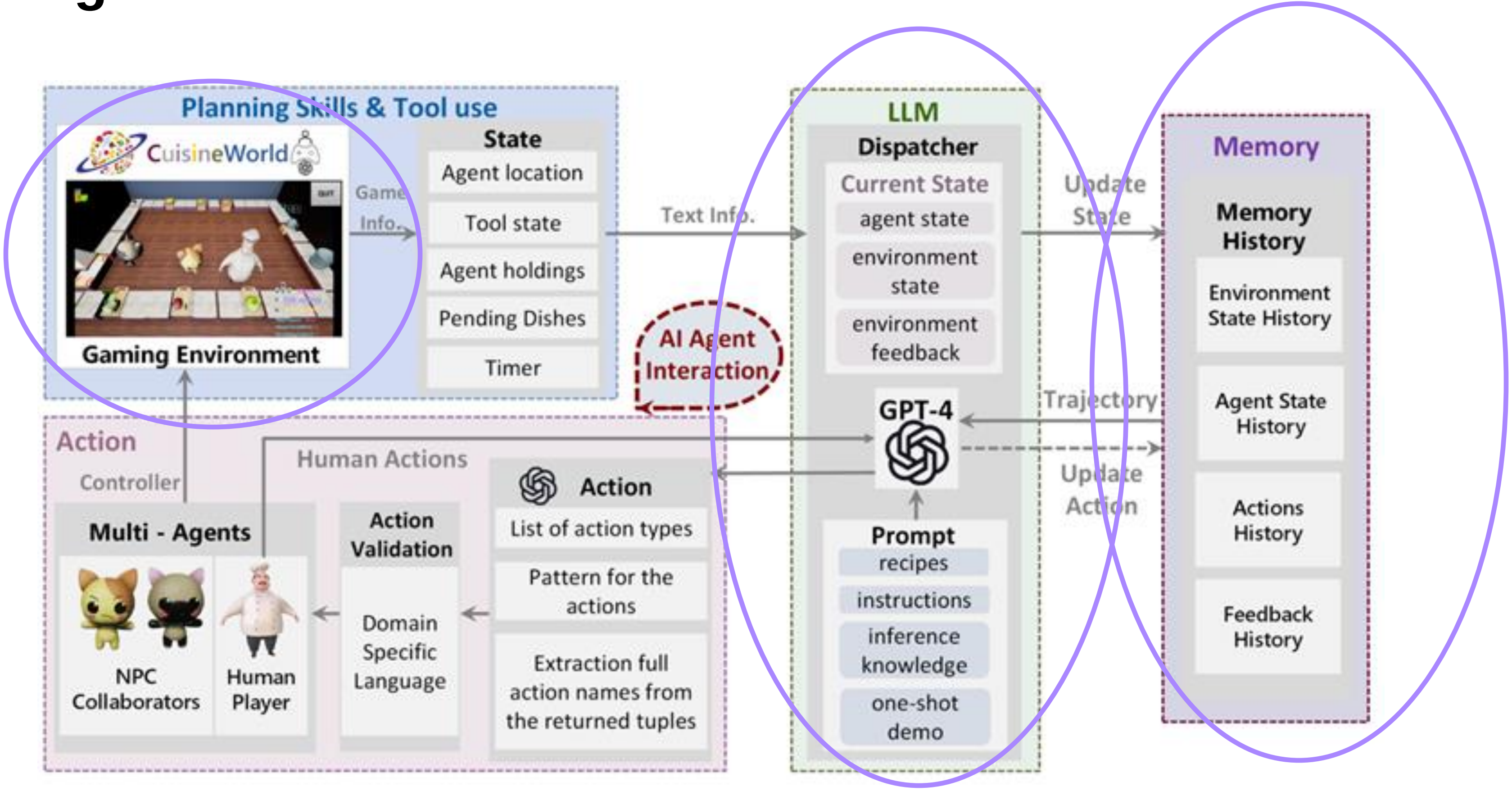

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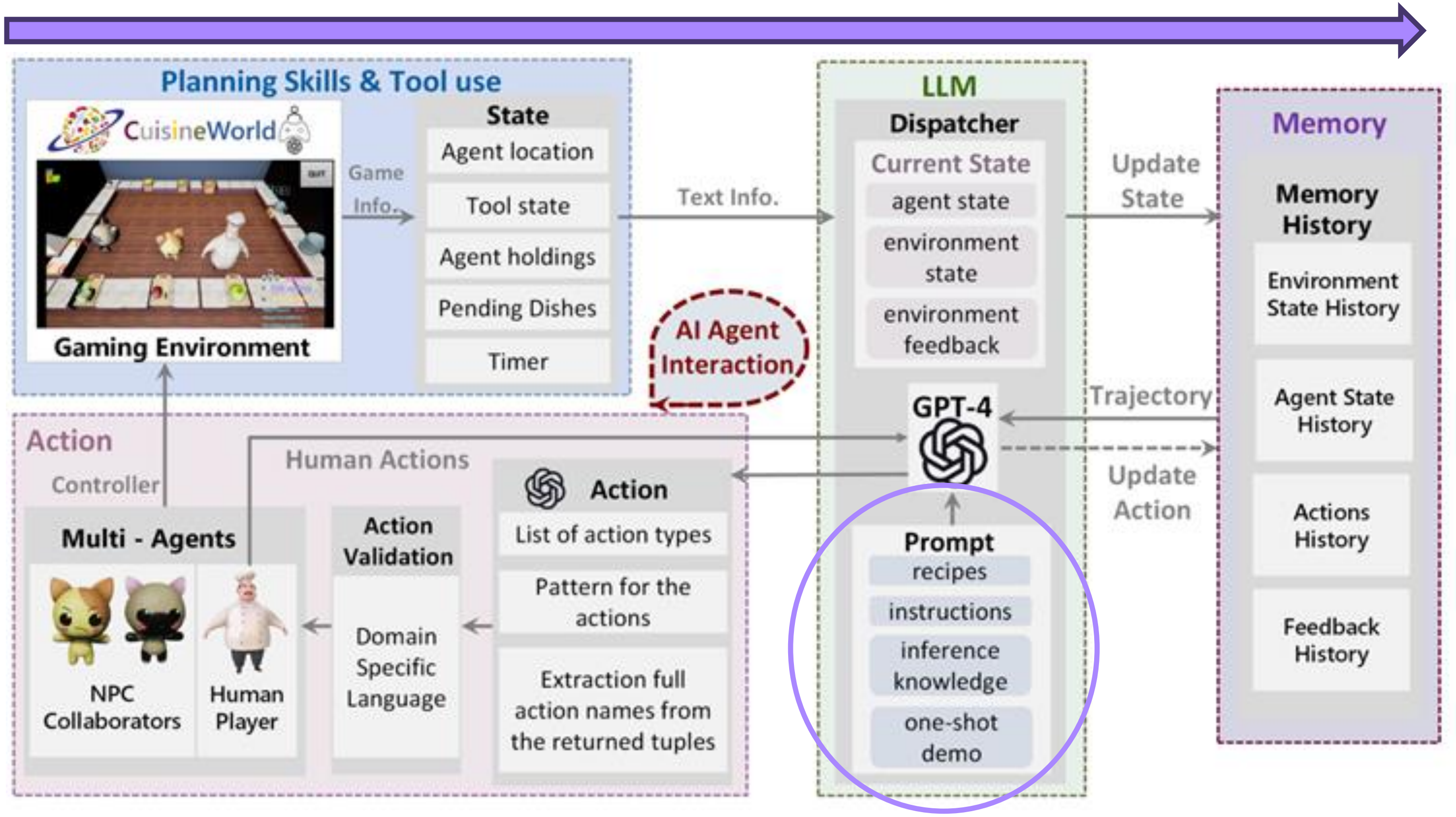
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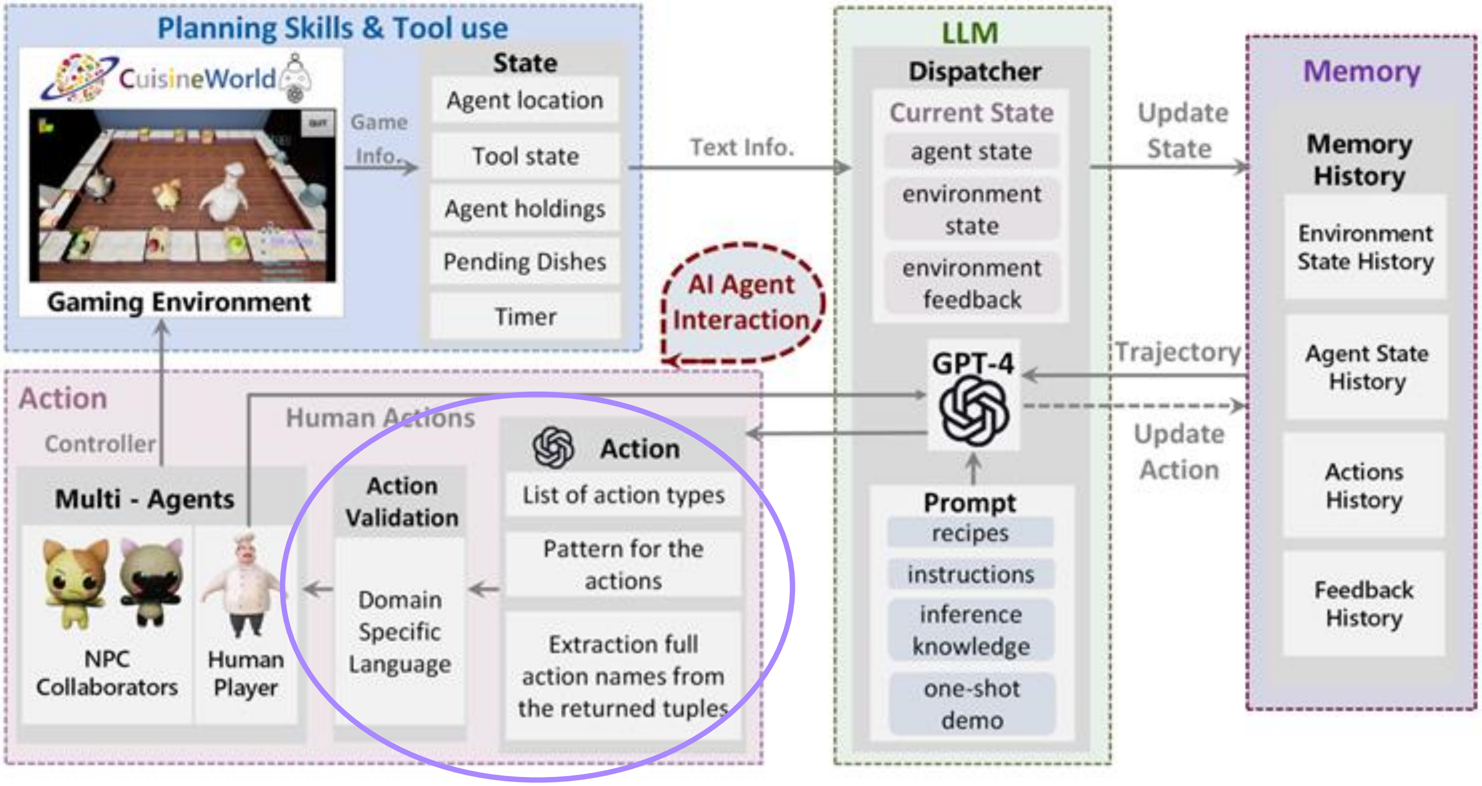

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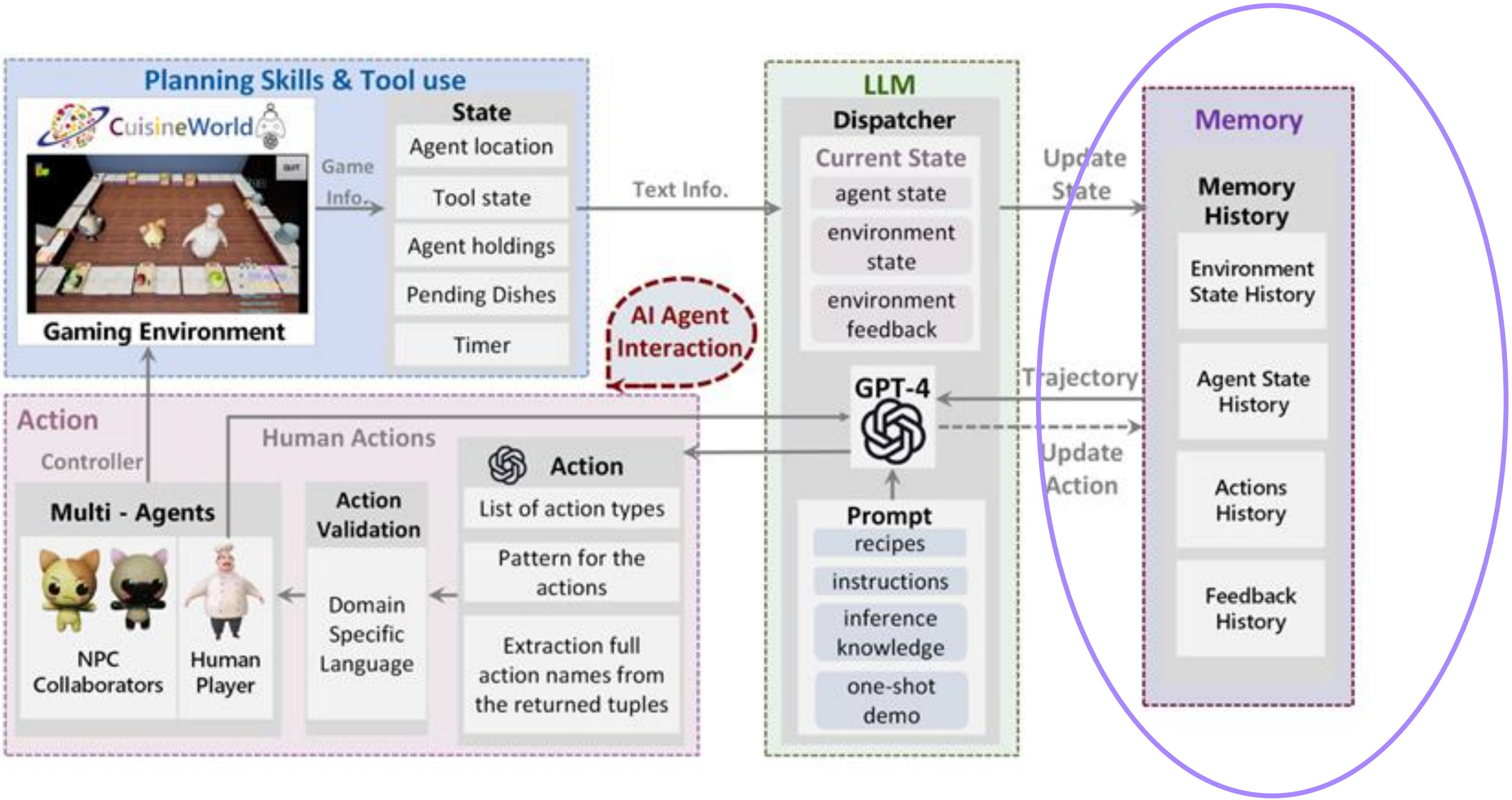

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MindAgent Mechanism

Multi-Agent Task Management

- The system handles **N agents**, each responsible for completing **P tasks**.
- Each task is further divided into **Mp sub-tasks**.
- The number and type of tasks are **unknown at the start**, and tasks arrive dynamically over time.

Task Scheduling and Expiry

- Tasks must be completed within a **time limit**.
- If a task **exceeds the time limit**, it is marked as **failed**.
- The system aims to **maximize completed tasks** while minimizing failures.

MindAgent Mechanism – Mathematical Model

We aim to find valid and optimal task planning, scheduling, and allocations. We define q_{pim} and c_{pim} as quality and cost, respectively, for allocating agent i to work on the sub-task m for the p th task in the episode. Then the combined utility for the sub-task is:

$$u_{pim} = \begin{cases} q_{pim} - c_{pim}, & \text{if agent } i \text{ can execute sub-task m for the } p \text{ th task in the episode} \\ -\infty. & \text{otherwise} \end{cases}$$

We define the assignment of sub-task m to agent i as

$$v_{pim} = \begin{cases} 1, & \text{agent } i \text{ is assigned to sub-task m for the } p \text{ th task in the episode} \\ 0. & \text{otherwise} \end{cases}$$

MindAgent Mechanism – Mathematical Model

$$\arg\max_{v} \sum_{p=1}^{P} \sum_{i=1}^{N} \sum_{m=1}^{M_p} u_{pim} v_{pim} \tag{2}$$

Subject to:

$$\begin{array}{rll} \sum_p \sum_i \sum_m \tau_{pim} v_{pim} & \leq T_{max} & \\ \sum_i v_{pim} & \leq 1 & \forall m \in M, \forall p \in P \\ v_{pim} & \in \{0,1\} & \forall i \in N, \forall m \in M, \forall p \in P \end{array}$$

- Constraints:
  - The total execution time does not exceed the maximum limit.
  - Each sub-task is assigned to at most one agent.
  - The assignment can only be 1 or 0.
- NP-hard

- The LLM receives **natural language feedback from the environment**, such as,
  - “Collect finish” → when an agent successfully picks up an item.
  - “Agent IDs cannot be the same” → when the same agent is assigned multiple tasks incorrectly.

Results – Collaboration Efficiency of LLMs in Multi-Agent Planning

Metric Used: Collaboration Score (CoS)

$$\text{CoS} = \frac{\#\text{Completed Tasks}}{\#\text{Completed Tasks} + \#\text{Failed Tasks}}$$

- the system performance is generally better when there are more agents -> LLM dispatcher can coordinate more agents to execute tasks more efficiently
- the system performance degrades with more agents in less demanding conditions -> LLM dispatcher struggles when there are fewer tasks

2-agent	very simple			simple			intermediate			advanced			Avg.
	level 0	level 1	level 7	level 2	level 4	level 8	level 3	level 9	level 10	level 5	level 11	level 12	
GPT4 $\tau_{\text{int},(1)}$	18/54	18/56	12/31	14/34	12/30	3/30	10/26	7/20	7/23	6/23	6/21	10/36	0.318
GPT4 $\tau_{\text{int},(2)}$	18/31	17/34	10/23	13/26	12/22	9/22	10/17	8/11	6/12	5/13	4/14	8/21	0.486
GPT4 $\tau_{\text{int},(3)}$	18/25	19/25	10/17	16/18	11/18	6/16	11/13	6/8	7/10	8/10	9/9	8/17	0.709
GPT4 $\tau_{\text{int},(4)}$	18/18	18/19	12/12	11/14	11/12	7/11	12/12	8/8	9/9	6/7	8/9	11/12	**0.912**
GPT4 $\tau_{\text{int},(5)}$	18/18	17/17	12/12	11/13	11/13	9/9	11/11	4/5	7/7	8/8	8/8	9/12	**0.937**
CoS	0.727	0.706	0.682	**0.687**	**0.664**	0.504	0.764	0.725	0.701	0.661	0.692	0.559	0.673

Table 3: 2 agents performance on different tasks

3-agent	very simple			simple			intermediate			advanced			Average
	level 0	level 1	level 7	level 2	level 4	level 8	level 3	level 9	level 10	level 5	level 11	level 12	
GPT4 $\tau_{\text{int},(1)}$	21/55	24/55	16/33	17/33	9/28	6/32	12/25	5/20	8/21	7/22	7/22	9/26	**0.368**
GPT4 $\tau_{\text{int},(2)}$	20/31	25/33	11/22	4/24	13/24	7/21	14/20	9/12	9/13	7/14	8/14	10/23	0.549
GPT4 $\tau_{\text{int},(3)}$	22/25	21/26	17/17	11/20	9/17	4/15	13/14	8/8	12/12	7/7	9/10	10/16	**0.791**
GPT4 $\tau_{\text{int},(4)}$	22/22	20/21	14/14	9/13	7/10	6/10	10/10	6/7	10/10	5/8	7/8	11/13	0.846
GPT4 $\tau_{\text{int},(5)}$	20/20	15/16	11/12	10/14	10/11	8/9	12/12	6/6	8/8	5/5	8/8	6/10	0.914
CoS	**0.781**	**0.778**	**0.780**	0.528	0.600	0.455	0.822	**0.771**	**0.815**	0.689	**0.733**	**0.570**	**0.694**

Table 4: 3 agents performance on different tasks

4-agent	very simple			simple			intermediate			advanced			Average
	level 0	level 1	level 7	level 2	level 4	level 8	level 3	level 9	level 10	level 5	level 11	level 12	
GPT4 $\tau_{\text{int},(1)}$	22/54	18/55	17/34	13/34	8/28	9/33	16/27	5/20	8/23	5/22	8/22	8/35	0.349
GPT4 $\tau_{\text{int},(2)}$	24/32	21/33	14/24	14/25	12/24	11/22	16/19	7/12	9/15	7/14	6/12	12/23	**0.590**
GPT4 $\tau_{\text{int},(3)}$	23/25	23/26	13/18	11/19	10/17	11/17	15/17	8/9	11/11	7/8	10/11	9/17	0.785
GPT4 $\tau_{\text{int},(4)}$	22/22	21/22	14/14	7/15	10/13	10/12	12/13	9/9	10/10	6/7	8/8	9/13	0.875
GPT4 $\tau_{\text{int},(5)}$	14/18	20/20	14/14	7/13	9/11	7/8	12/12	5/5	7/7	6/6	3/5	7/10	0.859
CoS	0.771	0.761	0.761	0.505	0.592	**0.626**	**0.848**	0.744	0.790	**0.692**	0.675	0.534	0.692

Table 5: 4 agents performance on different tasks

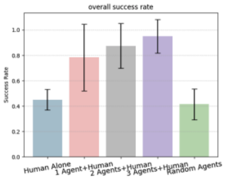
Results – Human-Agent Collaboration Study

Hypotheses Tested:

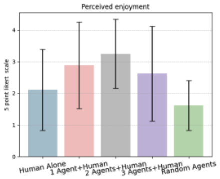
- H1: Humans perform better when collaborating with AI agents.
- H2: More AI agents improve human task productivity.
- H3: Players find the game more enjoyable when collaborating with AI agents.

Key Results:

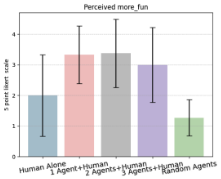
- Humans felt more productive with AI assistance (p = 0.0104).
- Collaboration led to higher engagement and enjoyment (p = 0.0126).
- The success rate of human-AI teams was significantly higher than humans alone.



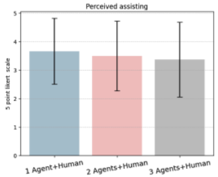
(a) **Collaboration score** We can tell that the collaboration score is higher if more agents are collaborating with human players, even though the difference is not significant.



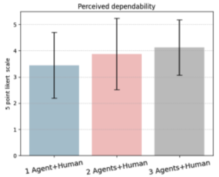
(b) **Perceived Enjoyment** Humans enjoy the game more if they collaborate with the right number of agents



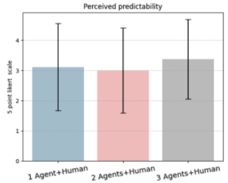
(c) **Perceived more fun** due to collaboration. Players enjoy the game more because of collaborating with competent agents.



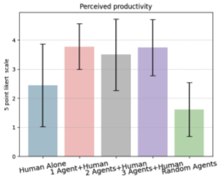
(d) **Perceived Assisting**. There is no significant difference in terms of human perceptions of helpfulness when collaborating with more agents, even though the task success rate is higher.



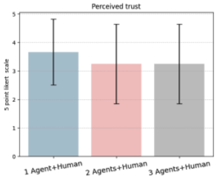
(e) **Perceived dependability**. When collaborating with more agents, players depend on the agents more.



(f) **Perceived Predictability**. There is no difference in terms of the predictability of agents' behaviors when collaborating with more agents.



(g) **Perceived productivity**. Players think collaborating with AI agents will improve productivity.



(h) **Perceived Trust**. There is no difference in terms of trust when collaborating with more agents.

Figure 5: Human Evaluations

Results – Emerging capabilities

Capability	What It Means	Example Behavior
Zero-shot multi-agent planning	Can handle unseen tasks with minimal examples	GPT-4 completes new game levels without explicit training
Scaling across different agent numbers	Learns from small settings and applies to larger ones	Trained with 2 agents, generalizes to 3 or 4 agents
Dynamic task adaptation	Adjusts plans in real time as new tasks arrive	Prioritizes urgent tasks, delays others
Self-correction	Learns from mistakes and avoids repeated failures	Stops assigning multiple agents to the same task

level_3	4agent using 4agent module	4agent using 2agent module	3agent using 3agent module	3agent using 2agent module
GPT4 $\tau_{\text{int},(1)}$	16/27	14/27	12/25	11/25
GPT4 $\tau_{\text{int},(2)}$	16/19	16/20	14/20	11/19
GPT4 $\tau_{\text{int},(3)}$	15/17	15/16	13/14	12/14
GPT4 $\tau_{\text{int},(4)}$	12/13	13/13	10/10	12/12
GPT4 $\tau_{\text{int},(5)}$	12/12	12/12	12/12	11/11
CoS	0.848	0.851	0.822	0.775

Table 8: Using different numbers of agent demos

Do you agree with these statements?

- "LLMs can perform zero-shot multi-agent planning, scheduling multiple agents into completing tasks without explicit training."
  → Do you believe the LLM really understands coordination, or is it just pattern-matching from prompts?
- "Without environmental feedback, LLMs make repeated errors, indicating that structured prompts are crucial for efficient planning."
  → If the LLM relies heavily on feedback, does it mean it lacks true adaptability?
- "LLMs exhibit emergent reasoning capabilities, successfully dispatching more agents than than the number seen in its prompt examples."
  → Do you believe this prove generalization ability can be extended to larger scale such as 10 or 100?