ChatGPT

Related Work Building on Generative Agents and Voyager (2023)

Several research efforts in 2024–2025 have extended the ideas from Park *et al.*'s *Generative Agents* and Wang *et al.*'s *Voyager* – namely long-term memory for LLM-driven agents and no-gradient skill acquisition:

Memory-Augmented LLM Agents (Beyond Generative Agents)

- **Retrieval & Reflection in Agents (R2-MGA, 2025):** Ji *et al.* introduce *R2-MGA*, a *"Retrieval and Reflection Memory-augmented Generative Agent"* for verifiable text generation [1]. R2-MGA retrieves relevant memory snippets from a persistent **memory bank**, then *reflects* on them to form reasoning, before generating answers [1]. In evaluations, this approach dramatically improved answer correctness and citation quality (up to +58% and +154% gains) by grounding outputs in retrievable facts [2].

- **Self-Reflective Agents (Reflexion, 2023):** Shinn *et al.* showed that letting an agent **critique its own actions** in natural language after each step leads to large performance gains [3] [4]. Their *Reflexion* framework has the agent note mistakes and lessons after each reasoning step, storing these notes in memory. Incorporating this feedback in subsequent prompts yielded a *97% success rate* on virtual task benchmarks, versus far lower success without such memory-feedback loops [4]. This validated that *self-reflection plus memory* makes LLM agents much more robust and "human-like" problem solvers [4].

- **Agentic Long-Term Memory (A-Mem, 2025):** Xu *et al.* address the *organization* of an agent's memories. Their **A-Mem** system applies Zettelkasten-style note-taking: each new observation is stored as a structured "note" (with context, keywords, etc.), and the system dynamically **links** it to related past notes [5] [6]. As new memories are added, *relevant connections* are automatically formed and even update old notes, creating an evolving knowledge graph [7] [6]. This approach enables more flexible and context-aware memory retrieval than fixed vector stores, and it improved long-horizon task performance over vanilla memory schemes [5] [8].

- **Memory-of-Thought Prompting (MoT, 2023):** Li *et al.* propose a strategy for **continual self-improvement** without gradient training [9]. In *MoT*, an LLM first tackles many problems and saves its high-confidence reasoning chains to an external memory. Later, when facing new tasks, it *retrieves* these past reasoning "thoughts" to inform its answer [10]. This simple memory-augmented prompting yielded *significant gains in math, commonsense, and factual QA*, effectively letting the model *learn from its own prior solutions* without updating weights [11]. It's a practical demonstration of long-term *"memory"* aiding an LLM agent across sessions.

Skill Libraries and Lifelong Learning Agents (Beyond Voyager)

- **Open-World Skill Libraries (Odyssey, 2025):** Chen *et al.*'s *Odyssey* agent builds directly on Voyager's no-gradient learning paradigm. It provides a shared **skill library** of Minecraft behaviors and uses a fine-tuned 8B LLM (instead of GPT-4) as the agent [12]. Notably, Odyssey's skill library allowed a smaller model to **match Voyager's performance** (e.g. complex tool use and exploration) at a fraction of the cost [13]. The authors show that removing the skill library causes a severe drop in performance, underscoring Voyager's insight that accumulating reusable code-skills is key to long-term improvement [14]. Odyssey demonstrates these benefits can be achieved with accessible open-source models [15].

- **Parameterized Skills for Planning (PLAP, 2025):** To extend skill-based learning into *adversarial long-horizon tasks*, Cui *et al.* introduced the **Plan-with-Language, Act-with-Parameter (PLAP)** framework [16]. PLAP uses (1) a library of **parameterized skills** (high-level action templates with slots), (2) an LLM-based *skill planner* to sequence those skills, and (3) a skill executor to ground them into low-level game actions [17]. In a real-time strategy simulation, a GPT-4-driven PLAP agent outperformed 80% of baselines zero-shot [18]. This work shows Voyager's idea (LLM as a high-level planner with a skill repository) can generalize beyond Minecraft – even to competitive, dynamic environments – by structuring skills with parameters.

- **Automated Curriculum & Continual Learning:** Beyond specific papers, a general trend is emerging around **automatic curriculum generation** for LLM agents. For instance, several 2024 works (e.g. Yuan *et al.* 2023; Zhou *et al.* 2024) explore having the agent *propose its own next tasks* based on competency gaps (extending Voyager's task-selection idea). These systems keep the agent in a growth loop: new challenges → new skills → new challenges, indefinitely. While much of this is in early stages, it aligns with the *no-gradient lifelong learning* vision – training an agent by *doing tasks* and storing the solutions, rather than updating weights.

Multi-Timescale Memory and Continual Architecture

- **Nested Learning & Continuum Memory (NeurIPS 2025):** Behrouz *et al.* introduced *Nested Learning*, which reconceptualizes a model as **multiple levels of learning** running in parallel (inspired by human brainwave frequencies). In their "continuum memory system," model components update at different rates (fast, medium, slow), so that short-term knowledge gradually consolidates into long-term memory without catastrophic forgetting [19]. Their prototype *Hope* architecture, which implements multi-frequency weight updates and self-referential modifications, achieved **state-of-the-art long-context performance** – outperforming standard transformers and prior memory-augmented models on language and reasoning tasks [20]. This suggests that *multi-timescale memory* (as discussed in Nested Learning) is a promising direction to give LLM agents more durable learning across sessions.

- **Titans & Memory Prioritization:** (Related to Nested Learning) Researchers have also explored architectures like *Titans* (Google, 2023) that maintain an explicit long-term memory buffer for surprising or important information. These ideas influenced Nested Learning's design of memory hierarchies [19]. The general finding is that **selectively retaining "important" experiences** can mitigate forgetting. Future agents will likely combine *episodic memory (fast)* and *semantic memory* *(slow)* – much like Generative Agents did with reflections – so the agent **remembers key lessons** over its lifetime.

Sources: The above insights synthesize recent papers including *Generative Agents: Interactive Simulacra* (Park *et al.*, 2023), *Voyager: Lifelong Learning in Minecraft* (Wang *et al.*, 2023), *Nested Learning: The Illusion of Deep Learning Architecture* (Behrouz *et al.*, 2025), and follow-ups like R2-MGA [1], Reflexion [4], A-Mem [5] [6], Odyssey [12], and PLAP [16]. These works collectively point toward **LLM-based agents that learn iteratively** – accumulating code skills and memories – rather than relying solely on gradient-based model updates.

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[1] [2] Towards Verifiable Text Generation with Generative Agent
https://chatpaper.com/paper/161990

[3] [4] [9] [10] [11] Recent Advances in In-Memory Prompting for AI: Extending Context, Memory, and Reasoning | by Jose F. Sosa | Medium
https://medium.com/@josefsosa/recent-advances-in-in-memory-prompting-for-ai-extending-context-memory-and-reasoning-f38cff8bf7ec

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[12] [13] [14] [15] Odyssey : Empowering Minecraft Agents with Open-World Skills
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