# MindAgent: Emergent Gaming Interaction

Ang Li

# Motivation

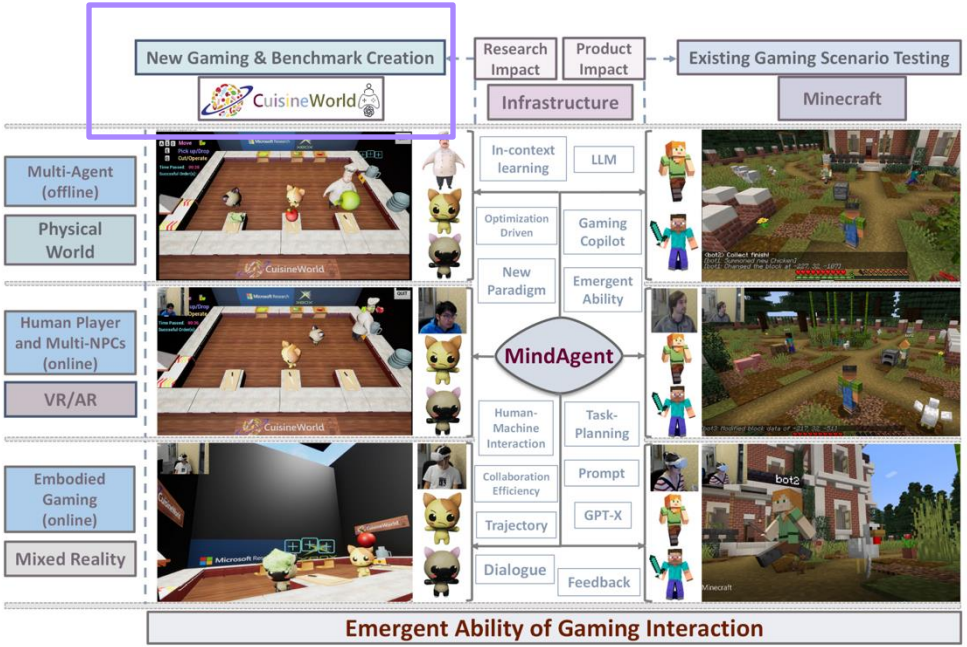
1. LLMs have demonstrated **strong planning abilities** in various domains (e.g., robotics, reasoning, task automation).
2. However, their capabilities in multi-agent planning and coordination remain largely **unexplored**.
3. The authors want to **evaluate how well LLMs can handle multi-agent planning**, 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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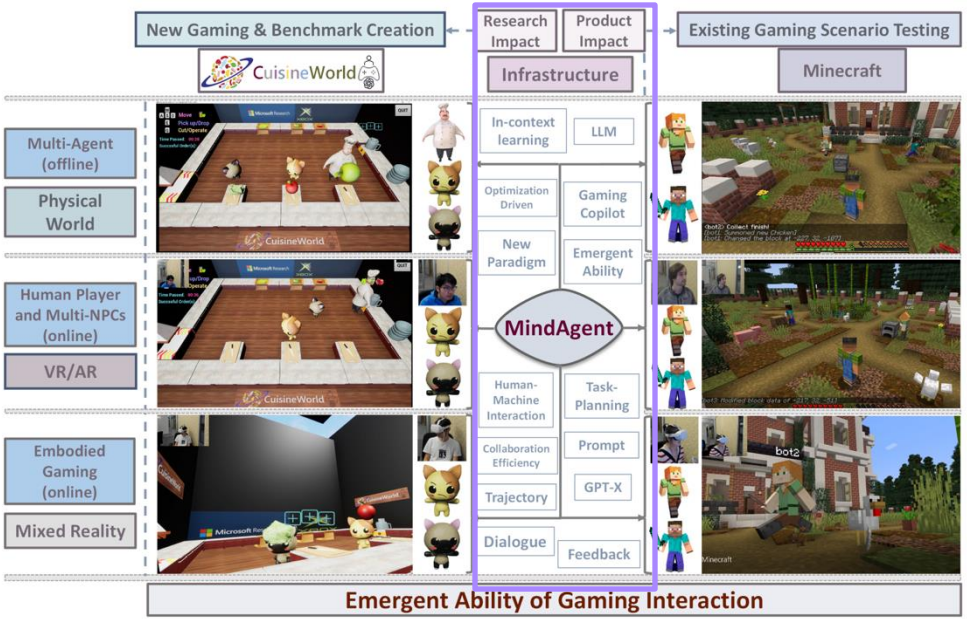

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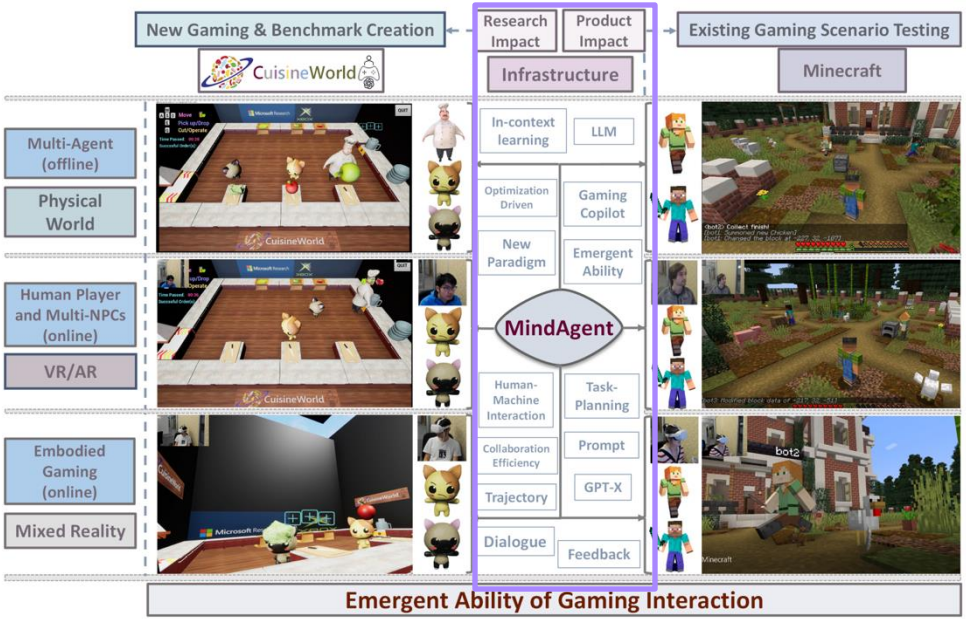
3. Tested LLMs on the Benchmark



# 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

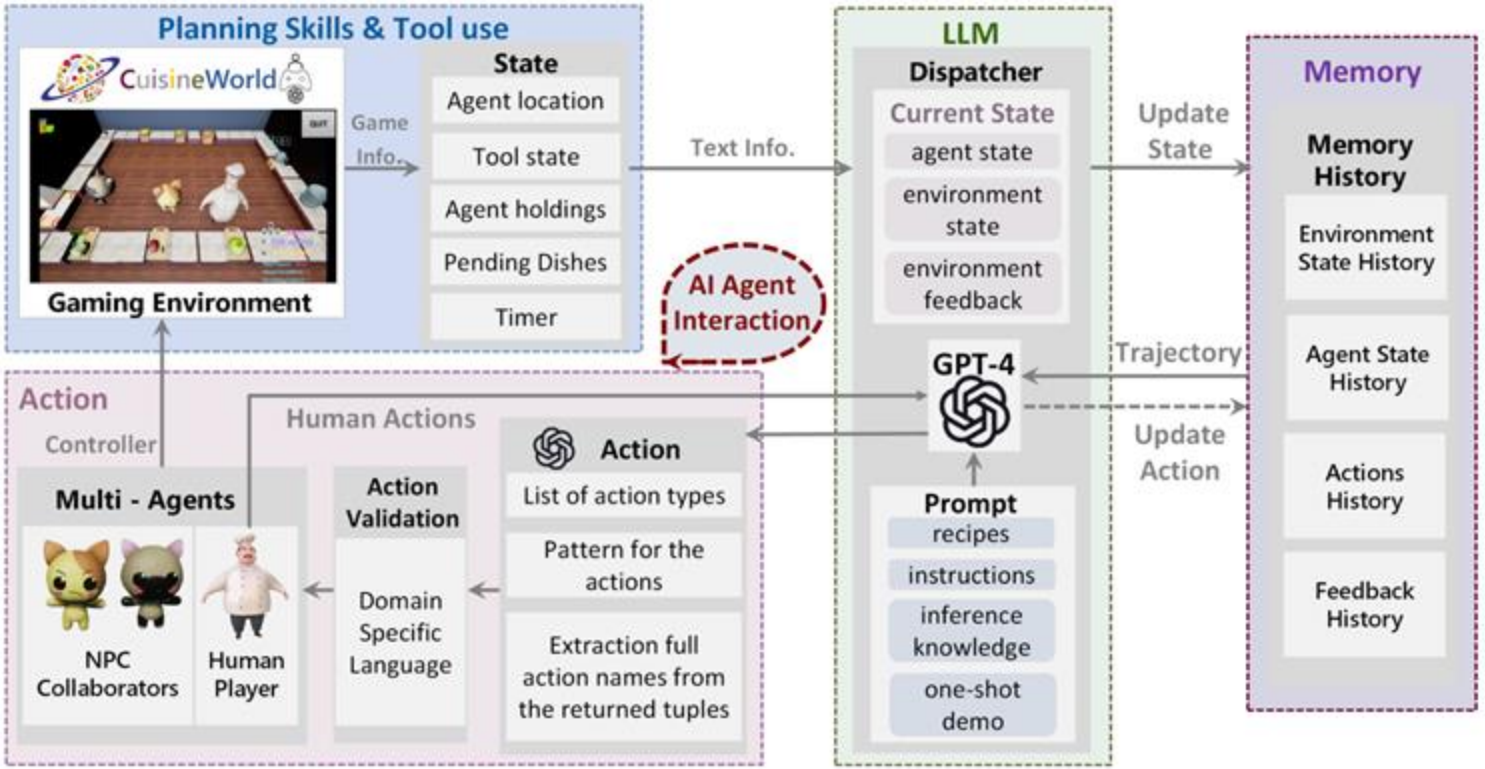
🔹 **Example: Traditional API vs. LLM-Controlled Agent**

| 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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one-shot demo
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Human Actions
Multi - Agents
NPC Collaborators
Human Player
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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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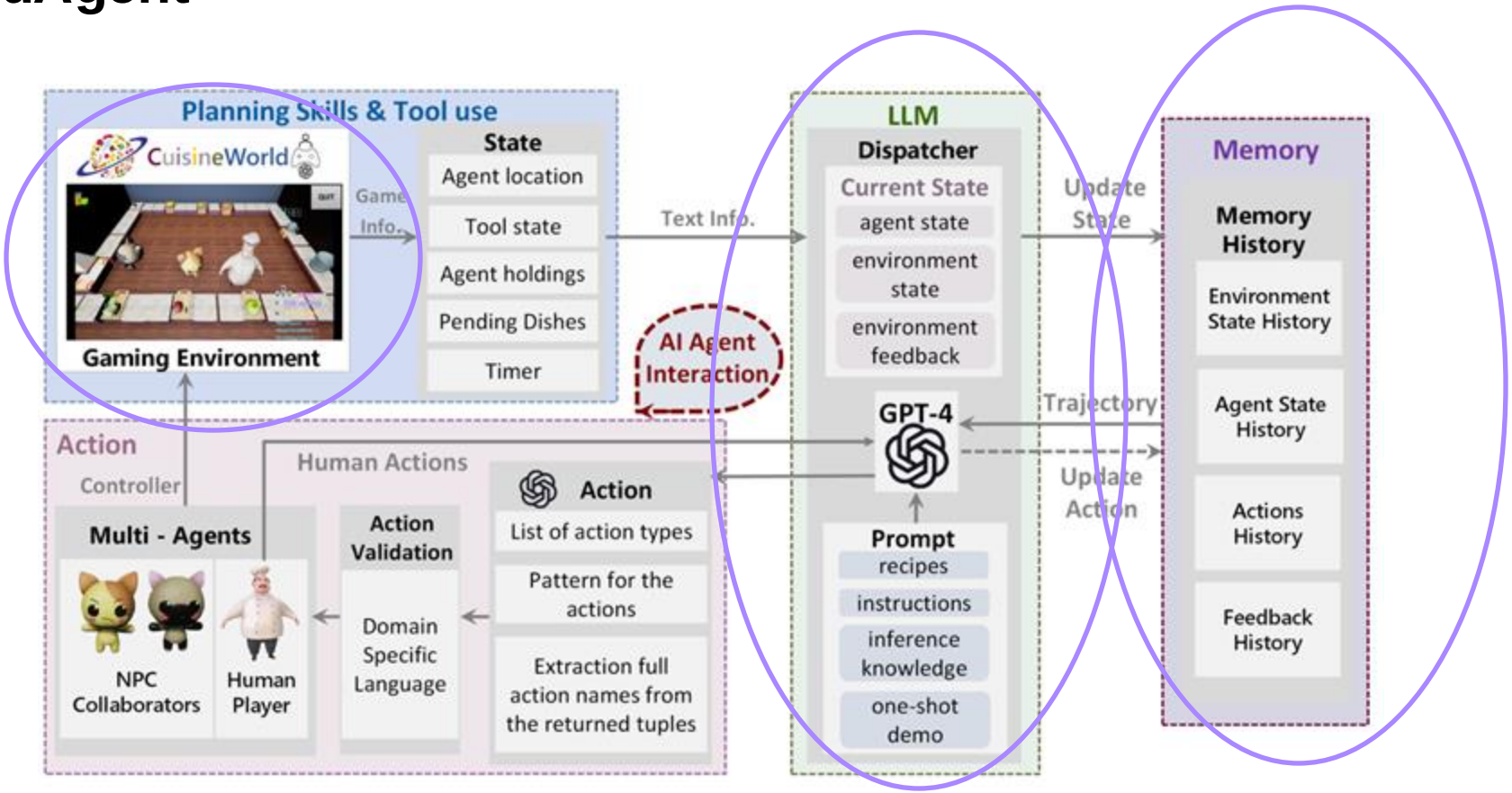
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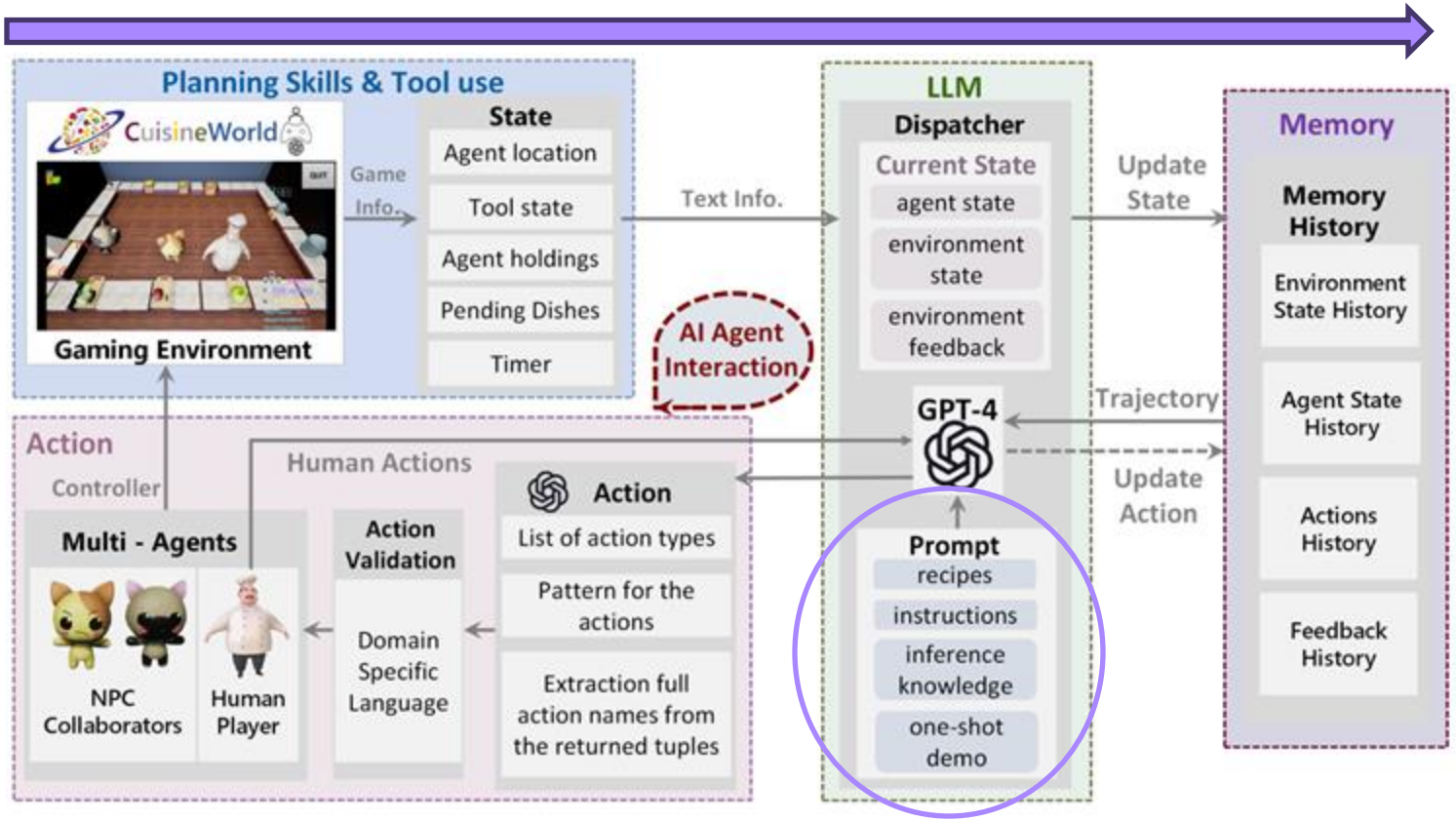
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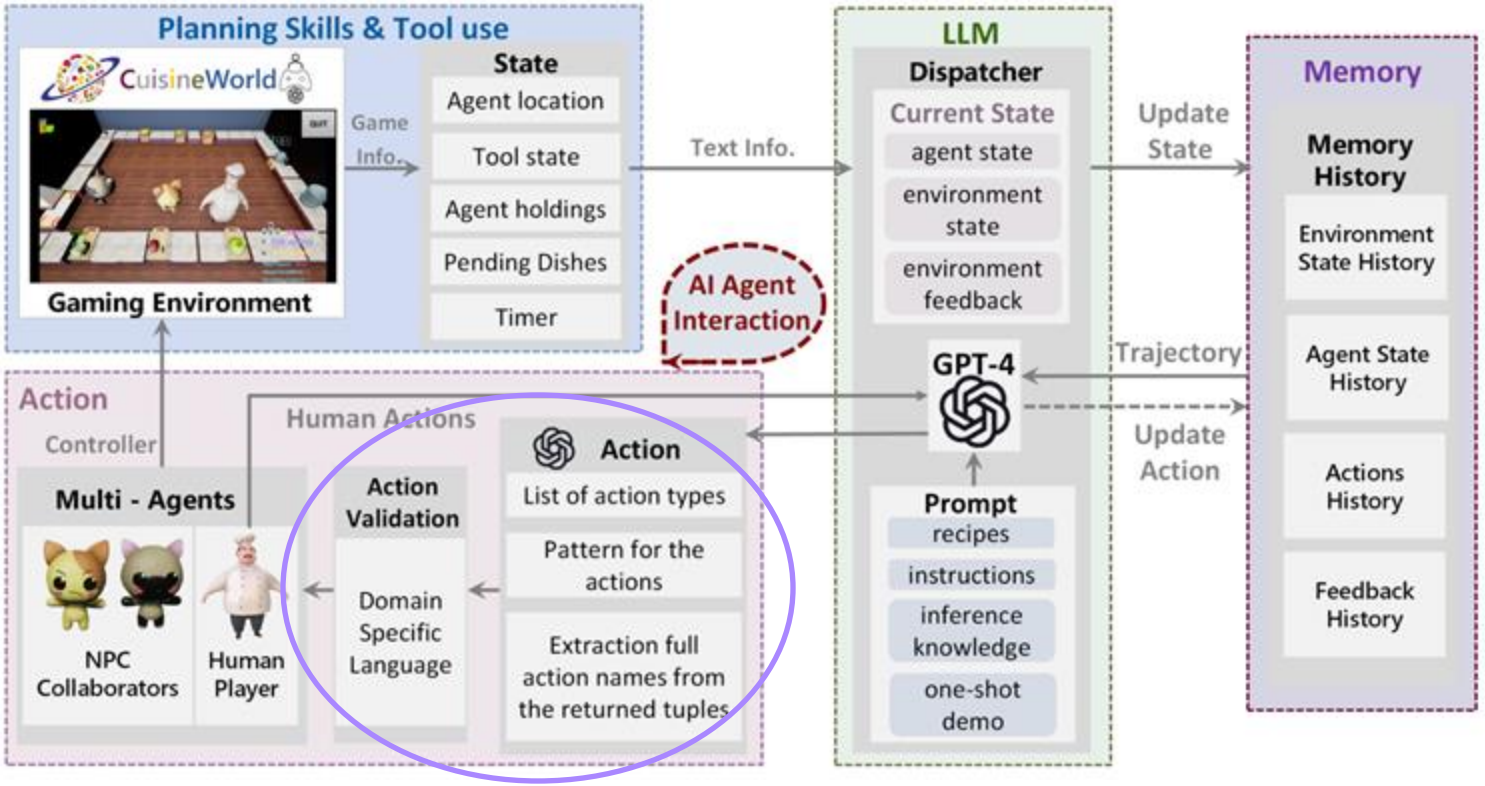
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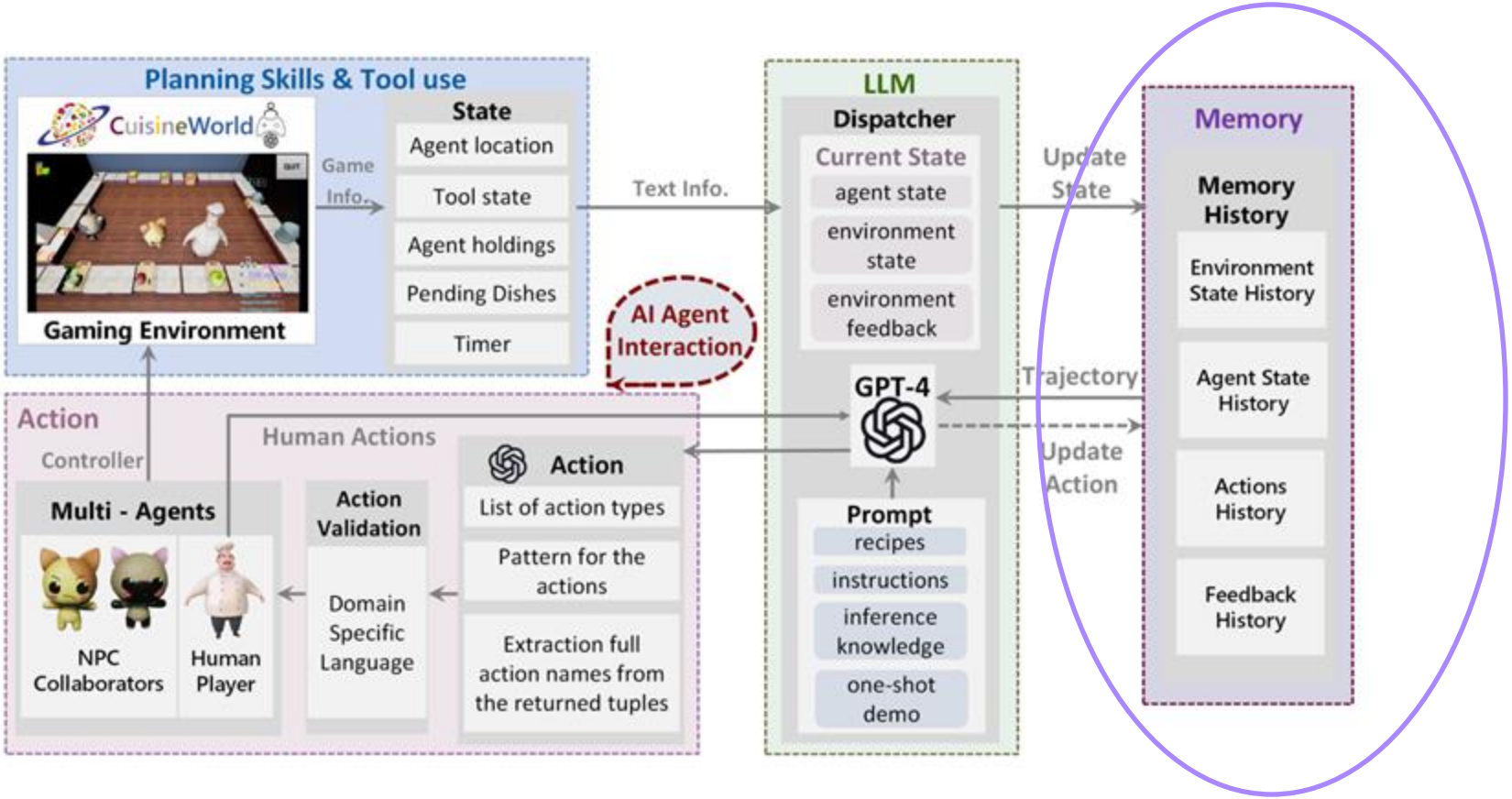
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# MindAgent Mechanism

**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:

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

- 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

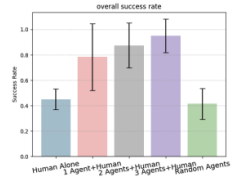
# Results – Human-Agent Collaboration Study

**Hypotheses Tested:**

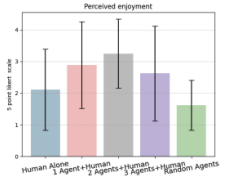
- H1: Humans perform better when collaborating with AI agents.
- H2: More AI agents improve human task productivity.
- H3: Players find the game more enjoyable when collaborating with AI agents.

**Key Results:**

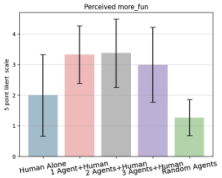
- Humans felt more productive with AI assistance ($p = 0.0104$).
- Collaboration led to higher engagement and enjoyment ($p = 0.0126$).
- The success rate of human-AI teams was significantly higher than humans alone.



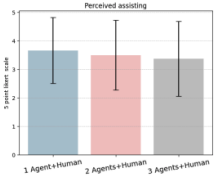

(a) **Collaboration score** We can tell that the collaboration score is higher if more agents are collaborating with human players, even though the difference is not significant.



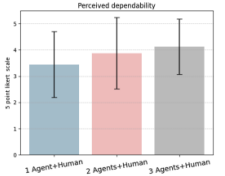

(b) **Perceived Enjoyment** Humans enjoy the game more if they collaborate with the right number of agents



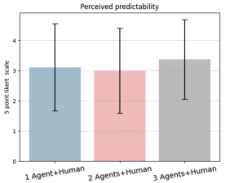

(c) **Perceived more fun** due to collaboration. Players enjoy the game more because of collaborating with competent agents.



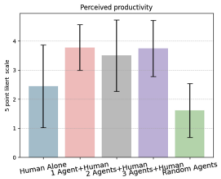

(d) **Perceived Assisting**. There is no significant difference in terms of human perceptions of helpfulness when collaborating with more agents, even though the task success rate is higher.



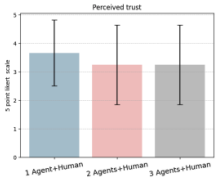

(e) **Perceived dependability**. When collaborating with more agents, players depend on the agents more.




(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?