Large Language Model based Multi-Agents: A Survey of Progress and Challenges

Taicheng Guo[1], Xiuying Chen[2], Yaqi Wang[3*], Ruidi Chang, Shichao Pei[4],
Nitesh V. Chawla[1], Olaf Wiest[1], Xiangliang Zhang[1†]
[1]University of Notre Dame, [2]King Abdullah University of Science and Technology
[3]Southern University of Science and Technology, [4]University of Massachusetts Boston

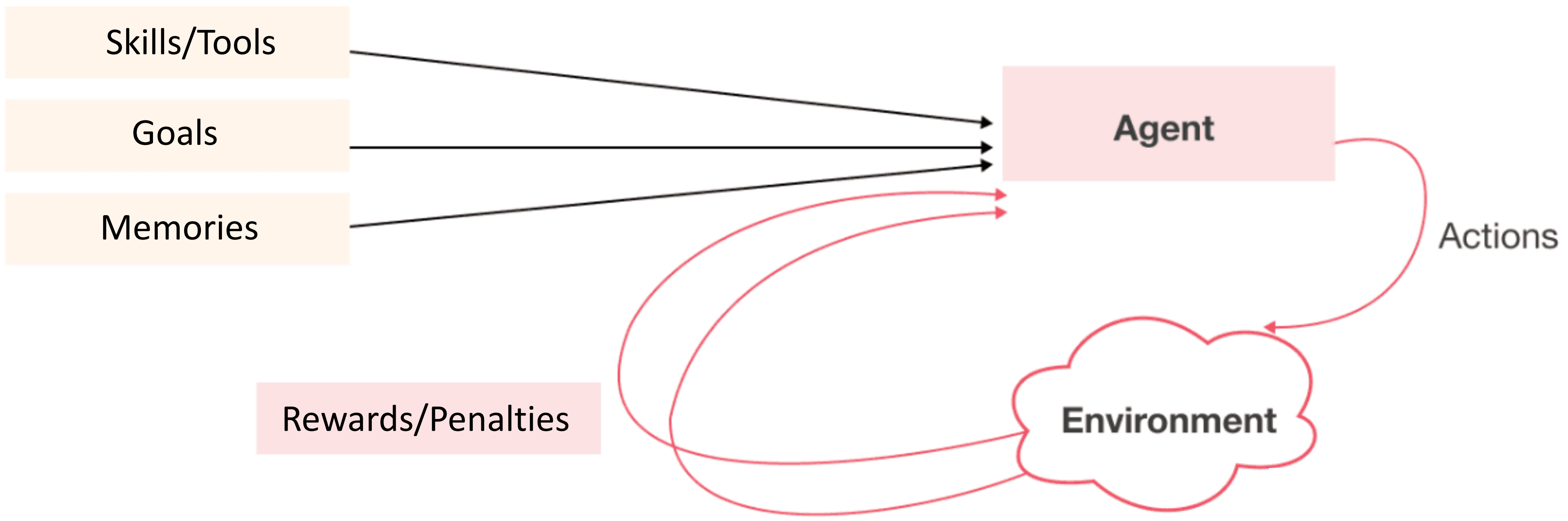
Large Language Model based Multi-Agent System Overview

A Survey of Progress and Challenges

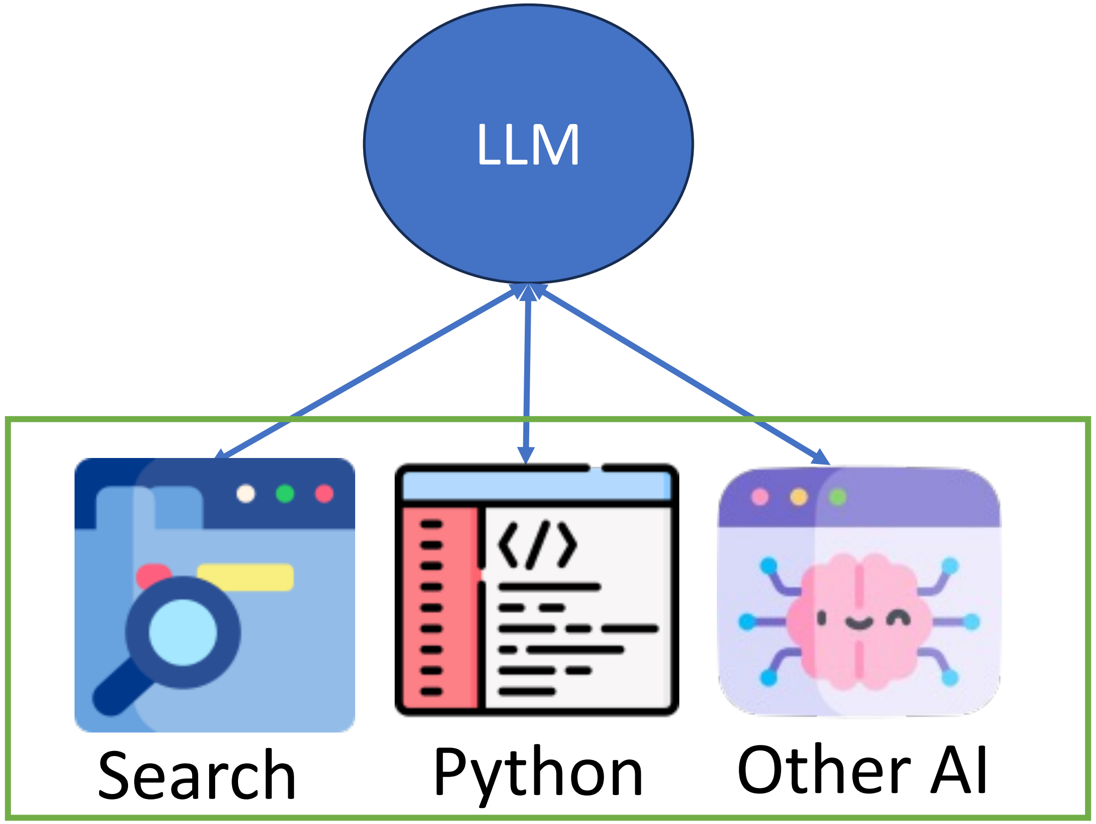
Yan Xu
Houston Machine Learning

What is an Agent?

An Agents is an **autonomous entity**, capable to interact with an environment, receive rewards or penalties, and learn an optimal policy for decision-making. Originate from Reinforcement Learning!

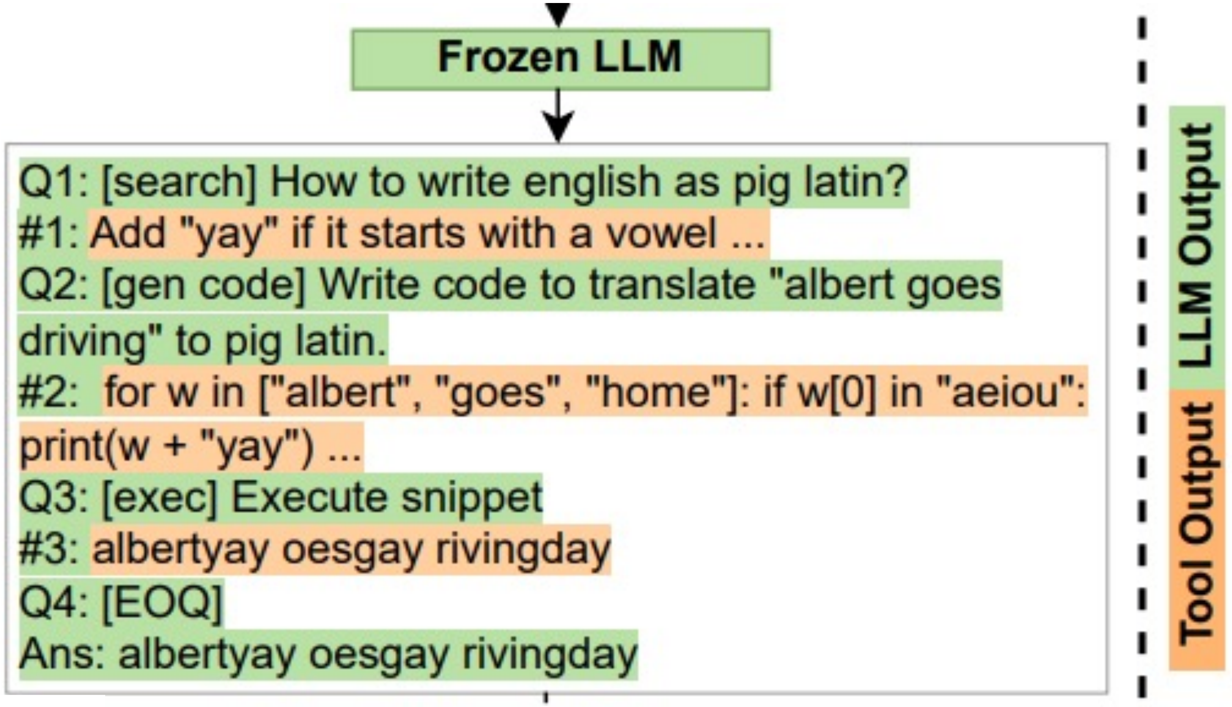


LLM Single-Agent



Single-Agent with Tools

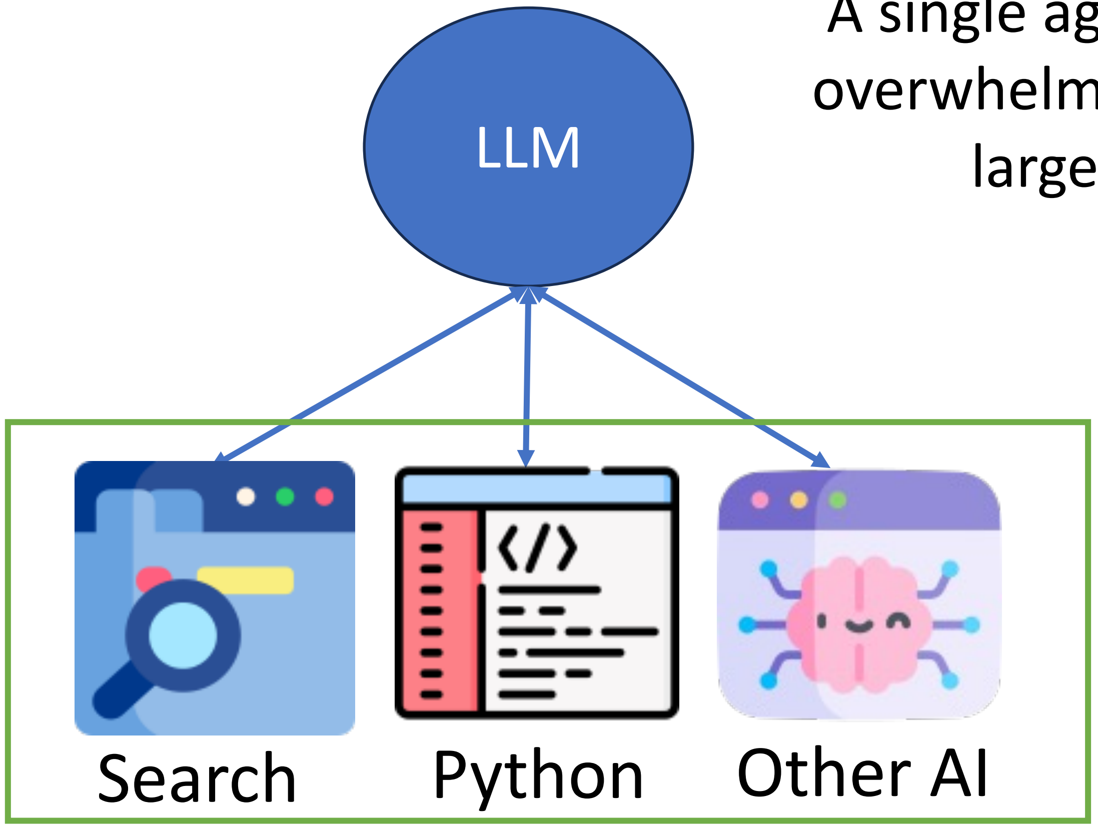
Input: Translate “albert goes driving” to pig latin.



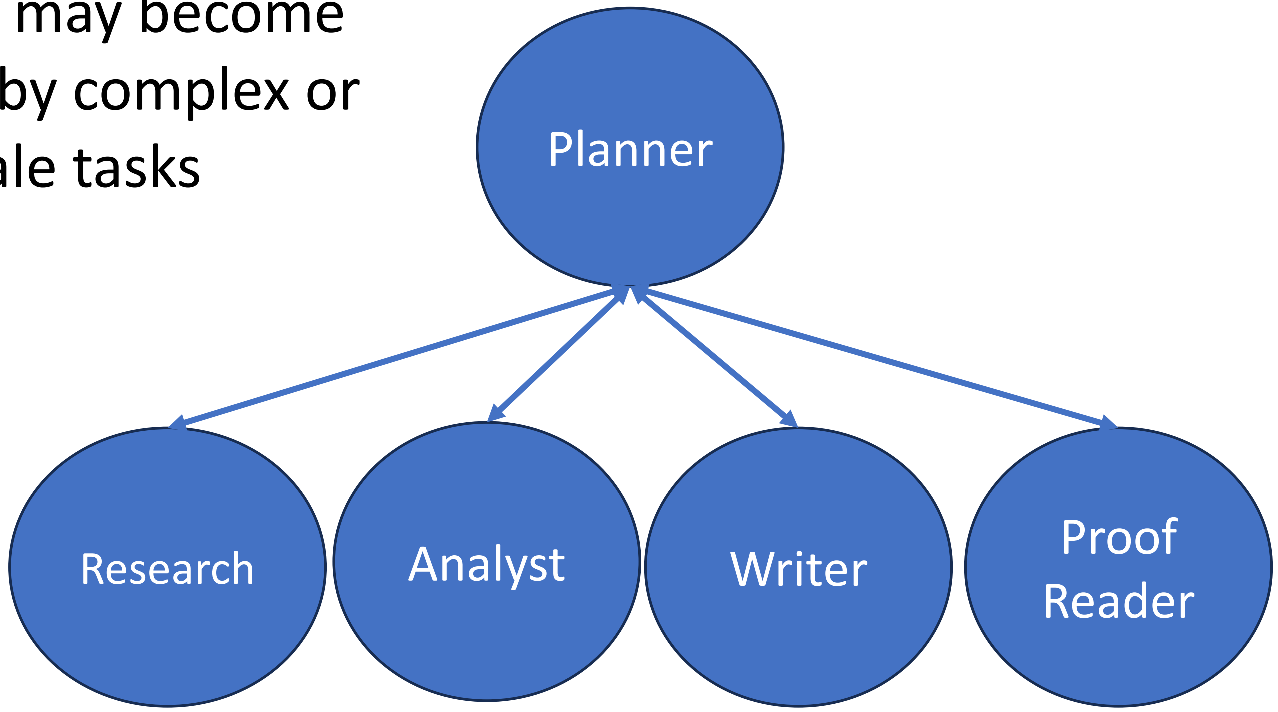
Break down the task step by step and call the right tools

LLM Single-Agent VS. Multi-Agent Systems

A single agent may become overwhelmed by complex or large-scale tasks



Single-Agent with Tools



Multi-Agent
(specialized agent with specialized tools)

LLM Single-Agent VS. Multi-Agent Systems

Multi-agent system (MAS) advantages:

Specialization and Expertise
More precise outcomes

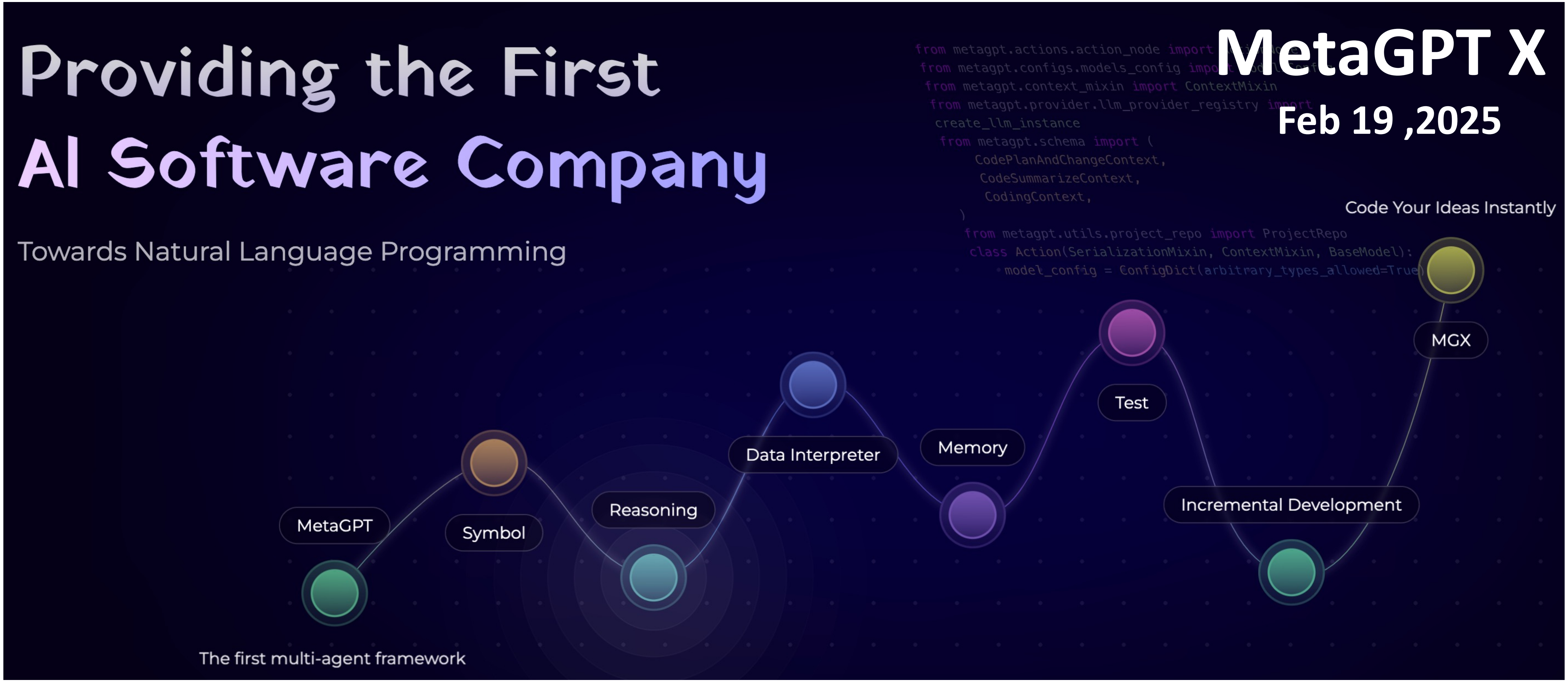
Parallel Processing
Improves system efficiency

Robustness and Reliability
Less depending on a single agent ensures continuity and reliability in operation

Scalability and Flexibility
New agents can be introduced to address new challenges

Collective intelligence?
Enable the system to tackle complex tasks beyond a single agent

Applications of Multi-agent System



AtomAgents: Alloy design and discovery through physics-aware multi-modal multi-agent AI

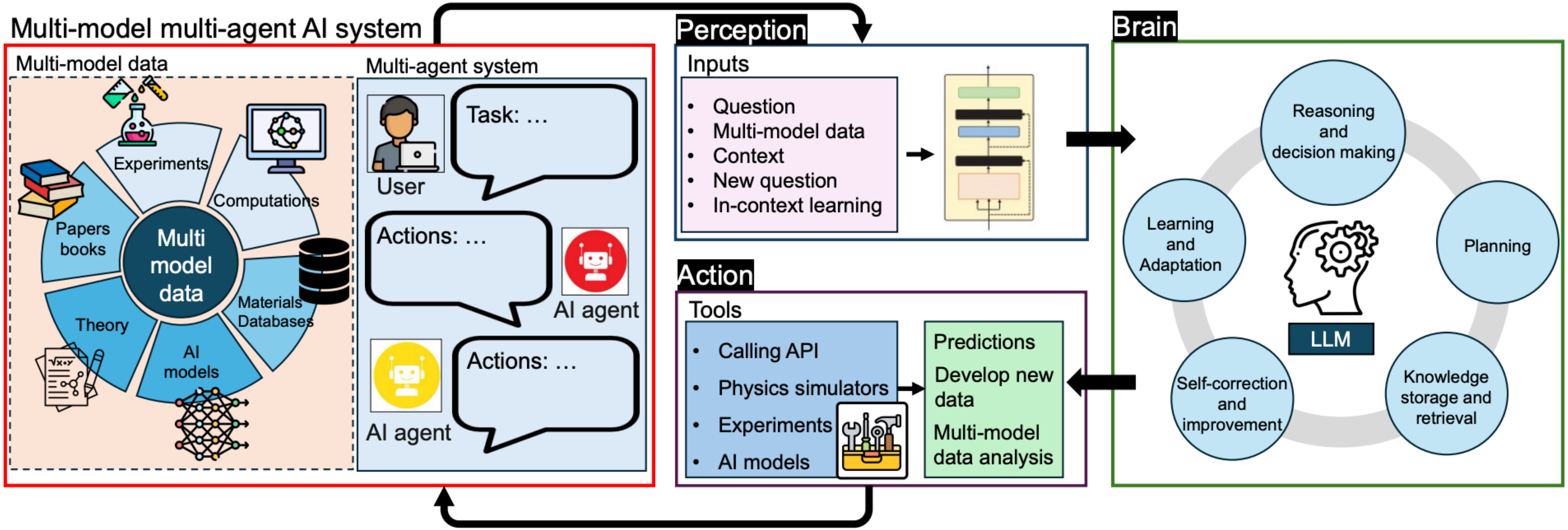


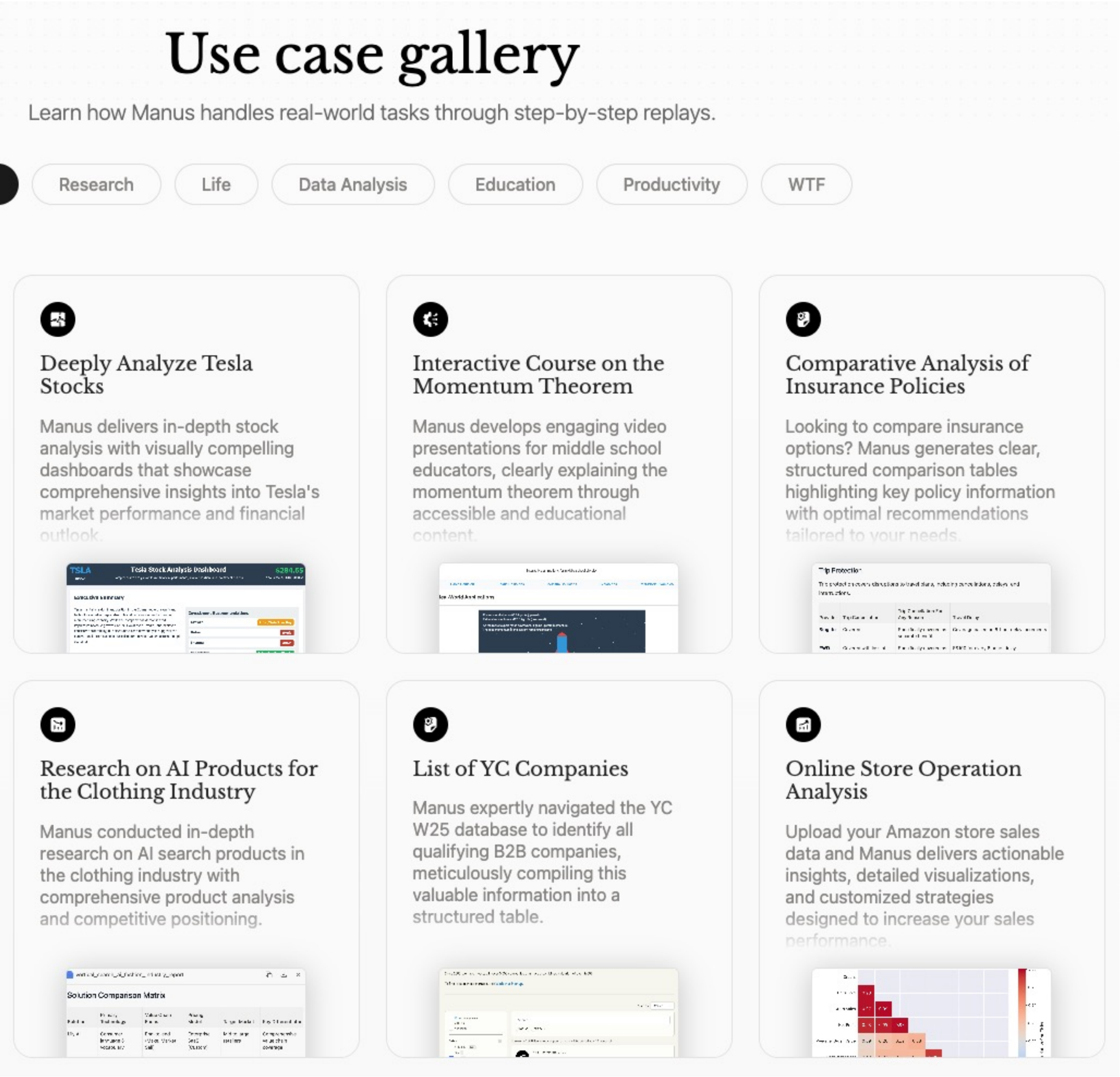
Figure 1: **Multi-model multi-agent approach as a flexible modeling strategy for materials discovery, modeling, and prediction.** Multi-agent modeling can extend the power of large-language models by enabling the integration of multimodal data from diverse sources, including simulations, experiments, materials databases, and theoretical models.

Laboratory for Atomistic and Molecular Mechanics (LAMM), MIT

MANUS AI

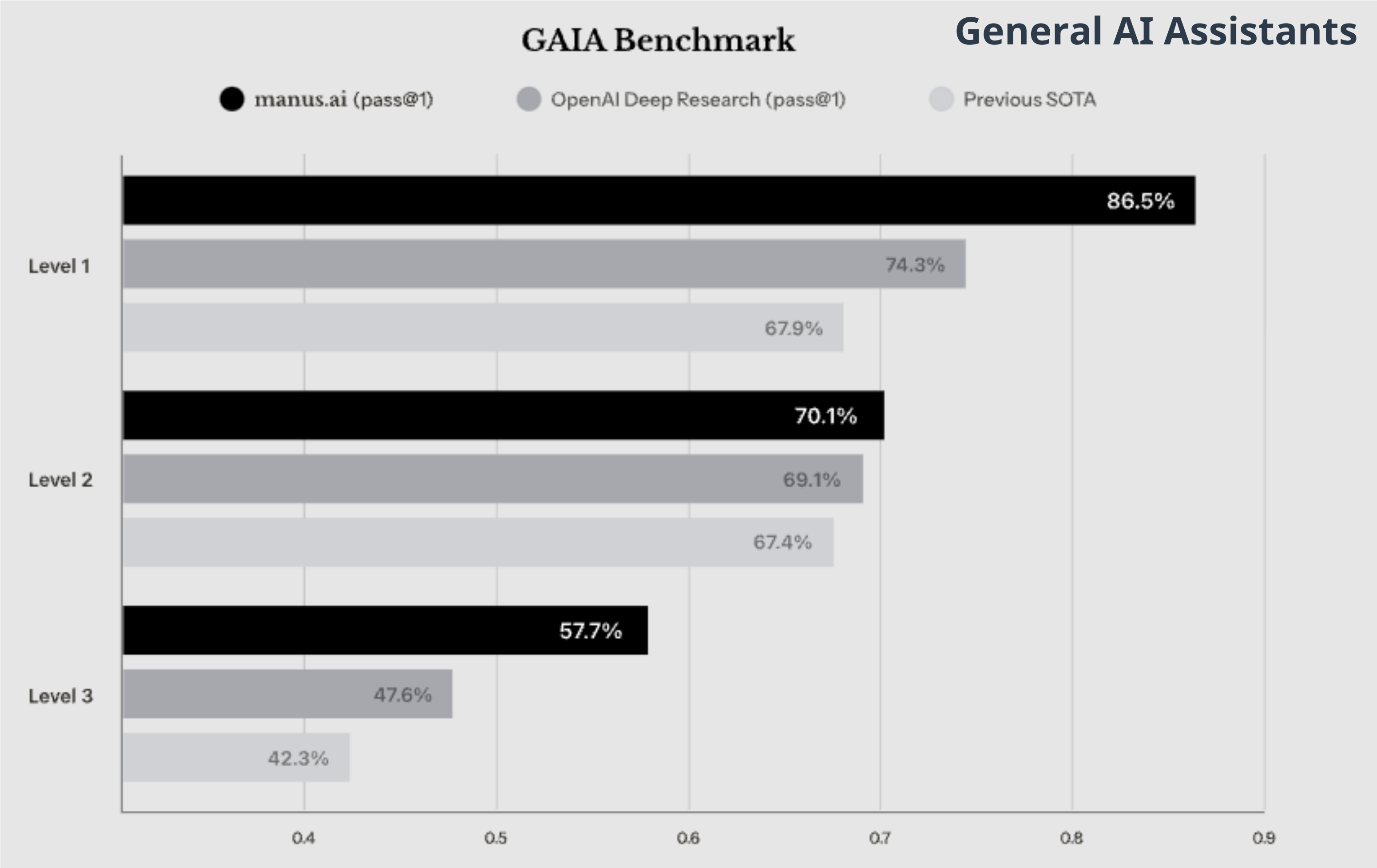
https://manus.im/

Manus is a general AI agent that bridges minds and actions:
it doesn't just think, it delivers results.



MANUS AI

https://manus.im/



OWL

open-source!

https://www.camel-ai.org/

CAMEL-AI

We are Building A HuggingFace-like Community for AI Agent Builders

OWL: Optimized Workforce Learning for General Multi-Agent Assistance in Real-World Task Automation

Documentation | chat 1.4k online | Follow @CamelAIOrg | r/CAMEL 47 | WeChat CamelAIOrg | WeChat OWLProject
Hugging Face CAMEL-AI | Stars 13k | License Apache 2.0

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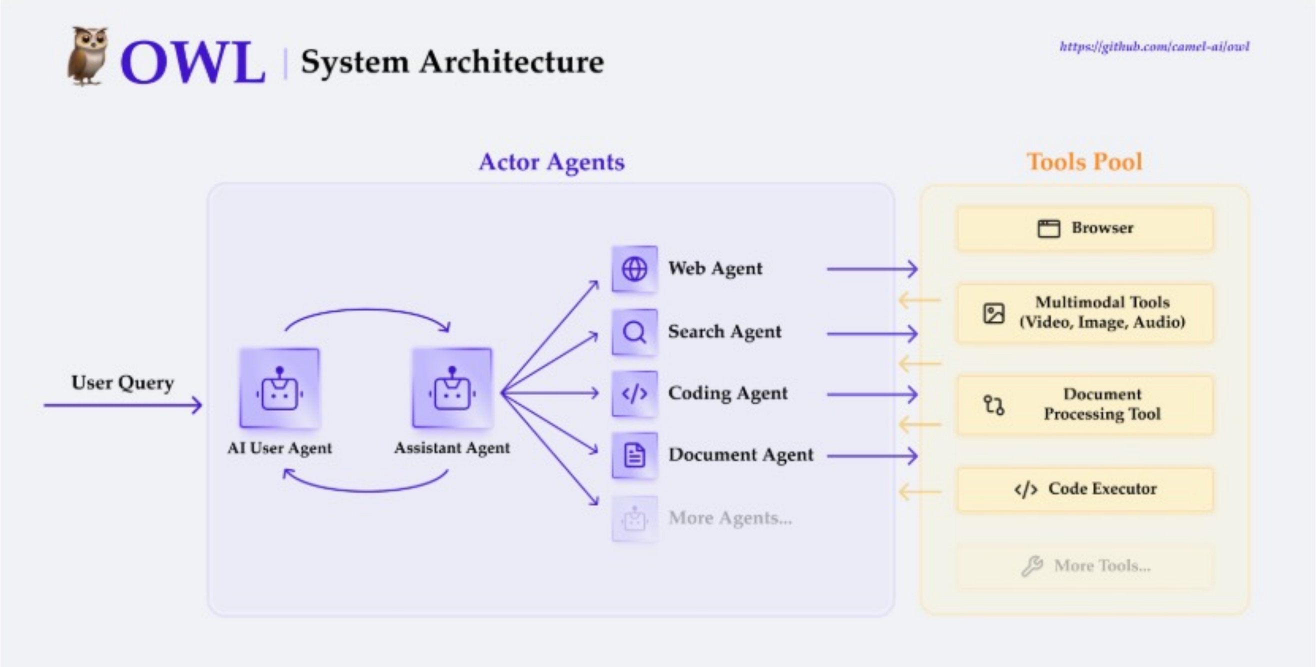
OWL achieves 58.18 average score on GAIA benchmark and ranks #1 among open-source frameworks!

OWL is a cutting-edge framework for multi-agent collaboration that pushes the boundaries of task automation, built on top of the CAMEL-AI Framework.

Our vision is to revolutionize how AI agents collaborate to solve real-world tasks. By leveraging dynamic agent interactions, OWL enables more natural, efficient, and robust task automation across diverse domains.



Dissecting LLM Multi-Agent Systems (MAS): Interface, Profiling, Communication, and Capabilities

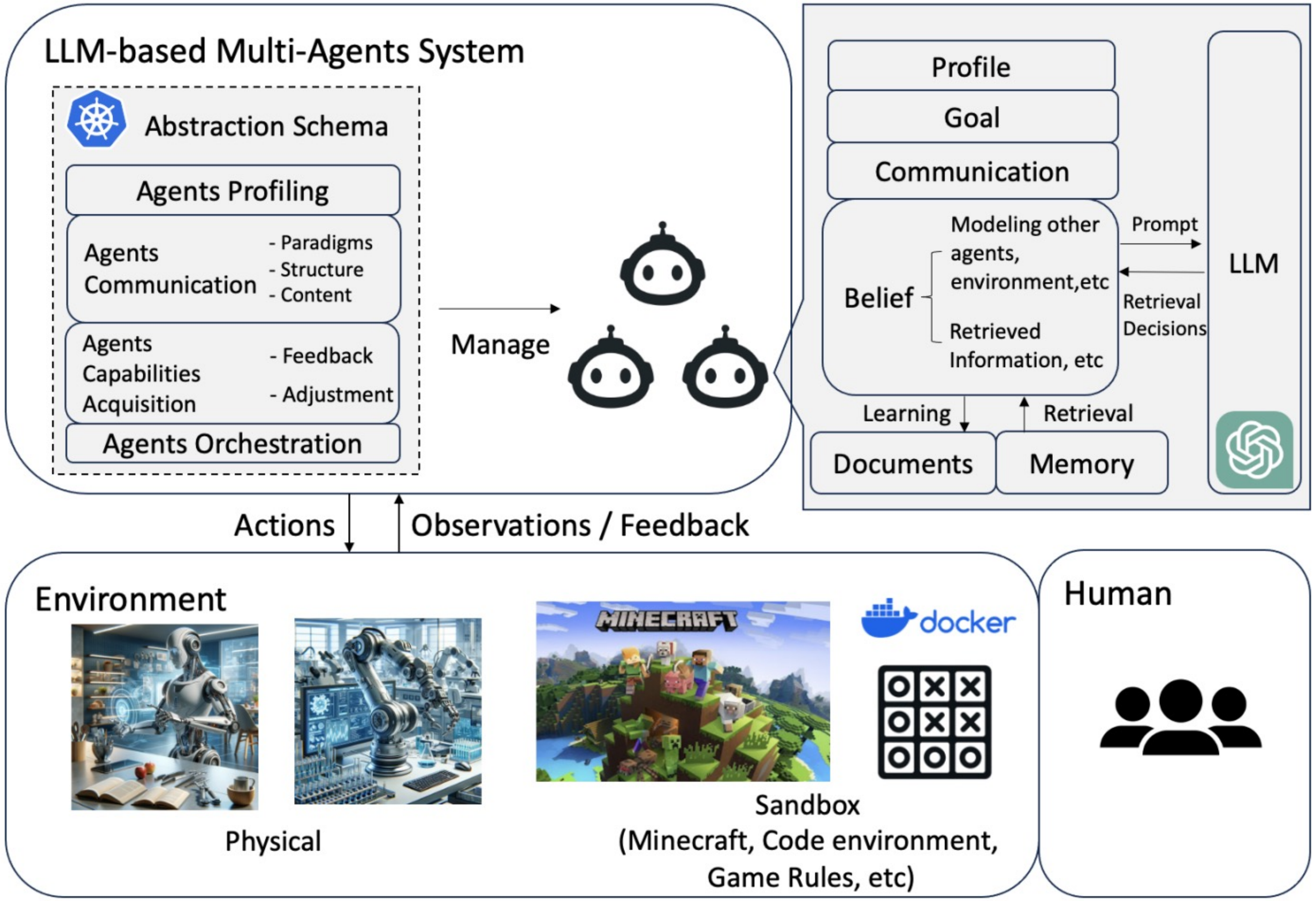


Figure 2: The Architecture of LLM-MA Systems.

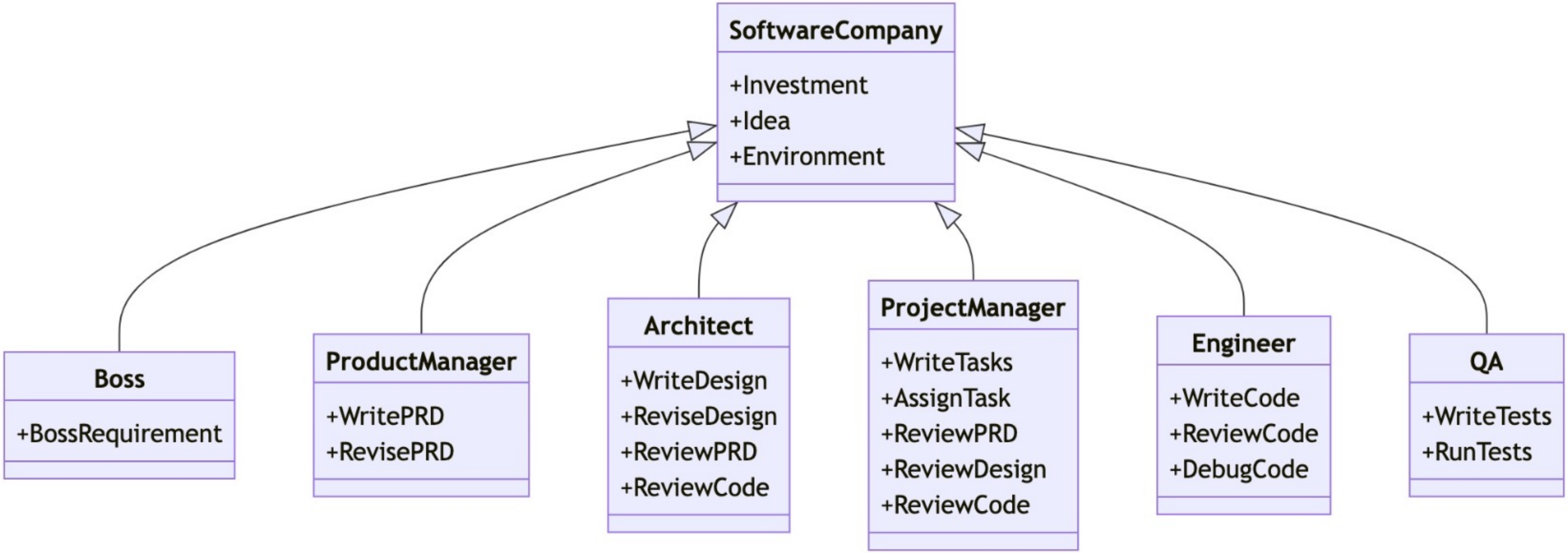
1. Agents-Environment Interface

- Specific contexts or settings in which the LLM-MA systems are deployed and interact.
  - Software development
  - Gaming
  - Financial market
- Through this interface, agents understand their surroundings, make decisions, and learn from the outcomes of their actions. We categorize the current interfaces in LLM-MA systems into three types:
  - Sandbox: simulated environment
  - Physical: real-world physics and constraints, e.g. robotics
  - None: no specific external environment, e.g. debate to reach a consensus

2. Agents Profiling

- Agents are defined by their traits, actions, and skills, which are tailored to meet specific goals. Agent Profiling Methods:
  - Pre-defined: explicitly defined by the human system designers
  - Model generated: created on the fly by LLM
  - Data-derived: constructed based on pre-existing datasets

Examples

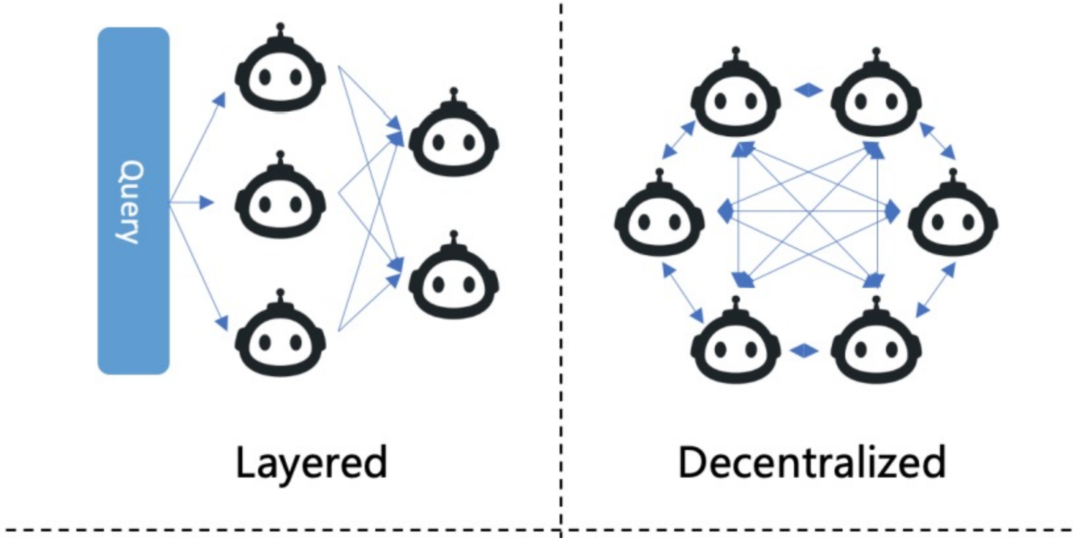

SoftwareCompany
+Investment
+Idea
+Environment
Boss
+BossRequirement
ProductManager
+WritePRD
+RevisePRD
Architect
+WriteDesign
+ReviseDesign
+ReviewPRD
+ReviewCode
ProjectManager
+WriteTasks
+AssignTask
+ReviewPRD
+ReviewDesign
+ReviewCode
Engineer
+WriteCode
+ReviewCode
+DebugCode
QA
+WriteTests
+RunTests

3. Agents Communication

- **Communication Paradigms:**
  - **Cooperative:** agents work together towards a shared goal
    - Software development, robotics
  - **Debate:** agents engage in argumentative interactions, presenting and defending their own viewpoints or solutions, and critiquing those of others.
    - AI-assisted legal or policy decision-making, scientific discovery.
  - **Competitive:** agents work towards their own goals that might be in conflict with the goals of other agents.
    - Stock market trading bots, cybersecurity defense

3. Agents Communication

- **Communication structure**
  - Layered:
    - Industrial automation
      - High-level: Factory-wide production scheduling
      - Mid-level: Machine coordination.
      - Low-level: Robotic arm control.
  - Decentralized:
    - Drone fleets for disaster relief: Each drone independently maps affected areas and coordinates with others without a central controller.



3. Agents Communication

- **Communication structure**
  - Centralized:
    - Logistics system: A central server assigns drivers or delivery vehicles based on demand, location, and traffic conditions.
  - Shared message:
    - Video Game AI with a Shared World State

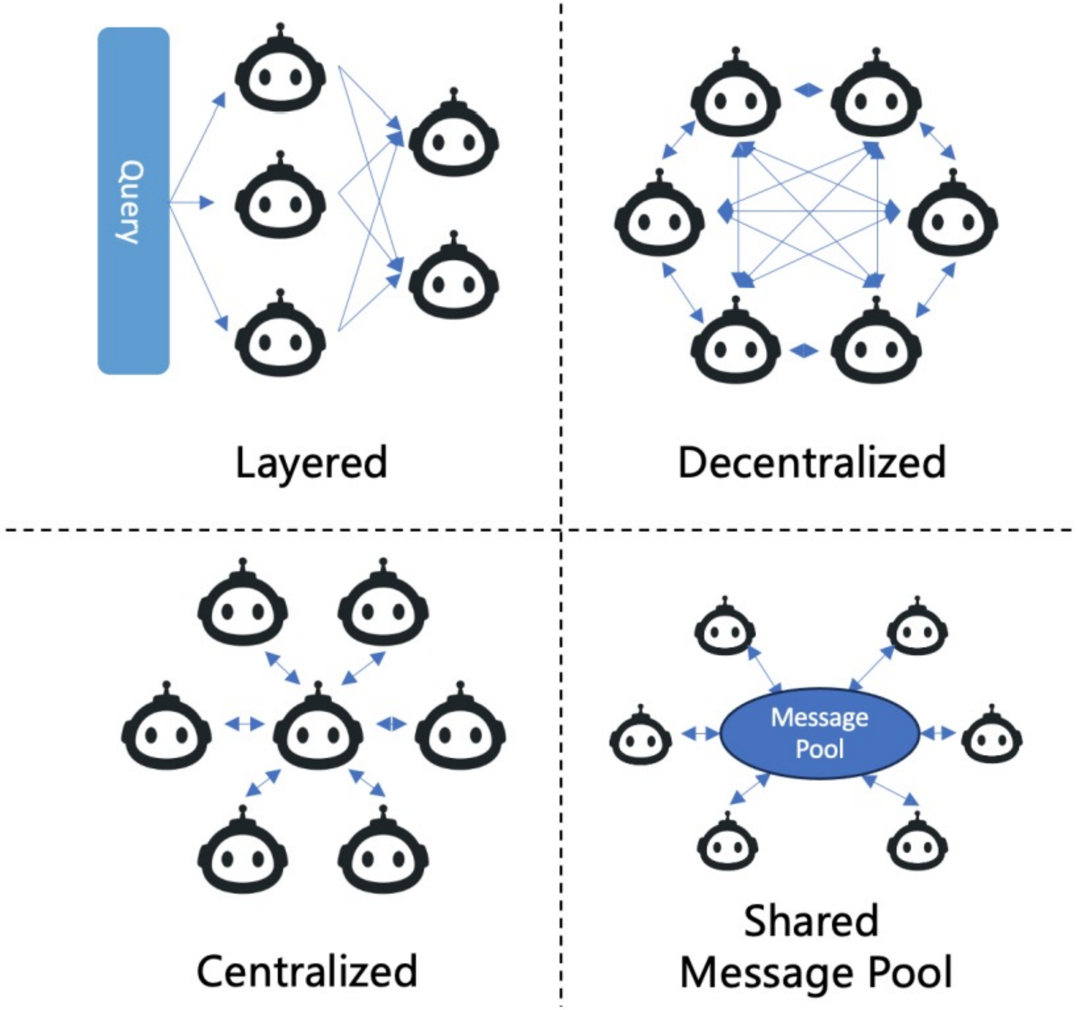


Figure 3: The Agent Communication Structure.

3. Agents Communication

- **Communication content:**
  - Text
  - Software development: code segment
  - Simulation of games: analysis, suspicions, strategies

  - Progressing toward multi-modalities

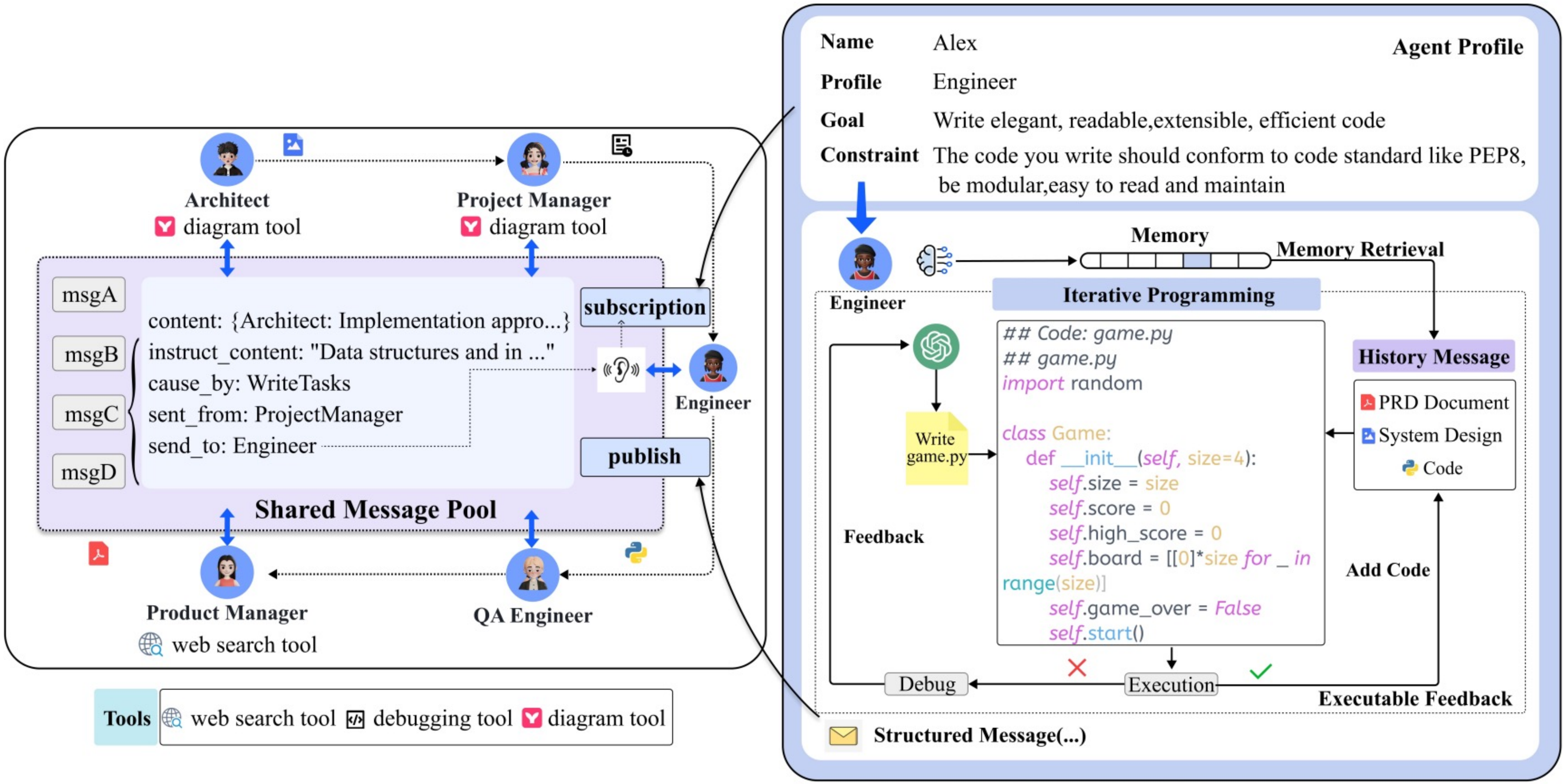


Figure 2: An example of the communication protocol (left) and iterative programming with executable feedback (right). **Left**: Agents use a shared message pool to publish structured messages. They can also subscribe to relevant messages based on their profiles. **Right**: After generating the initial code, the Engineer agent runs and checks for errors. If errors occur, the agent checks past messages stored in memory and compares them with the PRD, system design, and code files.

4. Agents Capabilities Acquisition

Enabling agents to learn and evolve dynamically according to feedbacks. Feedback sources:

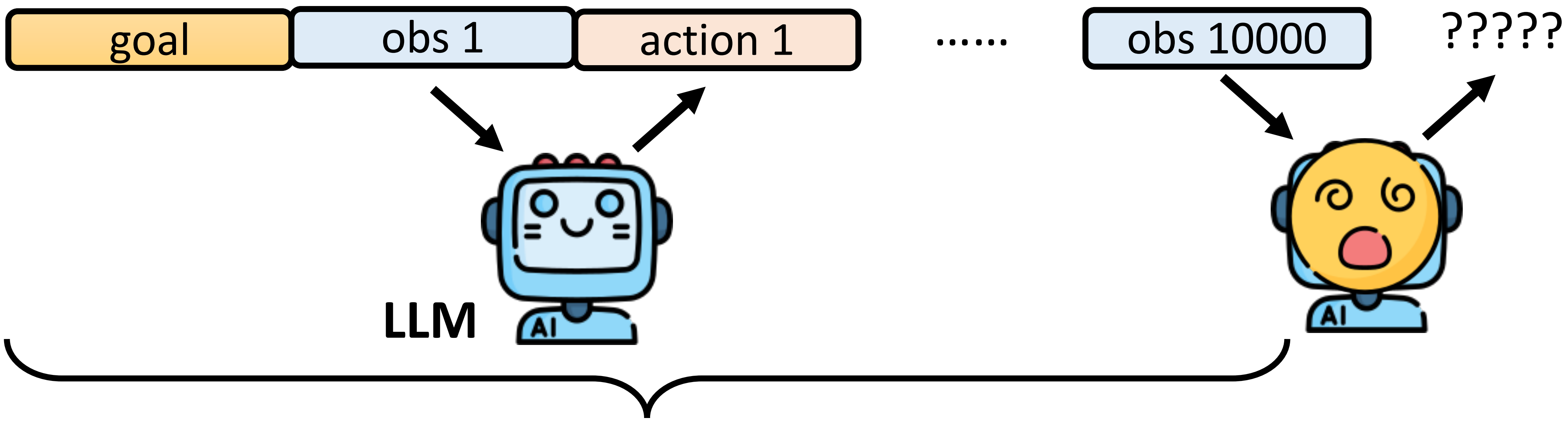
- Environment: e.g. feedback from Code Interpreter
- Agents interactions: e.g. feedback from the judgement of other agents.
- Human feedback: Align with human values and preferences
- None: No feedback, focusing on analyzing simulated results

4. Agents Capabilities Acquisition

Agents Adjustment to Complex Problems:

- Memory:
  - Leverage a memory module to store information from previous interactions and feedback. When performing actions, they can retrieve relevant and valuable memories, especially **successful actions**
- Self evolution:
  - Learning through Communication (LTC) paradigm, using the communication logs of multi-agents to generate datasets to train or fine-tune LLMs. LTC is most valuable when you need specialized, adaptive behavior that goes beyond the general capabilities of even powerful LLMs.
- Agents Orchestration
  - the system can generate new agents on-the-fly during its operation

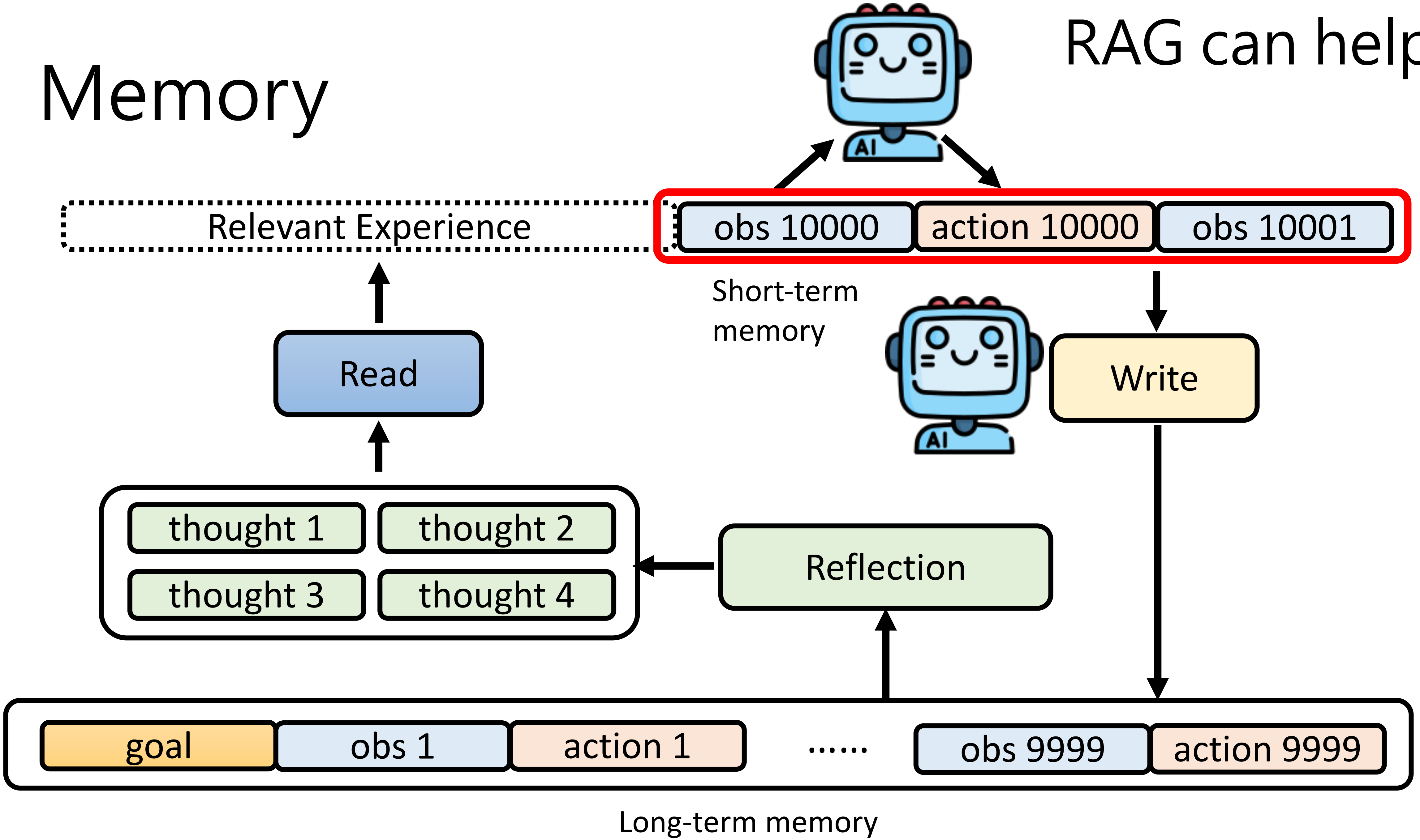
Memory



An agent struggling to replay the full history ☹

Memory

RAG can help!



Automated Design of Agentic Systems

March, 2025,
published at ICLR

Shengran Hu[1,2], Cong Lu[1,2], Jeff Clune[1,2,3]
[1]University of British Columbia, [2]Vector Institute, [3]Canada CIFAR AI Chair

Agents Orchestration

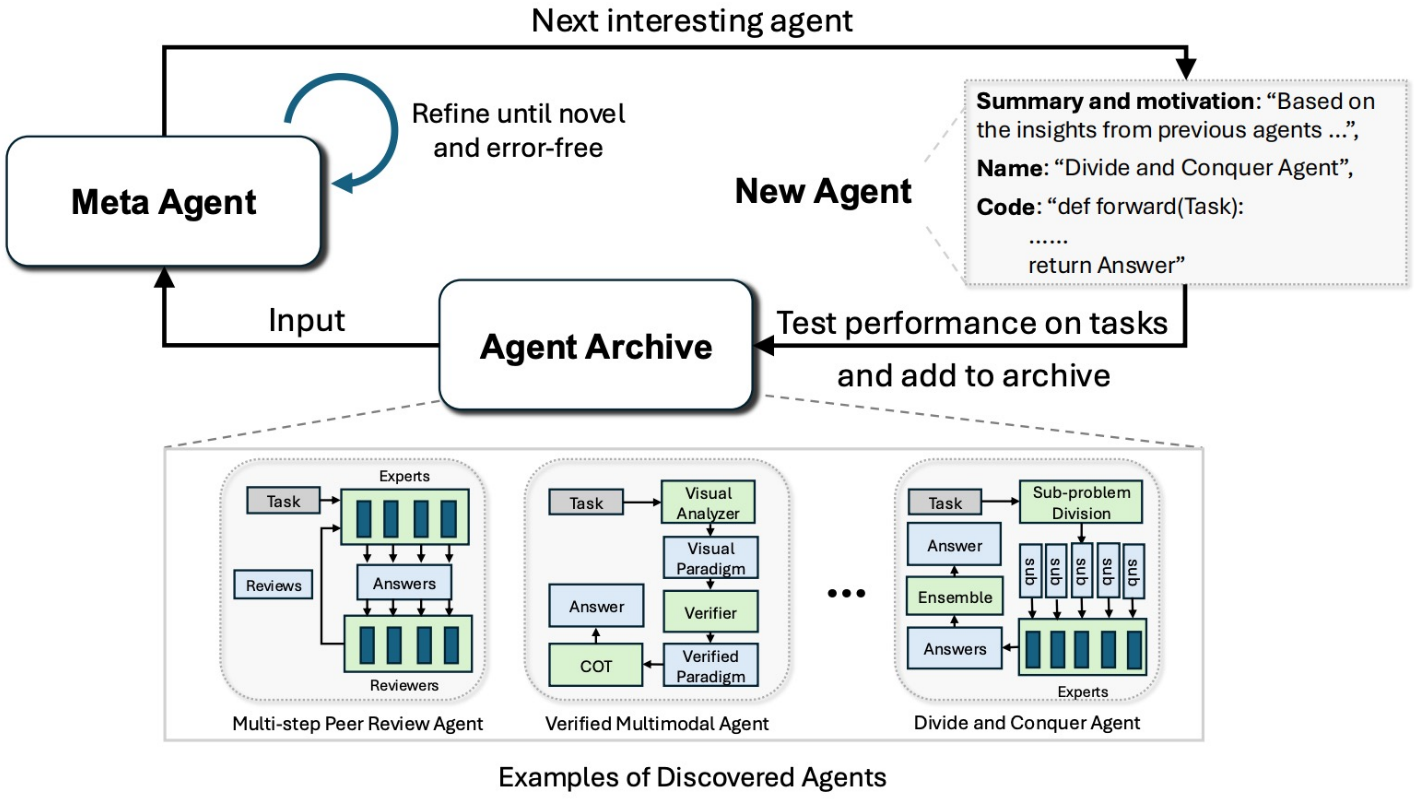


Figure 1: **Overview of the proposed algorithm Meta Agent Search and examples of discovered agents.** In our algorithm, we instruct the "meta" agent to iteratively program new agents, test their performance on tasks, add them to an archive of discovered agents, and use this archive to inform the meta agent in subsequent iterations. We show three example agents across our runs, with all names generated by the meta agent. The detailed code of example agents can be found in Appendix G.

Applications

Motivation	Research Domain & Goals		Work	Agents-Env. Interface	Agents Profiling		Agents Communication		Agents Capabilities Acquisition	
					Profiling methods	Profiles (examples)	Paradigms	Structure	Feedback from	Agents Adjustment
Problem Solving	Software development		[Qian *et al.*, 2023]	Sandbox	Pre-defined, Model-Generated	CTO, programmer	Cooperative	Layered	Environment, Agent interaction, Human	Memory, Self-Evolution
			[Hong *et al.*, 2023]	Sandbox	Pre-defined	Product Manager, Engineer	Cooperative	Layered, Shared Message Pool	Environment, Agent interaction, Human	Memory, Self-Evolution
			[Dong *et al.*, 2023b]	Sandbox	Pre-defined, Model-Generated	Analyst, coder	Cooperative	Layered	Environment, Agent interaction	Memory, Self-Evolution
	Embodied Agents	Multi-robot planning	[Chen *et al.*, 2023d]	Sandbox, Physical	Pre-defined	Robots	Cooperative	Centralized, Decentralized	Environment, Agent interaction	Memory
		Multi-robot collaboration	[Mandi *et al.*, 2023]	Sandbox, Physical	Pre-defined	Robots	Cooperative	Decentralized	Environment, Agent interaction	Memory
		Multi-Agents cooperation	[Zhang *et al.*, 2023c]	Sandbox	Pre-defined	Robots	Cooperative	Decentralized	Environment, Agent interaction	Memory
	Science Experiments	Optimization of MOF	[Zheng *et al.*, 2023]	Physical	Pre-defined	Strategy planers, literature collector, coder	Cooperative	Centralized	Environment, Human	Memory
	Science Debate	Improving Factuality	[Du *et al.*, 2023]	None	Pre-defined	Agents	Debate	Decentralized	Agent interaction	Memory
		Examining, Inter-Consistency	[Xiong *et al.*, 2023]	None	Pre-defined	Proponent, Opponent, Judge	Debate	Centralized, Decentralized	Agent interaction	Memory
		Evaluators for debates	[Chan *et al.*, 2023]	None	Pre-defined	Agents	Debate	Centralized, Decentralized	Agent interaction	Memory
		Multi-Agents for Medication	[Tang *et al.*, 2023]	None	Pre-defined	Cardiology, Surgery	Debate, Cooperative	Centralized, Decentralized	Agent interaction	Memory

Applications

World Simulation	Society	Modest Community (25 persons)	[Park *et al.*, 2023]	Sandbox	Model-generated	Pharmacy, shopkeeper	-	-	Environment, Agent interaction	Memory
		Online community (1000 persons)	[Park *et al.*, 2022]	None	Pre-defined, Model-generated	Camping, fishing	-	-	Agent interaction	Dynamic Generation
		Emotion propagation	[Gao *et al.*, 2023a]	None	Pre-defined, Model-generated	Real-world user	-	-	Agent interaction	Memory
		Real-time social interactions	[Kaiya *et al.*, 2023]	Sandbox	Pre-defined	Real-world user	-	-	Environment, Agent interaction	Memory
		Opinion dynamics	[Li *et al.*, 2023a]	None	Pre-defined	NIN, NINL, NIL	-	-	Agent interaction	Memory
	Gaming	WereWolf	[Xu *et al.*, 2023b] [Xu *et al.*, 2023c]	Sandbox	Pre-defined	Seer, werewolf, villager	Cooperative, Debate, Competitive	Decentralized	Environment, Agent interaction	Memory
		Avalon	[Light *et al.*, 2023a] [Wang *et al.*, 2023c]	Sandbox	Pre-defined	Servant, Merlin, Assassin	Cooperative, Debate, Competitive	Decentralized	Environment, Agent interaction	Memory
		Welfare Diplomacy	[Mukobi *et al.*, 2023]	Sandbox	Pre-defined	Countries	Cooperative, Competitive	Decentralized	Environment, Agent interaction	Memory
	Psychology	Human behavior Simulation	[Aher *et al.*, 2023]	Sandbox	Pre-defined	Humans	-	-	Agent interaction	Memory
		Collaboration Exploring	[Zhang *et al.*, 2023d]	None	Pre-defined	Agents	Cooperative, Debate	Decentralized	Agent interaction	Memory

Applications

World Simulation	Economy	Macroeconomic simulation	[Li *et al.*, 2023e]	None	Pre-defined, Model-generated	Labor	Cooperative	Decentralized	Agent interaction	Memory
		Information Marketplaces	[Anonymous, 2023]	Sandbox	Pre-defined, Data-Derived	Buyer	Cooperative, Competitive	Decentralized	Environment, Agent interaction	Memory
		Improving financial trading	[Li *et al.*, 2023g]	Physical	Pre-defined	Trader	Debate	Decentralized	Environment, Agent interaction	Memory
		Economic theories	[Zhao *et al.*, 2023]	Sandbox	Pre-defined, Model-Generated	Restaurant, Customer	Competitive	Decentralized	Environment, Agent interaction	Memory, Self-Evolution
	Recommender Systems	Simulating user behaviors	[Zhang *et al.*, 2023a]	Sandbox	Data-Derived	Users from MovieLens-1M	-	-	Environment	Memory
		Simulating user-item interactions	[Zhang *et al.*, 2023e]	Sandbox	Pre-defined, Data-Derived	User Agents Item Agents	Cooperative	Decentralized	Environment, Agent interaction	Memory
	Policy Making	Public Administration	[Xiao *et al.*, 2023]	None	Pre-defined	Residents	Cooperative	Decentralized	Agent interaction	Memory
		War Simulation	[Hua *et al.*, 2023]	None	Pre-defined	Countries	Competitive	Decentralized	Agent interaction	Memory
	Disease	Human Behaviors to epidemics	[Ghaffarzadegan *et al.*, 2023]	Sandbox	Pre-defined, Model-Generated	Conformity traits	Cooperative	Decentralized	Environment, Agent interaction	Memory
		Public health	[Williams *et al.*, 2023]	Sandbox	Pre-defined, Model-Generated	Adults aged 18 to 64	Cooperative	Decentralized	Environment, Agent interaction	Memory, Dynamic Generation

What can be measured can be improved!

Benchmark Datasets

Motivation	Domain	Datasets and Benchmarks	Used by	Data Link
Problem Solving	Software Development	HumanEval	[Hong *et al.*, 2023]	Link
		MBPP	[Hong *et al.*, 2023]	Link
		SoftwareDev	[Hong *et al.*, 2023]	Link
	Embodied AI	RoCoBench	[Mandi *et al.*, 2023]	Link
		Communicative Watch-And-Help (C-WAH)	[Zhang *et al.*, 2023c]	Link
		ThreeDWorld Multi-Agent Transport (TDW-MAT)	[Zhang *et al.*, 2023c]	Link
		HM3D v0.2	[Yu *et al.*, 2023]	Link
	Science Debate	MMLU	[Tang *et al.*, 2023]	Link
		MedQA	[Tang *et al.*, 2023]	Link
		PubMedQA	[Tang *et al.*, 2023]	Link
		GSM8K	[Du *et al.*, 2023]	Link
		StrategyQA	[Xiong *et al.*, 2023]	Link
		Chess Move Validity	[Du *et al.*, 2023]	Link
World Simulation	Society	SOTOPIA	[Zhou *et al.*, 2023b]	/
		Gender Discrimination	[Gao *et al.*, 2023a]	/
		Nuclear Energy	[Gao *et al.*, 2023a]	/
	Gaming	Werewolf	[Xu *et al.*, 2023b]	/
		Avalon	[Light *et al.*, 2023b]	/
		Welfare Diplomacy	[Mukobi *et al.*, 2023]	/
		Layout in the Overcooked-AI environment	[Agashe *et al.*, 2023]	/
		Chameleon	[Xu *et al.*, 2023a]	Link
		Undercover	[Xu *et al.*, 2023a]	Link
	Psychology	Ultimatum Game TE	[Aher *et al.*, 2023]	Link
		Garden Path TE	[Aher *et al.*, 2023]	Link
		Wisdom of Crowds TE	[Aher *et al.*, 2023]	Link
	Recommender System	MovieLens-1M	[Zhang *et al.*, 2023a]	Link
		Amazon review dataset	[Zhang *et al.*, 2023e]	/
	Policy Making	Board Connectivity Evaluation	[Hua *et al.*, 2023]	Link

Table 2: Datasets and Benchmarks commonly used in LLM-MA studies. " / " denotes the unavailability of data link.

Challenges and Opportunities

- Advancing into Multi-Modal Environment:
  - Integrating LLMs into multi-modal environments presents additional challenges, such as processing diverse data types and enabling agents to understand each other and respond to more than just textual information
- Addressing Hallucination
  - Cascading effect: misinformation from one agent can be accepted and further propagated by others in the network
  - How to manage the flow of information between agents to prevent the spread of these inaccuracies throughout the system.

Challenges and Opportunities

- Acquiring Collective Intelligence
  - LLM-MA systems mainly learn from instant feedback
  - Memory and Self-Evolution do not fully capitalize on the potential collective intelligence of the agent network
- Scaling Up LLM-MA Systems
  - Scaling up the number of these agents in an LLM-MA system significantly increases resource requirements
  - Effective Agents Orchestration facilitates harmonious operation among agents, minimizing conflicts and redundancies

Challenges and Opportunities

- Evaluation and Benchmarks
  - A notable shortfall in the development of comprehensive benchmarks across domains at multi-agent system level
- Applications and Beyond
  - there are opportunities to explore LLM-MA systems from various theoretical perspectives, such as Cognitive Science, Symbolic Artificial Intelligence, Cybernetics, Complex Systems, and Collective Intelligence.

Multi-Agent Systems (MAS): Conclusion

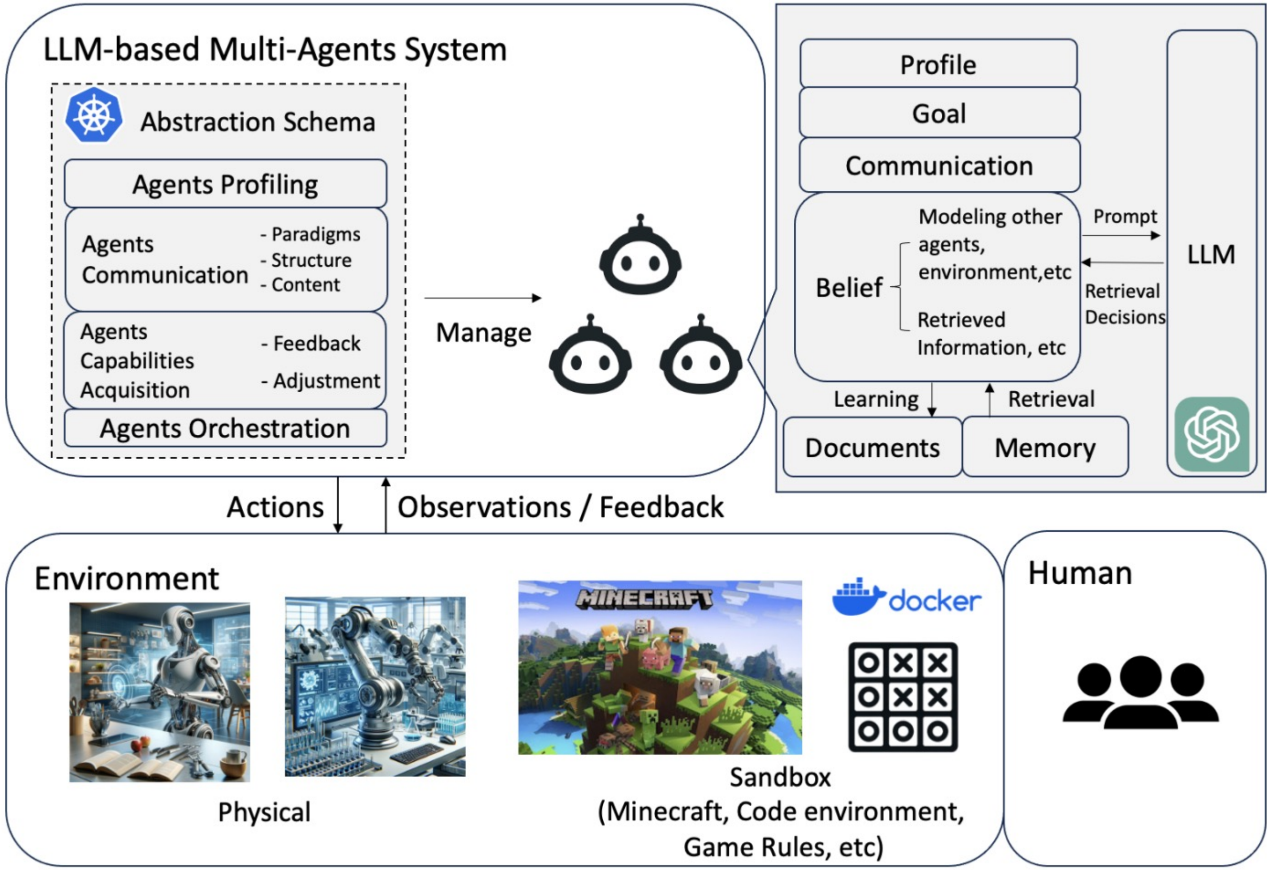
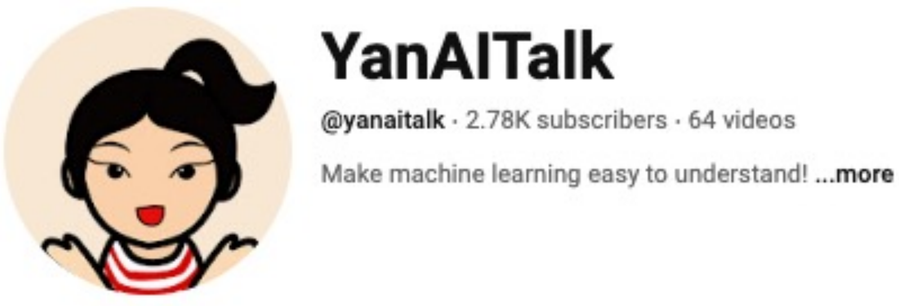


Figure 2: The Architecture of LLM-MA Systems.

Slides posted at:
https://github.com/YanXuHappygela/LLM-reading-group

Recordings posted at:



Upcoming meetups – Open to proposals and guest speakers!

- MetaGPT paper – first AI software company
- Multi-agent use case and best practice – guest speaker
- Memories
- Agent orchestrations
- Open source frameworks
- Hands-on