# A Survey on Large Language Model Based Game Agents

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The development of game agents holds a critical role in advancing towards Artificial General Intelligence. The progress of Large Language Models (LLMs) offers an unprecedented opportunity to evolve and empower game agents with human-like decision-making capabilities in complex computer game environments. This paper provides a comprehensive overview of LLM-based game agents from a holistic viewpoint. First, we introduce the conceptual architecture of LLM-based game agents, centered around three core functional components: memory, reasoning and in/output. Second, we survey existing representative LLM-based game agents documented in the literature with respect to methodologies and adaptation agility across six genres of games, including adventure, communication, competition, cooperation, simulation, and crafting & exploration games. Finally, we present an outlook of future research and development directions in this burgeoning field. A curated list of relevant papers is maintained and made accessible at: https://github.com/git-disl/awesome-LLM-game-agent-papers.

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# 1 Introduction

Intelligence emerges in the interaction of an agent with an environment and as a result of sensorimotor activity.

- The Embodied Cognition Hypothesis [129]

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Large language models (LLMs) [99] represent an important milestone in Artificial Intelligence. Empowered by training on massive amounts of diverse web data with hundreds of billions of parameters, LLMs demonstrate astonishing capabilities of generalizing knowledge from huge text corpus and displaying conversational intelligence in natural language. The emergence of multimodal LLMs (MLLMs) [3, 140] marks another milestone, enabling LLMs to perceive and understand visual input. These successes fuel an unprecedented opportunity in the pursuit of human-like Artificial General Intelligence (AGI): the cognitive capabilities previously thought to be exclusive to humans, such as reasoning, planning, and reflection, with a degree of self-control, self-understanding, and self-improving, are now achievable by integrating appropriately prompting of LLMs with built-in cognitive capabilities.

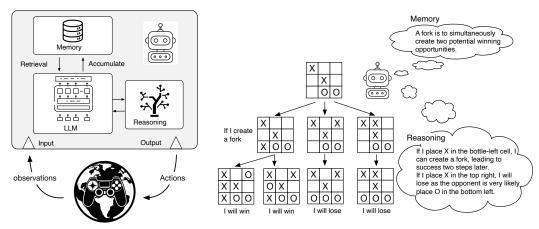
We define an LLM-based agent as an intelligent entity that employs LLMs<sup>1</sup> as a core component to conduct a human-like decision-making process [136]. Even though LLM-based agents are capable of cognitive processing similar to humans, a distinction between existing agents and human intelligence is evident: current agents mainly rely on knowledge derived from pre-training data [25], while humans are capable of discovering new knowledge through trial-and-error learning in the real world [42, 43]. Inspired by the process of intelligence development in human infants, the embodied cognition hypothesis [129] posits that the intelligence of an agent emerges from observing and interacting with its environment, *i.e.*, grounding the agent in a world that integrates physical, social, and linguistic experiences is vital for fostering conditions conducive to the development of human-like intelligence.

Digital games are recognized as ideal environments for cultivating AI agents due to their complexity, diversity, controllability, safety, and reproducibility. From classical chess and poker [61, 126, 132] to modern video games like Atari [11], StarCraft II [146], DOTA II [1], and sandbox worlds such as Minecraft [95], these environments have long been instrumental in advancing AI research. Unlike traditional symbolic agents [24, 98, 126, 127] that consume and produce symbolic input and output, constructing LLM-based game agents capable of employing cognitive abilities to gain fundamental insights into environments, potentially aligns more closely with the pursuit of AGI.

Existing surveys on LLM-based agents [39, 149, 165] primarily review general-purpose LLM-based agents, while paying limited attention to their development and applications in game environments. More recent survey papers [36, 137] focus on game development aspects but cover only a narrow subset of the current literature on LLM-based game agents. To address these gaps, this paper presents a comprehensive, systematic survey of recent developments in LLM-based game agents. Specifically, the survey paper is organized into four synergistic parts: (i) Game agent framework. We introduce a unified reference framework that outlines the fundamental elements for enabling LLM-based game-playing, illustrated through concrete examples; (ii) Core components. We categorize and discuss the three core components of these agents, *i.e.*, memory, reasoning, and input/output modules, analyzing a range of approaches under each category; (iii) Game Taxonomy. We introduce LLM-based game agents operating in six major game categories, detailing the technical challenges, representative game environments, and widely used optimization strategies for each; (iv) Future directions. Finally, we propose key directions for future research and development, highlighting open questions and opportunities in this rapidly expanding area.

In summary, this survey paper serves as a comprehensive review of the literature on LLM-based game agents. It aims to catalyze progress within this nascent research area and to inspire further innovation in research and development. Given that this is a new and burgeoning research field, this survey paper will be continuously updated to keep track of the latest studies. A curated list of

<sup>&</sup>lt;sup>1</sup>In this paper, LLMs refers to both large language models (LLMs) and multimodal large language models (MLLMs).



(a) LLM-based game agent framework

(b) An example of playing Tic-Tac-Toe

Fig. 1. (a) The overall framework for LLM-based game agent, involving three essential components: memory, reasoning and in/output module; (b) An example of an LLM-based game agent to play tic-tac-toe, where reasoning adopts a tree search approach [173] by traversing potential possibilities and evaluate them.

relevant literature is maintained and accessible at https://github.com/git-disl/awesome-LLM-game-agent-papers.

# 2 Game Agent Framework

## 2.1 Setting

In a typical game setting, an agent pursues certain goals g while interacting with an environment over a series of steps. The interaction process is often modeled as a Markov Decision Process (MDP): At each step t, the environment reveals its current state  $s_t$ , the agent outputs an action  $a_t$  according to a policy  $\pi(a_t \mid s_t)$ , then the environment transitions to a new state  $s_{t+1}$  according to a dynamic function  $P(s_{t+1} \mid s_t, a_t)$ , while providing a reward  $r_t = R(s_t, a_t)$  that reflects the desirability of the chosen action. A complete run from an initial state  $s_0$  to a terminal state  $s_T$ , signifying a win, loss, or other ending condition, is referred to as an *episode*, *trial*, or *trajectory*. In a conventional Reinforcement Learning (RL) setting, the optimal policy is a policy that maximizes the expected cumulative reward.

What sets LLM-based agents apart is their reliance on LLMs to process natural languages. Instead of producing purely numeric or symbolic moves, these agents can represent their policy in a textual form, writing out a line of reasoning and ultimately deciding on an action. The environment in turn may present states as text, allowing the LLM to parse and interpret the current situation. In essence, an LLM-based policy can be viewed as

$$\pi_{\text{LLM}}(rs_t, a_t \mid s_t),$$

indicating that the model first generates reasoning  $rs_t$  conditioned on the observed state  $s_t$  and then outputs the action  $a_t$ .

# 2.2 Components

We introduce three essential components in designing an LLM-based game agent: memory, reasoning, and input/output module.

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**Memory**: Agents rely on memory to store past experiences, thoughts, and skills, from which they retrieve essential information. With memory, agents can recall relevant facts, maintain consistent narratives across episodes, and refine their strategies over time. How memories are accumulated, organized, and retrieved has a strong impact on the agent's capability to conduct reasoning, adapt to new situations, and minimize hallucinations.

**Reasoning**: Reasoning is human-like cognitive process that differentiates LLM-based agents from conventional AI agents. Since action generation via LLM can be deemed as auto-regressive search of a good action in the latent space, explicit reasoning enables the agent to traverse a longer distance in that space, enabling them to address more complex tasks. Given that the original reasoning capability comes from pre-trained corpus, it is also important to develop techniques that can improve its reasoning ability via interacting with the environments.

**Input/Output**: The input module converts the game world into natural language, a protocol that LLMs have been trained to understand through extensive corpora. This allows the agent to leverage pre-trained knowledge rather than learning from scratch, as conventional RL agents do. The output module then translates the generated action into a symbolic command that the environment can execute, enabling the agent to act in gameplay.

# 2.3 Example 1 (Tic-Tac-Toe)

Tic-Tac-Toe is played on a  $3 \times 3$  grid by two players, one marking X and the other marking 0. Each turn, a player chooses an empty cell to place their symbol, with the goal of forming a line of three horizontally, vertically, or diagonally. The game ends when one player achieves this or when no further moves are possible.

**Input**: At the time step t, the game state  $s_t = [['X', '', ''], ['', 'X', ''], ['', '0', '0']]$ . The input module first converts the symbolic game state into a textual description:

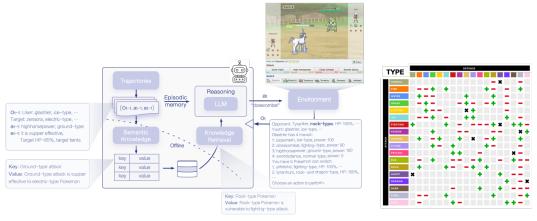
"The board is a 3x3 grid. The top-left and middle-middle cells are 'X'; The bottom-middle and bottom-right cells are 'O'; All other cells are empty."

**Memory**: The agent leverages a memory system to generate, organize, and retrieve memories. For example, two forms of memory can be leveraged in tic-tac-toe: (1) Episodic memory that consists of the moves made in the past steps within current episode and previous episodes; (2) Semantic knowledge that represents the understanding of game tactics, which can be generated from reflecting on the previous episodes:

"A fork is a move that simultaneously creates two potential winning opportunities, forcing the opponent to address only one of them in their next turn. By doing so, the forking player is guaranteed to complete the second threat, leading to an unavoidable victory."

**Reasoning**: For Tic-Tac-Toe, the reasoning process can be framed as a tree search over possible moves:

- Move A: Place 'X' in the bottom-left cell
  - Opponent's responses:
    - \* Opponent tries to block row threat  $\rightarrow$  I capture column  $\rightarrow$  Win
    - \* Opponent tries to block column threat  $\rightarrow$  I capture row  $\rightarrow$  Win
  - Outcome: Guaranteed fork leading to victory.
- Move B: Place 'X' in other empty cells
  - Opponent is very likely to place 'O' in the bottom-left cell to win.
  - Outcome: Likely lose.



(a) An example of playing Pokémon Battles

(b) Type-effectiveness Chart

Fig. 2. (a) The agent accumulates and extracts semantic knowledge from the trajectories, which is organized as key-value pairs and retrieved during the game. (b) The type-effectiveness relationship chart is the most important semantic knowledge in Pokémon battles, where "+" denotes super-effective, "-" denotes not very effective, and "×" denotes no effect.

**Output**: Based on reasoning, the LLM then outputs a textual action description: "Place an 'X' in the bottom-left cell." The output module then converts it into a symbolic action  $a_t$ , and the environment updates the  $3\times3$  board array accordingly (e.g., [['X','',''],['','X',''],['','']]).

## 2.4 Example 2 (Pokemon Battles)

In a 1v1 Pokémon Battle, two players have multiple Pokémon, one of which is active in battle while the others remain on the bench. On each step, each player chooses one action: either use one of the active Pokémon's moves or switch to another one from the bench. The battle ends when one player has no remaining Pokémon able to fight.

Pokémon Battles offers a wealth of game knowledge: there are over 1,000 Pokémon species, each with a unique combination of type, abilities, and stats, and over 900 battle moves characterized by varying effects, types and power values [2]. Moreover, as the most important game knowledge, there are advantages and weaknesses between types of moves and types of targeted Pokémon, as shown in Figure 2(b). For example, Fire-type moves deal double damage to Grass-type Pokémon, while Fire-type Pokémon are vulnerable to Water-type moves. Ungrounded LLMs lacking of game knowledge will struggle with hallucinations in reasoning [57].

**Input:** Suppose at time step t, the environment provides a symbolic representation of the battle state:

```
s_t = \begin{cases} &\text{ActivePokemon: Pikachu (HP=75, Moves=[Thunderbolt, QuickAttack, DoubleTeam])} \\ &\text{BenchPokemon: [Bulbasaur(HP=68, Moves=[VineWhip, SleepPowder, Growl]),} \\ &\text{Charmander(HP=60, Moves=[Ember, Scratch, Smokescreen]),} \\ &\text{Squirtle(HP=90, Moves=[WaterGun, Tackle, Withdraw]), . . . ]} \\ &\text{OpponentPokemon: Onix (HP=120, Moves=[Earthquake, RockThrow, Harden])} \end{cases}
```

The symbolic state is translated into text by the input module:

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"My active Pokémon is Pikachu (HP 75). I have Bulbasaur (HP 68), Charmander (HP 60), Squirtle (HP 90), and (...) on my bench. The opponent's Onix (HP 120) is on the field. My Pikachu can use Thunderbolt, Quick Attack, or Double Team. Bulbasaur has Vine Whip, Sleep Powder, and Growl. Charmander has Ember, Scratch, and Smokescreen. Squirtle has Water Gun, Tackle, and Withdraw. Onix may use Earthquake, Rock Throw, or Harden. Choose a move for Pikachu or switch to a bench Pokémon."

**Memory:** The memory system stores the episodic observation from the recent steps:

"(E1) In the last turn, Onix used Earthquake, severely damaging Pikachu. Pikachu used Thunderbolt, which is inefficient to Onix."

This reflects the outcomes of moves taken in the previous step. The memory system can be designed to infer type-effectiveness relationships from such episodic memories, as illustrated in Figure 2(a):

- (S1) Electric-type attacks are ineffective against Ground-type Pokémon."
- (S2) **Ground-type** attacks are especially effective against **Electric-type** Pokémon."

Here, the extracted knowledge is organized as key-value pairs (with keys highlighted in bold). Semantic knowledge is accumulated during gameplay and retrieved when the current state involves relevant key entities, which can significantly reduce hallucinations and improve the reasoning quality [57].

**Reasoning**: With state description and retrieved memories, the LLM generates a chain-of-thoughts [160] reasoning trace as below:

"Onix is Ground/Rock-type, so Thunderbolt from Pikachu is largely ineffective (S1). It just used Earthquake, which is very dangerous to Pikachu (E1, S2). Squirtle's Water Gun is super-effective against Rock/Ground types (retrieved knowledge), and Bulbasaur's Vine Whip is also super-effective (retrieved knowledge). Switching to Squirtle or Bulbasaur could both be good moves. Between the two, Squirtle has a higher HP value, which seems like the safest and most effective option now."

**Output:** The LLM outputs a textual action decision "Switch Pikachu out and send in Squirtle to use Rain-boosted Water Gun against Onix", which is converted to symbolic action  $a_t = Switch(Pikachu, Squirtle)$  and sent to the game environment. After receiving the actions from both players, the game engine calculates the next step of game state  $s_{t+1}$ .

# 2.5 Roadmap

In the following sections, we elaborate on the design of memory system (Section 3), reasoning technique (Section 4), and input/output module (Section 5). Section 6 illustrates the applications of LLM-based agents in six game genres. Section 7 is the discussion and future directions.

## 3 Memory System

Humans rely on memory systems to memorize prior experiences for recalling, learning, and applying knowledge in future scenarios. Similarly, LLM-based agents necessitate memory systems to ensure operational coherence and efficiency, serving as a repository for their past observations, thoughts, actions, and skills, from which agents retrieve essential information for strategy formulation and decision-making.

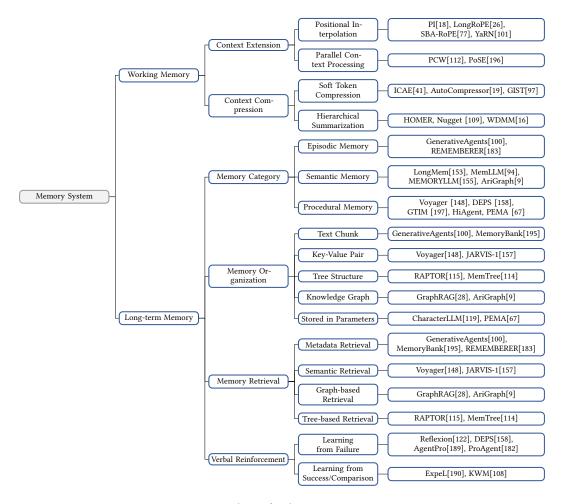


Fig. 3. Mind map for the memory system.

## 3.1 Working memory

In the human brain, working memory provides the biological brain with the ability to hold information temporarily [92]. In an agentic system, the capacity of working memory most closely corresponds to the ability of recalling information within short-term contextual windows.

*3.1.1 Context Extension:* Since pre-training often limits LLMs to a fixed context length, extending this window is crucial for handling longer sequences.

**Positional Interpolation/Extrapolation:** Methods adjust position indices within the model's learned distribution to extend context without retraining. For instance, Position Interpolation (PI) linearly rescales positional indices, enabling context windows up to 32K tokens [18]. LongRoPE dynamically adjusts scaling factors, allowing extrapolation beyond 2 million tokens. SBA-RoPE further refines this by segmentally adjusting the base of Rotary Position Embeddings (RoPE), optimizing positional encoding for extended sequences [77]. YaRN introduces a learned nonlinear mapping, achieving efficient extrapolation up to 128K tokens [101].

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**Parallel Context Processing:** Approaches enhance efficiency by structuring attention over disjoint segments. PCW divides input into independent chunks with shared embeddings, allowing off-the-shelf LLMs to process longer texts without additional training [112]. PoSE employs a skipwise encoding strategy to simulate long-range dependencies within a fixed window, reducing memory overhead [196].

3.1.2 **Context Compression:** Existing research reveals that LLMs often "forget" or fail to juggle large amounts of data simultaneously when performing on the n-back experiments, a standard cognitive task in which a subject is presented with a continuous stream of stimuli and must indicate when the current item matches one displayed n steps before [44]. Empirical results show that LLMs exhibit memory limits resembling human short-term memory, *i.e.*, the performance deteriorates significantly as information load increases, comparable to humans' abrupt drop in accuracy once n-back goes beyond 3-back [44].

**Soft Token Compression**: Soft tokens refer to a short set of special trainable tokens [41, 71, 97] that stand in for much longer text inputs. By adding small learned parameters [53, 79], they create a compact prefix which the model then conditions on, instead of reprocessing the entire text. For instance, AutoCompressor employs an unsupervised objective to produce short summary vectors segment by segment [19]; In-Context Autoencoder [41] uses a LoRA-enhanced encoder that transforms lengthy documents into "memory slots," and GIST [97] modifies attention masks so the model compresses inputs into a few gist tokens.

**Hierarchical Summarization**: Existing approaches [16, 109] split the input and summarize each piece in a multi-level fashion, which is conducted by traversing summary trees to find relevant segments. For instance, Nugget clusters adjacent tokens into contiguous "nuggets," each serving as a higher-level semantic unit [109]. WDMM constructs a memory tree and navigates it iteratively, retrieving only essential parts of the text [16].

# 3.2 Long-term Memory

The Long-term memory system stores observations and knowledge spanning multiple episodes. This reservoir of experiences, facts, and procedures enables LLM-based agents to recall and exploit historical insights.

3.2.1 **Memory Category:** Long-term memory can be categorized into three types based on cognitive science principles [8]: episodic memory (storing specific experiences), semantic memory (storing factual knowledge), and procedural memory (storing task-specific procedures).

**Episodic memory**: Episodic memory systems store specific events or experiences (e.g., user interactions, gameplay events) to contextualize interactions over time. Recent methods emphasize structured organization of episodic memories. For instance, Generative Agents maintains streams of observations and interactions, along with metadata like recency and importance for retrieval purpose [100]; MemoryBank stores user interaction histories as discrete episodes (e.g., chat logs, emotional states) and periodically updates them via relevance scoring [195].

**Semantic Memory**: Semantic memory captures facts, commonsense knowledge, or domain-specific information independent of individual episodes. For instance, LongMem [153], Mem-LLM [94] and MEMORYLLM [155] both maintain a pool of factual data or key-value structures for retrieval augmented generation; AriGraph [9] establishes a knowledge graph by extracting semantic triplets (object1, relation, object2) from episodic observations.

**Procedural Memory**: Procedural memory systems store task-specific skills (e.g., combat strategies, task-solving plans) as action sequences or subgoal hierarchies, which emphasize the reusability for dynamic environments. For example, Voyager [148] maintains a skill library with successful executed program stored in vector database for reusing; DEPS [158], GTIM [197] and HiAgent [54]

decomposes complex tasks into hierarchical subgoals, caching successful trajectories as procedural memories. Furthermore, procedural knowledge can be stored implicitly in parameters: PEMA [67] adopts a parameter-efficient module to store partial "procedures". Although it is primarily about parameter adaptation, one can view these small adaptation matrices as a rudimentary procedural memory.

3.2.2 *Memory Organization*. Below we summarize the data structure stored in the memory system and how memory is updated in offline and online.

**Text chunk:** Chunks are raw text with a fixed length limit, and are a widely used structure to store memory in existing LLM agent systems [100]. It is very easy for inserting new piece of memory for chunk-based memory system. To facilitate retrieval, metadata (e.g., timestamps, importance scores, Q values [183]) can be attached to each memory chunk.

**Key-value Pair:** Keys typically represent unique identifiers or semantic representations of stored information, while values contain the corresponding memory content. The structure supports fast lookup based on exact or approximate key matches and supports various data modality beyond text. For instance, in Voyager [148], the keys are representations of program descriptions and the values are corresponding program codes; In JARVIS-1 [157], the keys are composition of tasks and observations in image, while the values are the successfully executed plans.

Tree Structure: Building on the idea that memories often present subtopics and hierarchical structures, Generative Agents [100], RAPTOR [115] and MemTree [114] organize memories into hierarchical trees by clustering similar memories based on semantic similarity and summarizing each cluster recursively. The process yields a bottom-up tree with raw chunks at the leaves and higher layers are more abstract summaries. While RAPTOR operates offline, Generative Agents updates in batches, and MemTree processes memory in a streaming fashion: when a new piece of memory comes in, it traverses the tree from the root down, deciding whether to merge the new text with an existing node or create a new child node, updating the parent nodes along with the path.

**Knowledge Graph:** In knowledge graph, memory is organized in knowledge triplets, describing the semantic relationship between entities: <head entity, relation, tail entity>. Existing methods [9, 28, 78] begin by segmenting raw text into chunks and prompt LLMs to extract knowledge triplets, where nodes represent entities, while edges represent relationships. GraphRAG [28] further clusters nodes into communities for summarization to maintain a hierarchical structure; In AriGraph [9], the agent dynamically updates a heterogeneous knowledge graph that includes semantic knowledge triplets representing objects or concepts, and episodic triplets representing episodic events.

**Stored in Parameters:** As human brain does not have any explicit storage for text or structured knowledge, storing memory in a parametric form seems more aligned with the human cognitive system. Studies have shown that fine-tuning on high-quality experience or domain knowledge can implicitly integrate episodic/semantic/procedural memory into LLMs [32, 141]. An interesting instance is CharacterLLM [119], which fine-tunes LLMs on imaginary experience built from characters' profiles for role-playing. Each experience involves cognitive processes, utterances, or actions of a character in a certain scene. After fine-tuning, the model is able to recall detailed knowledge about people, events, and objects associated with the role, and exhibits a stronger personality.

3.2.3 **Memory Retrieval**. Memory retrieval is tightly coupled with the underlying data structure used for storage. Below, we categorize retrieval techniques based on memory structures, including text, vectors, graphs, trees and parametric storage.

**Metadata Retrieval**: When each memory item is stored, it will be attached with metadata (e.g., timestamps, importance scores) for retrieval. For example, both Generative Agents and Memory-Bank retrieves memories by weighting recency (exponential decay) to simulate the Ebbinghaus forgetting curve. Generative Agents adopts LLM to evaluate the importance score of each memory

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to differentiate core information from mundane details. REMEMBERER [183] records observation-action pairs in memory with Q-values and retrieves relevant actions with the highest and lowest values as encouraged and discouraged examples.

**Semantic Retrieval**: Semantic retrieval involves searching the closest memories related to a query object in the semantic space. The query object can be various forms, such as self-instructed question [100], task description [148] or game state [157]. For instance, Generative Agents computes the cosine similarity between a self-instructed question and stored text memories; For memories stored as (key, value) pairs, semantic comparison occurs between the query and the key object, returning the corresponding value. The modality of the query and the key is usually the same but can differ from that of the value. For instance, in Voyager [148], the keys are program descriptions and the values are program codes; In JARVIS-1 [157], the keys are composed of task and observations in image, while the values are the successfully executed plans.

**Graph-based Retrieval:** Retrieval in a knowledge graph typically involves three steps. First, when a query is received, the system identifies the most relevant nodes in the graph by assessing semantic similarity or using keyword matching. Second, the system traverses the graph along its connecting edges to reach multi-hop neighbors. Third, the collected subgraph is transformed into a coherent narrative that can be processed by LLMs.

**Tree-based Retrieval:** Tree-based systems adopt tree traversal to retrieve memory in the leaf node [114, 115]. Tree traversal starts at the root level of the tree and retrieves the top-k nodes based on cosine similarity to the query vector. At each level, it retrieves the top-k nodes from the child nodes of the previous layer's top-k. They also support "collapsed tree search", i.e., collapses the tree into a single layer and retrieves nodes based on semantic similarity.

3.2.4 **Verbal Reinforcement:** Using episodic memory as few-shot exemplars, semantic knowledge or procedural memory are straightforwardly effective, yet does not fully exploit the cognitive capabilities of LLMs. Studies demonstrate that LLM agents can evolve themselves by reflecting on the historical experience and reuse the insights gained in language [122]. To differentiate this line of research from traditional reinforcement learning, we use the name *verbal reinforcement*.

Learn from Failure: Reflection on failure is the most straightforward way to correct the same mistakes. Some environments provide instant feedback after the execution of action trajectories, such as "I cannot make stone shovel because I need 2 more stick" in MineCraft. Agents like Voyager [148], GTIM [197] directly incorporates these failure feedbacks to iteratively refine the plan. Furthermore, Reflexion [122], DEPS [158], AgentPro [189] and ProAgent [182] instruct agents to reflect on the failure with chain-of-thought thinking to locate the errors in the previous trail, and reuse the reflective thoughts to improve in the subsequent trials. In some environments where feedback signals are sparse, heuristics and evaluator LLMs are adopted to provide informative feedback [122].

**Learn from Comparison:** Learning from success can consolidate one's advantages, or gain insights from others' experience. ExpeL [190] reflects on the most relevant successful experiences to summarize patterns and also derives insights by comparing success-failure trajectories. KWM [108] prompts LLMs to extract task knowledge from expert-demonstrated trajectories and fine-tunes an LLM as a world knowledge model to guide the agent model's planning.

## 4 Reasoning

Reasoning is the primary cognitive function that differentiates LLM-based agents from traditional AI agents, involving the formation of strategies using language to search for actions. Recent advances in reasoning can be categorized as following four classes:

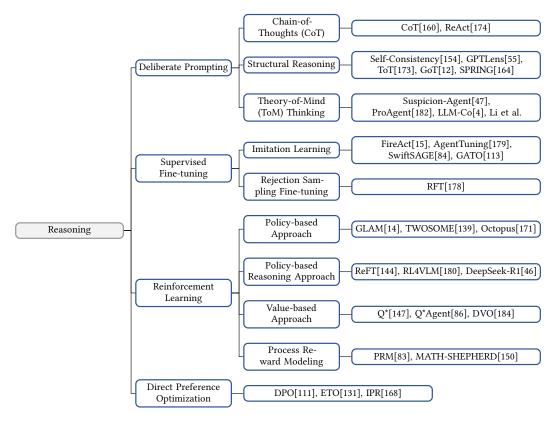


Fig. 4. Mind map for the reasoning module.

## 4.1 Deliberate Prompting

"Prompting" refers to eliciting the reasoning capabilities of LLMs at test time without explicit training for reasoning, while "deliberate" means that the reasoning workflow is controlled in a pre-designed manner.

Chain-of-Thoughts (CoT): CoT [160] is the first approach that prompts LLMs to conduct intermediate reasoning before generating the answers. Since generation can be seen as an autoregressive process of searching the next token in the latent space, the introduction of intermediate reasoning enhances the ability to traverse greater distances in that latent space, making LLMs capable of addressing more complex tasks. The ReAct [174] agent interleaves CoT reasoning and actions using few-shot prompting in text-based games. In their approach, reasoning acts as a mechanism for the agent to periodically check its task progress and plan its next steps.

The intermediate reasoning introduces stochasticity in generation, which can lead to inconsistent answers/actions. An example is that in Pokemon Battles, applying CoT can cause inconsistent actions (frequently switch new Pokemon in consecutive turns) [56]. This problem can be addressed by iteratively refining the thoughts from the last step rather than generating a new one.

**Structural Reasoning:** Self-Consistency [154] alleviates inconsistency by prompting LLMs to generate multiple chains of thoughts independently, and conduct majority voting on the final answer to find the most consistent reasoning path. GPTLens [55] replaces the majority voting with a self-criticism mechanism to criticize, score, and rank the reasoning for selection. The idea of

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self-criticism is also introduced in Self-Refine [90] and RCI [66], where the entire process consists of CoT, self-critique, and refinement.

Tree-of-Thoughts [173] argues that a complete chain of thoughts can contain incorrect intermediate thoughts. Instead, it decomposes a task into multiple steps, generates single thoughts for one step and selects the most correct one, making the reasoning look like traversing a tree of thoughts. Graph-of-Thoughts [12] can further aggregate single thoughts on different reasoning paths, converting a tree-of-thoughts into a DAG. SPRING [164] prompts LLMs to summarize the Crafter paper [51] and construct a template DAG where each node represents a question or instruction used to prompt LLMs for progressive reasoning.

Theory-of-Mind (ToM) Thinking: ToM thinking is the ability to understand that others have mental states, such as beliefs and intentions [35, 70]. Existing approaches prompt LLMs with specific questions to explicitly infer what others think (first-order) and what others think about its own thoughts (second-order). In imperfect information games like Leduc Hold'em, Suspicion-Agent [47] demonstrates that higher-order ToM lead agents to adopt more aggressive strategies (higher Raise rate) and reduce passive following (lower Call rate), and thus can accumulate more chips. In collaboration games such as Overcooked, ToM thinking enables LLM agents to adjust their actions to adapt to their partners' actions and offer assistance when necessary [4]. ProAgent [182] introduces a belief revision module to revise the wrong belief toward their partners when they observe partners' new actions; Li et al. [74] demonstrates that maintaining a belief state toward teammates' past observations and task-relevant objects can significantly improve ToM capabilities by reducing hallucination.

# 4.2 Supervised Fine-tuning

Supervised fine-tuning involves fine-tuning LLMs on collected trajectories to maximize the likelihood of the reasoning and actions demonstrated in those trajectories.

**Behavior Cloning:** The most straightforward way is to directly imitate expert players by fine-tuning on trajectories generated by experts. Some approaches learn from trajectories generated by state-of-the-art agents [84, 113]. Some methods adopt a teacher LLM to generate trajectories for fine-tuning a student LLM [15, 179]. Behavior cloning is widely adopted for training an initial policy model for RL training [131, 171].

**Rejection Sampling Fine-tuning:** Rejection Sampling Fine-tuning involves generating multiple samples, selecting ones that meet predefined criteria, and fine-tuning LLMs on the selected samples. For example, RFT [178] selects the successful trajectories based on the binary signal (success/fail) for fine-tuning LLMs. However, this might lead to inefficient learning when the agent is not proficient at the beginning of gameplay. Selection can also be based on rewards, whether provided by the environment or estimated by the model [143].

## 4.3 Reinforcement Learning

In RL training, as parameters updated to encourage good actions, intermediate reasoning is concurrently enhanced to elicit better outputs. Policy-based RL algorithms (e.g. PPO) widely adopted in conventional symbolic agents, can also be applied to LLM-based agents.

**Policy-based Approach:** Policy gradient approaches involve training an LLM as a policy  $\pi(a_t \mid s_t)$  for decision-making. The main idea is to use agents to collect rollouts and updates its policy to increase the likelihood of selecting actions that lead to higher rewards over time.

Existing game agents [14, 27, 139, 171] mainly adopt the PPO [117] algorithm to fine-tune LLM-based policy  $\pi(a_t, r_t \mid s_t)$ . Besides learning a policy model, PPO also learns a value model to estimate advantages for state-action pairs, which measures how much better an action is compared to the

average expected return in that state. The algorithm then optimizes the policy using advantage-weighted gradients while applying a clipping mechanism to ensure stable learning. The challenge of applying RL algorithms is that the generation space is huge, thus LLMs are likely to generate inadmissible actions. Therefore, some methods calculate the probability distribution of admissible actions by the chain rule for sampling, rather than direct generation [14, 139].

Reinforced Fine-Tuning (ReFT) [144] is the first approach that introduces explicit CoT reasoning during RL training to enhance the reasoning capabilities of LLMs. The main idea is to leverage PPO to increase the likelihood of a reasoning path  $P(rs, a \mid s)$  if the reasoning rs leads to a correct final answer. Zhai et al. [180] identify that CoT reasoning tokens are generally much longer than action tokens, causing RL training to focus more on the reasoning rather than the action. They propose scaling down the likelihood of reasoning and demonstrate that a moderate relative scale (0.3-0.5) can achieve optimal practice in games. A recent success is DeepSeek-R1 and R1-Zero [46] trained using Group Relative Policy Optimization (GRPO) [120] algorithm. GRPO is a variant of PPO but foregoes learning a value model and instead evaluates a policy by deriving a baseline from the reward statistics of a group of reasoning paths. DeepSeek-R1-Zero [46] demonstrates that even a pure RL fine-tuning solution can greatly enhance the problem-solving abilities of LLMs.

**Value-based Approach:** Value-based methods aim to learn a value function that estimates the expected return-to-go of taking action *a* in state *s*. A typical algorithm is Q-learning [93], which updates the Q-function via Bellman equations so that it reflects the future value of each state-action pair. When applied to LLM-based reasoning, each state may represent the partial generated content, and each action is a new reasoning step or token expansion. A key challenge in LLM reasoning is that the generation space is huge, making search algorithms essential for expanding reasoning steps. In practice, one can employ strategies such as Best-of-N sampling, Monte Carlo tree search, or A\* algorithms to explore and evaluate candidate expansions with Q-function m odel [86, 147, 184].

**Process Reward Modeling:** A key challenge in RL for reasoning is that conventional reward signals are given only on actions rather than reasoning, providing no direct feedback about where or why a chain of thought goes wrong. To this end, Process Reward Model (PRM) [83] has been proposed to supply dense feedback by evaluating each intermediate reasoning step.

However, training a PRM generally demands extensive annotations or carefully engineered heuristics to grade the intermediate steps. Recent works seek to approximate these process rewards without exhaustive human labeling [150, 176]. For instance, MATH-SHEPHERD [150] uses Monte Carlo sampling of multiple possible continuations at a given step and takes the average of final outcomes as the step-level reward. With these augmented rewards, both policy-based and value-based methods become more efficient for improving the intermediate reasoning steps.

# 4.4 Direct Preference Optimization

DPO [111] enables an LLM to learn in a contrastive learning style, *i.e.*, it maximizes the margin between the likelihoods of good and bad generations. The advantage of DPO is that it eliminates the need for learning value models, thus streamlining the training and reducing the memory cost. Specifically, ETO [131] involves iterating between the exploration stage and the fine-tuning stage. In the exploration stage, the agent interact with the environment to collect trajectories, while in the fine-tuning stage, it applies DPO on pairs of success and failure trajectories. IPR [168] further introduces step-wise DPO on pairs of steps, paired based on the average reward calculated via Monte Carlo method.

# 5 Input/Output

LLM-based game agents rely on an input (perception) module to interpret the game. Conversely, the output module ensures that the agent's decisions translate into executable game commands.

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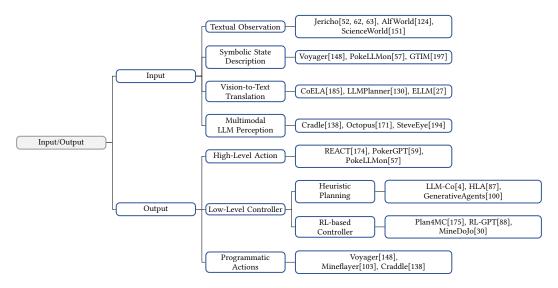


Fig. 5. Mind map for the Input/Output module.

The quality of input/output module directly impacts the agent's ability to engage with game environments.

# 5.1 Input (Perception)

Approaches for tackling input can be categorized based on the modality of the game state.

**Textual Observation**: In text-based or dialogue-centric games [62, 124, 169], the environment state is already described in natural language. The agent can directly take these text descriptions as input without additional preprocessing [122, 174].

**Symbolic State Description**: Some game environments provide structured state information through APIs or internal game engines [57, 80, 89, 95]. Recent systems access these symbolic state variables (e.g., an avatar's stats, object properties, or game world coordinates) and then convert them into textual or structured prompts for the LLM. For example, Mineflayer [103] enables users to access a character's health, inventory, or nearby entities from the Minecraft game engine, which can then be filled into a prompt template to generate a summary of the current state [57]. This approach works best when the symbolic state can sufficiently capture the essential context.

**Vision-to-Text via Encoder**: For games with important visual components, a common approach is to employ an external vision model to translate video frames into text before feeding it to the LLM. Recent studies have used object detectors or pre-trained visual encoders, *e.g.*, CLIP [110] to generate captions for vision-to-text translation. For example, an agent in a 3D environment can use an object detector to list visible objects ("a key on the floor, a locked door ahead") and is inserted into the prompt template [130, 185]. The agent can also adopt a visual encoder to map images into pre-defined text descriptions [27, 157, 158], or a text decoder to generate the caption [27, 96] to summarize the scene.

**Multimodal LLM Perception**: An emerging trend is the use of multimodal large language models to directly process images alongside text. These models align visual and textual information in a shared representation space, allowing an agent to feed raw images or pixels to the model and get an immediate understanding. Recent works [23, 138, 181] leverage general-purpose multimodal LLMs (e.g., GPT-4 Vision [3]) to interpret game visuals. This direct approach can generalize well to

new games, but still requires mechanisms to correct errors or uncertainties in its perceptions [138, 171]. Game-specific multimodal models have also been introduced, *e.g.*, LLMs finetuned on paired image-instruction data for a particular game, such as SteveEye [194] or learned from environmental feedback through RL such as Octopus [171].

# 5.2 Output

LLMs typically generate high-level textual actions, such as "open the door", which might not be compatible with game controls or commands. The role of the output module is translating an LLM's decisions into concrete in-game actions.

**Direct High-Level Action**: In games where actions are naturally expressed in language or discrete choices, an LLM's output can be directly used as the agent's action. For example, in choice-based games or dialogue scenarios [56, 59], an LLM can select one of the provided options as the next action. In parser-based environments, such as text adventure games or interactive narratives [52, 91], the model needs to output a command like "open the door" or "pick up the sword," which will be parsed by the game engine for execution. As a result, a challenge here is ensuring the LLM's output is admissible for the game. Researchers have introduced methods to constrain or correct the LLM's free-form text to match the game's expected commands, *e.g.*, semantically mapping a phrase to the closest permissible action [130], or calculating the probability of admissible actions rather than generation [5, 14].

Translation via Low-Level Controller: Many video games require sequences of low-level controls (keystrokes, mouse movements, joystick inputs) to perform a desired high-level action. Therefore, a translation layer is introduced to convert the LLM's intended action ("go to the red key and pick it up") into a series of concrete game controls. One approach is heuristic planning [4, 87, 100]. For instance, if the LLM decides "chop a tree" in Minecraft, the agent will invoke a navigation algorithm (e.g., A\*) to find the nearest tree, then execute a sequence of movements along with the chop action [197]. Another approach is adopting low-level controllers conditioned on the LLM's high-level action decisions [27, 88, 175, 197]. In this setup, the action provided by an LLM is regarded as a goal, and an RL policy takes over to produce the low-level control outputs, learning to fulfill the LLM's intention through trial-and-error and feedback rewards, based on the semantic similarity between the goals and the agent's transitions.

**Programmatic Actions**: An alternative choice is to have the LLM output actions in a structured format (e.g., code) that can be executed in the game environment [138, 148]. For example, an LLM-based agent can generate a snippet of code like *bot.equip(sword)*; which is then executed in the game's modding API [103], or even operate at the computer control level, such as *key\_press("M")*. To prevent repetitive generation of low-level control code, the agent can accumulate a skill library to only generate high-level code that calls low-level functions [138]. The benefit of structured output is that it removes ambiguity, allowing the agent to perform complex operations reliably. However, ensuring the code format is syntactically and semantically correct often requires careful prompt design or self-correction steps [148].

# 6 Applications in Gameplay

We categorize existing studies into six categories based on the main characteristics of the games they support, including adventure, communication, competition, cooperation, simulation, and crafting & exploration. Figure 6 illustrates the core gameplay mechanics associated with each genre:

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Fig. 6. The depiction of six game categories.

- Adventure: Adventure games emphasize story-driven gameplay, where players explore environments, solve quests and interact with characters and objects to progress the game. Representative games: Zork I [62] and Red Dead Redemption 2 (RDR2) [138].
- **Communication**: Communication games revolve through the turns of communication, negotiation, deduction and even deceptions among multiple players. Representative games: Werewolf [169] and Diplomacy [29].
- Competition: Competition games pit players against each other in challenges that test skill or strategy, aiming to outperform others for victory. Representative games: StarCraft II [89] and Pokémon Battles [57].
- Cooperation: Cooperation games are designed around players working together towards common goals, emphasizing teamwork, collaborative problem-solving, and shared achievements. Representative games: Overcooked [13].
- **Simulation**: Simulation games replicate real-world events in detail, allowing players to experience and manage scenarios ranging from building a civilization or living another life. Representative games: The Sims [65, 100] and Civilization [106].
- Crafting & Exploration: Crafting & Exploration games provide open worlds where players gather resources, craft items, and explore within expansive environments, encouraging creativity and discovery. Representative games: Minecraft [95] and Crafter [51].

We summarize existing studies on LLMGAs in Table 2. In this section, we will walk through six game categories, highlighting key findings and methodologies employed in the current research landscape.

## 6.1 Adventure Games

Adventure games typically progress through storylines or quests. We categorize existing works into two types based on modality: text-based adventure games and video adventure games.

**Text adventure games**: A text adventure game provides a text-based environment in which players use text commands to interact with the world, exploring and completing quests. TextWorld [21] is a generator of synthetic text games [91, 177] with varying difficulty levels by adjusting parameters such as the number of rooms and objects, quest length and complexity; Jericho [52] is a collection of 56 human-made games originally designed for human players, covering fictions such as the *Zork* series [62, 63] and *Hitchhiker's Guide to the Galaxy* [10]; ALFWorld [124] is aligned to the embodied environment ALFRED [123], where agents are requested to accomplish six types of household tasks; ScienceWorld [151] simulates a primary school science curriculum, such as thermodynamics and electrical circuits. To complete a quest, an agent needs to navigate to specific rooms, obtain necessary items, conduct experiments, and analyze the results; BabyAI-Text [14] is a text extension of BabyAI [20], a procedurally generated minigrid environment where an agent navigates and interacts with objects.

Studies	Category	Game	Base Model	Fine-tuning	Modality
CALM [172]	Adventure	Jericho	GPT-2	✓	Txt
CanPlayWell [145]	Adventure	Zork I	GPT-3.5	Х	Txt
ReAct [174]	Adventure	ALFWorld	PaLM	Х	Txt
Reflexion [122]	Adventure	ALFWorld	GPT-3	Х	Txt
ADAPT [102]	Adventure	ALFWorld	GPT-3.5	Х	Txt
SwiftSAGE [84]	Adventure	ScienceWorld	GPT-4 & T5	✓	Text
GLAM [14]	Adventure	BabyAI-Text	FLAN-T5	✓	Txt
Cradle [138]	Adventure	RDR2	GPT-4V	Х	Txt & Img
Xu et al. [169]	Communication	Werewolf	GPT-3.5	Х	Txt
Xu et al. [170]	Communication	Werewolf	GPT-4	Х	Txt
Thinker [162]	Communication	Werewolf	ChatGLM-6B	✓	Text
ReCon [152]	Communication	Avalon	GPT-4	Х	Txt
AvalonBench [82]	Communication	Avalon	GPT-3.5	Х	Txt
CodeAct [?]	Communication	Avalon	GPT-4	Х	Txt
Cicero [29]	Communication	Diplomacy	BART	✓	Txt
WarAgent [58]	Communication	Diplomacy-like	GPT-4	Х	Txt
CosmoAgent [64]	Communication	Diplomacy-like	GPT-4	Х	Txt
DEEP [81]	Communication	Word Guess	GPT-4	Х	Txt
GameEval [107]	Communication	Word Guess	GPT-4	Х	Txt
PokéLLMon [57]	Competition	Pokémon Battles	GPT-4	Х	Txt
CoS [89]	Competition	StarCraft II	GPT-3.5	Х	Txt
SwarmBrain [118]	Competition	StarCraft II	GPT-3.5	Х	Txt
ChessGPT [31]	Competition	Chess	RedPajama-3B	✓	PGN
OthelloGPT [76]	Competition	Othello	GPT	✓	PGN
PokerGPT [59]	Competition	Texas Hold'em	OPT-1.3B	✓	Txt
GoodPoker [49]	Competition	Texas Hold'em	GPT-4	×	Txt
SuspicionAgent [47]	Competition	Leduc Hold'em	GPT-4	×	Txt
AgentPro [189]	Competition	Leduc Hold'em	GPT-4	Х	Txt

Table 1. Summarization of LLM-based game agents (Table 1)

Due to the lack of graphics, text games rely on the commonsense knowledge as a prior for how to interact with the environment. In parser-based text games, generating a three-word sentence with a small vocabulary of size 1,000 leads to 1 billion combinatorial candidates. Pre-trained LMs featuring human knowledge can effectively narrow down the action space and thus have been widely utilized as linguistic priors for guiding RL agents [121, 128, 135, 172]. Recently, LLMGAs are employed to playing text adventure games: Tsai et al.[145] suggest that the game-playing ability of GPT-3.5 is on par with state-of-the-art reinforcement learning (RL) approaches[7, 48], but it is incapable of constructing the entire map of a partially-known environment; REACT [174] and Reflexion [122] prompt LLMs to generate additional reasoning and reflection to condition the generation of actions; To solve challenging tasks, Adapt [102] and SwiftSage [84] adopt an LLM planner to decompose complex tasks into subgoals as needed; GLAM [14] leverage online RL to ground an LLM in BabyAI-text as a policy.

**Video adventure game**: Red Dead Redemption 2 (RDR2) is a 3D action-adventure game in which players assume the role of an outlaw, and follow the storyline of his life as part of a criminal gang. The game features an important characteristic, i.e., it guides the player what to do next with instant instructions. Cradle [138] is an LLMGA that perceives the game screen, analyzes

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Table 2. Summarization of LLM-based game agents (Table 2)

Studies	Category	Game	Base Model	FT	Modality
LLM-Co [4]	Cooperation	Overcooked	GPT-4	Х	Txt
MindAgent [45]	Cooperation	Overcooked	GPT-4	Х	Txt
ProAgent [182]	Cooperation	Overcooked	-	Х	Txt
HLA [87]	Cooperation	Overcooked	GPT-3.5&LLaMA2	Х	Txt
S-Agents [17]	Cooperation	Minecraft	GPT-4	Х	Txt
HAC [193]	Cooperation	Minecraft	GPT-4V	Х	Txt & Img
CoELA [185]	Cooperation	TDW-T&WAH	GPT-4	Х	Txt & Img
GenerativeAgents [100]	Human Simulation	SmallVille	GPT-3.5	Х	Txt
HumanoidAgents [159]	Human Simulation	Social	GPT-3.5	Х	Txt
LyfeAgent [65]	Human Simulation	Lyfe Game	GPT-3.5	Х	Txt
AgentSims [85]	Human Simulation	AgentSims	-	Х	Txt
CivRealm [106]	Civil. Simulation	Civilization	-	Х	Txt
ZeroShotPlanner [60]	Embodied Simulation	VirtualHome	GPT-3	Х	Txt
LLMPlanner [130]	Embodied Simulation	ALFRED	GPT-3	Х	Txt & Img
E2WM [167]	Embodied Simulation	VirtualHome	LLaMA-13B	1	Txt
Octopus [171]	Embodied Simulation	Behavior-1K	CLIP & MPT-7B	1	Txt & Img
Voyager [148]	Craft & Explore	Minecraft	GPT-4	Х	Txt
DEPS [158]	Craft & Explore	Minecraft	MineCLIP & GPT-4	Х	Txt & Img
GTIM [197]	Craft & Explore	Minecraft	GPT-3.5	Х	Txt
JARVIS-1 [157]	Craft & Explore	Minecraft	MineCLIP & GPT4	Х	Txt & Img
Plan4MC [175]	Craft & Explore	Minecraft	GPT-3.5	Х	Txt & Img
RL-GPT [88]	Craft & Explore	Minecraft	GPT-4	Х	Txt & Img
MineDoJo [30]	Craft & Explore	Minecraft	MineCLIP	1	Txt & Img
LLaMARider [32]	Craft & Explore	Minecraft	LLaMA-2-70B	1	Txt & Img
SteveEye [134]	Craft & Explore	Minecraft	CLIP & LLaMA2	1	Txt & Img
CreativeAgent [181]	Craft & Explore	Minecraft	GPT-4V	Х	Txt & Img
MCReward [75]	Craft & Explore	Minecraft	GPT-4	Х	Txt & Img
ELLM [27]	Craft & Explore	Crafter	Codex	Х	Txt & Img
SPRING [164]	Craft & Explore	Crafter	GPT-4	Х	Txt & Img
AdaRefiner [188]	Craft & Explore	Crafter	LLaMA2 & GPT-4	1	Txt & Img
OMNI [186]	Craft & Explore	Crafter	GPT-3	Х	Txt & Img
PlayDoom [23]	Others	Doom	GPT-4V	Х	Txt & Img
GATO [113]	Others	Atari	GATO	1	Img
Motif [68]	Others	NetHack	LlaMA-2	Х	Txt

instructions, generate action plans and control the character through mouse/keyboard operations using GPT-4V.

# 6.2 Communication Games

Communication (or conversational) games revolve around turns of communication, negotiation, deduction and deception among multiple players. The challenge of communication games lies in inferring others' intention behind ambiguous or misleading language utterances, and hiding one's own intention if necessary.

**Werewolf**: The game pits two groups against each other, *i.e.*, werewolves and non-werewolves (villagers, witch, guard and seer), and alternates between night phases, where werewolves secretly attack, and day phases, where survivors discuss and vote to eliminate suspects. The witch, guard,

and seer each possess unique abilities. Xu et al. [169] propose to retrieve and reflect on historical communications for enhancement, and observe that GPT-3.5 demonstrates strategic behaviors such as trust, confrontation, camouflage, and leadership. Xu et al. [170] employ a RL policy to select the optimal action from among the diverse actions generated by LLMs, aiming to overcome the LLMs' prior preference for specific actions. Wu et al. [162] introduce a RL policy to generate the next action by taking as input the reasoning generated by the LLM, and employ another LLM to generate descriptions aligned to the action.

**Avalon**: The game progresses through rounds of discussion and voting to decide who participates in the quests. The goal for the good team is to successfully complete quests, while the bad team aims to secretly sabotage these quests or identify the role of Merlin, who knows the identities of the bad players. Light et al. [82] suggest that GPT-3.5 struggles to formulate and execute simple strategies and sometimes reveals its own bad identity. Wang et al. [152] introduce a reasoning approach that takes into account first-order and second-order perspective shifts to combat pervasive misinformation. To combat hallucination, Shi et al. [?] propose to generate reasoning substeps in a code format that are interpreted as actions subsequently.

**Diplomatic games**: Diplomacy is the first diplomatic board game from the 1950s where players assume the roles of seven powers striving to conquer Europe during WW1. Each turn is marked by private negotiations, trust-building, and tactical coordination among players. Cicero [29] is a human-level agent in Diplomacy that integrates a RL policy for planning and a BART [72] model conditioned on the plan for generating consistent negotiation messages; WarAgent [58] simulates the participating countries, decisions, and consequences in WW I and WW II; CosmoAgent [64] mimics the communication, conflicts, and cooperation among various universal civilizations.

**Others**: Studies have demonstrated the game-playing abilities of LLMs in various games, including SpyGame (Who is Spy) [81, 107], Ask-Guess [81, 107], Tofu Kingdom [107], and Murder Mystery Games [161], known as Jubensha in Chinese.

## 6.3 Competition Games

Competition games, governed by strict rules, challenge agents with varied-level opponents, demanding advanced reasoning and skills. Competition games serve as benchmarks for evaluating reasoning and planning abilities of LLMGAs directly against human players. Reaching human-level performance is a crucial achievement that highlights the agent's prowess in complex decision-making and strategic implementation.

**StarCraft II**: StarCraft II is a real-time strategy game in which players are tasked with gathering resources, building bases, creating armies, and engaging in combats to defeat the opponent. Ma et al. [89] introduce TextStarCraft II, a natural language interface that enables LLMs to play StarCraft II and Chain-of-Summarization for efficient reasoning and decision-making; SwarmBrain [118] introduce an Overmind Intelligence Matrix for high-level strategic planning and a Swarm ReflexNet for rapid tactical responses. These LLM-based agents exhibit comparable performance against the game's built-in AI at high difficulty levels.

**Pokémon Battle**: Pokémon battles are turn-based tactical games, with two players each sending out one Pokémon and choosing either to attack or switch Pokémon each turn. Hu et al. [57] introduce an environment that enables LLMs to play Pokémon battles and a human-level agent PokéLLMon that consumes instant feedback to iteratively refine the policy, retrieves external knowledge to combat hallucination, and generates consistent actions to alleviate the panic switching problem caused by CoT [160] reasoning.

Chess: Feng et al. [31] introduce a large-scale chess gameplay dataset stored in Portable Game Notation format and ChessGPT [31] fine-tunes on mixed chess and language datasets to support board state evaluation and chess playing; Toshniwal et al. [142] and Li et al. [76] discover that

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LMs trained to predict next move in chess are capable of tracking the state of the board given a move sequence, *i.e.*, LMs are capable of playing blindfolded. This suggests that LMs do not merely memorize surface statistics but also learn a causal model of the sequence-generating process.

**Poker**: In Texas Hold'em, Gupta et al. [50] observe that GPT-4 plays like an advanced yet aggressive player who raises with a wide range of hands pre-flop, avoids limping, and exhibits unconventional play; PokerGPT [59] demonstrates that OPT-1.3B [187] with supervised fine-tuning and RLHF [99] can achieve comparable performance to a RL-based method Alphaholdem [191] with significantly less training cost: 9.5 GPU hours compared to Alphaholdem's 580 GPU hours. Guo et al. [47] and Zhang et al. [189] demonstrate that prompting LLMs to predict opponents' thoughts, known as Theory of Mind [35, 70], results in significant improvements in Texas Hold'em, BlackJack and Leduc Hold'em [132].

# 6.4 Cooperation Games

Cooperation among individuals can enhance the efficiency and effectiveness of task accomplishment. There are primarily three types of cooperative tasks in games: (1) **Cooperative cooking** [13, 45, 163] requires agents to collaborate to cook and deliver as many dishes as possible within the given time. To prepare an onion soup in Overcooked-AI [13], two agents need to load three onions into a cooker, starting a cooking process that lasts 20 time steps, and transfer the soup to a plate for delivery; (2) **Embodied household cooperation** [38, 105] requires agents to collaboratively accomplish tasks like transporting as many objects as possible to the goal position in embodied environments with partial observation [37, 104]; (3) **Cooperative crafting** [17, 45] & **exploration** [193] in Minecraft can be accelerated through cooperation between multiple agents. Existing cooperative game settings can be categorized into decentralized and centralized cooperation.

Decentralized cooperation: A decentralized structure is a democratic structure ( ) where there is no central task dispatcher. In Overcooked, the ability to infer the partner's intent and next action based on the its historical actions, known as Theory-of-Mind, is crucial to prevent conflicts. Agashe et al. [4] show that agent based on GPT-4 is able to recognize and offer assistance to partners in need, and show robustness in adjusting to different partners. ProAgent [182] introduces a belief correction module to rectify incorrect beliefs on partners and consistently outperforms RL approaches [80, 117, 192]. Moreover, HLA [87] integrates a proficient LLM and a lightweight LLM to balance efficacy and efficiency in real-time human-agent interaction; In partially-observable embodied environments, CoELA [185] introduce an efficient communication module to determine what and when to communicate, exhibiting better performance compare to MCTS-based and rule-based planners on Watch-and-Help [105] and TDW Transport tasks [38].

Centralized cooperation: In Minecraft, S-Agents [17] and MindAgents [45] adopts a centralized dispatcher/planner to decompose a challenging goal into subtasks and dispatches them to agents for execution, forming a hierarchical architecture. HAS [193] introduces an auto-organizing mechanism to dynamically adjust key roles and action groups during cooperation, and an intra-communication mechanism to ensure efficient collaboration.

# 6.5 Simulation Games

Simulation games provide simulated environments for real-world events or scenarios, enabling players to experience realistic interactions and decision-making in open-ended game playing. Existing studies can be categorized as human & social simulation, civilization simulation and embodied simulation.

**Human and social simulation**: Generative Agents [100] marks the first LLM-based human simulation experiment that leverages LLMs' prior knowledge to simulate human-like daily life and

social activities. Specifically, GPT-3.5 assumes the roles of 25 generative agents with unique persona and social relationship, residing in a small virtual town. A cognitive architecture is introduced to support agents in remembering, retrieving, reflecting, planning, and acting within dynamic environments. During the two-day simulation, emergent behaviors like exchanging information, forming new relationships and coordinating joint activities are observed.

On the basis of Generative Agents, Humanoid Agents [159] further considers the effects of states like basic needs (e.g., hunger, health, and energy), emotions, and closeness in relationships on agents' behavior generation; For other simulation environments, AgentSims [85] is a programmable and extendable environment; LyfeGame [65] is an 3D virtual small town in Japan. Three experimental scenarios are designed to assess the social behaviors of LLM-based agents, including a murder mystery, a high school activity fair, and a patient-in-distress scenario.

Civilization simulation: CivRealm [106] is a game environment based on Civilization [34], where each player governs a civilization simulating the progress of human history. As an openended game, it features diverse victory conditions, requiring players to strategically develop the economy, military, diplomacy, culture, and technology of their civilizations. Mastaba [106] introduces an advisor and an AutoGPT [125]-style worker, where the advisor aids in generating context-specific objectives while the workers handle the execution of these goals through generated actions. Experiments show that the advisor brings an advantage at the early game stage, yet the advantage diminishes as the game progresses.

**Embodied simulation**: In simulated 3D environments, embodied agents perceives their surroundings from an egocentric perception similar to human and engage with realistic objects to carry out a wide range of tasks by following instructions like "Rinse off a mug and place it in the coffee maker". Existing benchmarks include AI2-THOR [69], Virtual Home [104], ALFRED [123], iGibson [166], Habitat [116], ThreeDWorld [38], Behavior [133] and Behavior-1K [73]. Existing approaches [5, 60, 130, 167] primarily adopt LLMs as planners to decompose an instruction into action plans. Specifically, ZeroShotPlanner [60] prompts LLMs in zero-shot manner for planning; SayCan [5] uses a learned affordance function to assist LLMs in selecting valid actions during planning; LLMPlanner [130] adopts an KNN retriever to select few-shot examples and dynamically re-plan based on the observation in the current environment; E2WM [167] fine-tunes an LLM with embodied experience collected through action space search and random exploration to enhance the understanding of the environments.

# 6.6 Crafting & Exploration Games

Minecraft and Crafter are two game environments that have been widely studied for game agents with a focus on crafting & exploration. Minecraft [95] is a 3D sandbox game that offer players the great freedom to traverse a world made up of blocky, pixelated landscapes, facilitated by the procedurally generated worlds. The resource-based crafting system enables players to transform collected materials into tools, build elaborate structures and complex machines. Crafter [51] is a 2D open-world game that mirrors the survival mode of Minecraft. It challenges players to manage their resources carefully to ensure sufficient water, food, and rest, while also defending against threats like zombies. The game's world is also procedurally generated for the exploration purpose, and it includes 22 tasks for players to accomplish.

Existing agents can be divided as goal-conditioned agents that implement the task given an instruction (crafting), or autonomous exploration agents that navigate within the open-world based on self-determined objectives (exploration).

**Crafting**: The key challenge in crafting tasks lies in their complexity: agents must gather diverse materials scattered across the world and understand intricate recipes and the sequential steps involved. Consequently, planning is widely employed to address crafting tasks. Existing

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agent design such as DEPS [158], GITM [197], JARVIS-1 [157], Plan4MC [175], RL-GPT [88] and S-Agents [17] mainly follow a paradigm that adopts LLMs as a planner to decompose the goal into subgoals and further generate action plans for each sub-goals. Specifically, DEPS introduces error correction on initial plans by integrating description of the plan execution and self-explanation of feedback when encountering failures; GITM [197] leverages external knowledges like item crafting/smelting recipes, and is equipped with a long-term memory to maintain common reference plans for encountered objectives; JARVIS-1 [157] chains MineCLIP [30] and an LLM together to perceive multimodal input and utilizes a multimodal memory to store experiences; Plan4MC [175] and RL-GPT [88] integrate the LLM planner with a low-level RL policy for action execution; S-Agents [17] and HAS [193] dispatches subtasks to multiple agents for cooperative task execution;

**Exploration**: Navigating through procedurally generated world without specific goals can overwhelm agents with numerous possible actions. Previous works leverage curriculum learning [33] to identify suitable tasks while now LLMs can directly act as goal generators. In Minecraft, Voyager [148] adopts an automatic curriculum in a self-directed way [156], *i.e.*, it asks LLM to generate goals that adapts to the agent's current state, inventory, acquired skills, and environment. In Crafter, OMNI [186] utilizes LLMs to determine interesting tasks for curriculum design, overcoming the previous challenge of quantifying "interest". ELLM [27], SPRING [164] and AdaRefiner [188] prompt LLMs to generate goals for agents. Specifically, ELLM [27] queries LLMs for next goals given an agent's current context, and rewards agents for accomplishing those suggestions in the sparse-reward setting; SPRING [164] uses LLMs to summarize useful knowledge from the Crafter paper [51] and progressively prompts the LLM to generate next action; On the basis of ELLM, AdaRefiner [188] cascades a learnable lightweight LLM with fixed LLMs for better goal plan generation.

#### 7 Discussion and Future Directions

Game benchmark: High-quality game benchmarks are crucial for advancing the capabilities of LLM-based agents. Different game genres can be developed to cultivate specific skills. For instance, when focusing on knowledge discovery, game benchmarks should include rich semantic knowledge for agents to acquire, such as Type-effectiveness relationships in Pokémon battles [57]. To foster more sophisticated reasoning, benchmarks should incorporate a large number of possibilities and complex decision spaces. Action game benchmarks can assess agents' efficiency and effectiveness under time constraints, as well as their visual perception and low-level control abilities during intensive gameplay [89, 138]. Competitive and cooperative game benchmarks can evaluate theory-of-mind reasoning. For human or society simulation benchmarks, the environments could integrate sufficiently realistic elements and maintain a high degree of freedom, such as open-world or sandbox-style settings, to encourage emergent behaviors and ensure the resulting insights are both meaningful and robust.

**Self-evolution in environments**: Self-evolution involves continuously and autonomously enhancing an agent's in-game performance. For LLM-based game agents, there are two primary directions to consider going forward: (i) Model-based approaches, which focus on refining the agent's outputs based on a given input. For example, RL algorithms can be utilized for LLM-based agents to improve their reasoning processes and decision-making. Future research might explore how to integrate language-based feedback signals, devise suitable reward functions, and maintain stability and sample efficiency while training LLM-based agents with RL; (ii) Memory-based approaches, which focus on enhancing the quality of the agent's inputs, often by leveraging more structured or contextually rich memories. Techniques may include extracting and storing useful semantic knowledge, *i.e.*, knowledge discovery, or generating higher-level reflections and insights, *i.e.*, verbal reinforcement. Future work could investigate how to build and manage memory

modules that effectively capture and retrieve relevant information, as well as how reflection-based strategies can help an LLM-based agent revise and improve its behaviors over time.

Agent society simulation: Recent social simulation experiments [6, 22, 100] show promise in constructing believable human simulacra, an intriguing step toward human-like intelligence. These simulations exhibit emergent human-like behaviors such as group formation, information diffusion, and the development of new relationships and coordination strategies. Future work could expand this field along three primary directions: (i) Cognitive framework, which supports the psychological processes that underlie surface-level behaviors. Building cognitive frameworks that can accurately capture the complexity of human cognition, including beliefs, intentions, emotions, and social awareness are crucial for believable human simulation; (ii) Realistic modeling: the physical world in which humans live is significantly more complex, interactive, and freedom-rich compared to current simulation environments. Future research could focus on crafting more detailed and realistic environments to enable deeper insights into and representation of the complexities of human interaction; (iii) Large-scale simulation: most existing studies involve only a small number of agents [100], which is still far from the complexity featured by a society or civilization. Developing large-scale simulations involves challenges in parallel computation to handle numerous agents within a single world [6, 40]. Effectively scaling these simulations remains an open research and technical problem.

## 8 Conclusion

We have presented a systematic literature review on LLM-based game agents, covering four important aspects of the subject. First, we introduce the overall framework for LLM-based game agents with illustrative game-play examples. Second, we delve into three core components, *i.e.*, memory, reasoning, and input/output modules, providing comprehensive technical categorizations of approaches, and covering common design considerations for each. Third, we introduce LLM-based game agents in six game categories: adventure, communication, competition, cooperation, simulation, and crafting & exploration. We provide detailed discussion and analysis of the game environments, key tasks, and common strategies in each category, adopted by existing game agents in the literature. Finally, we outline several important directions for future research, from improved grounding in complex environments to large-scale simulation of open-world societies. This survey paper provides a comprehensive review of the key concepts, design principles and techniques, as well as the recent developments fueled by the large language model technology advancements. This survey not only serves as a valuable introduction for researchers exploring LLM-based game agents, but also a practical reference for industry researchers and developers working in both the gaming and software sectors for developing advanced AI-agent systems, toolkits, and applications.

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