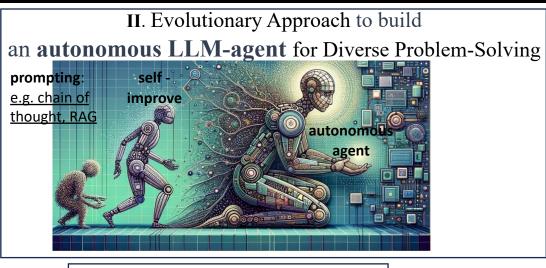
# Self-Improve LLM-based Agent and its Prospects

Yule Wang, PhD Misson Cloud, MLE (Consulting)

# Outline





#### **IV**. LLM-agent Prospects



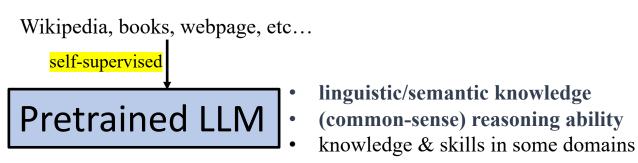
# III. Create your own independent autonomous LLM-agent



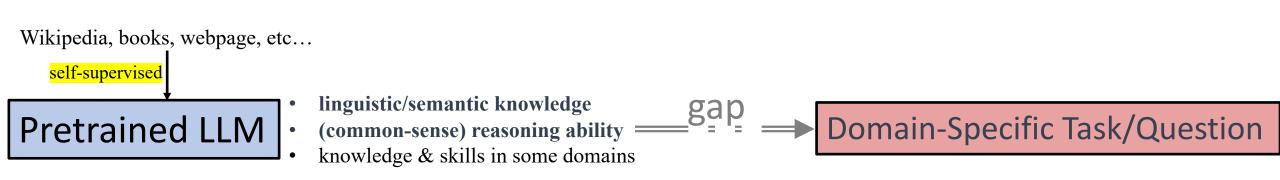
# I. What is an LLM-Agent?



# Strategy on Downstream NLP TasksFine-tuningvsPrompting & Agent

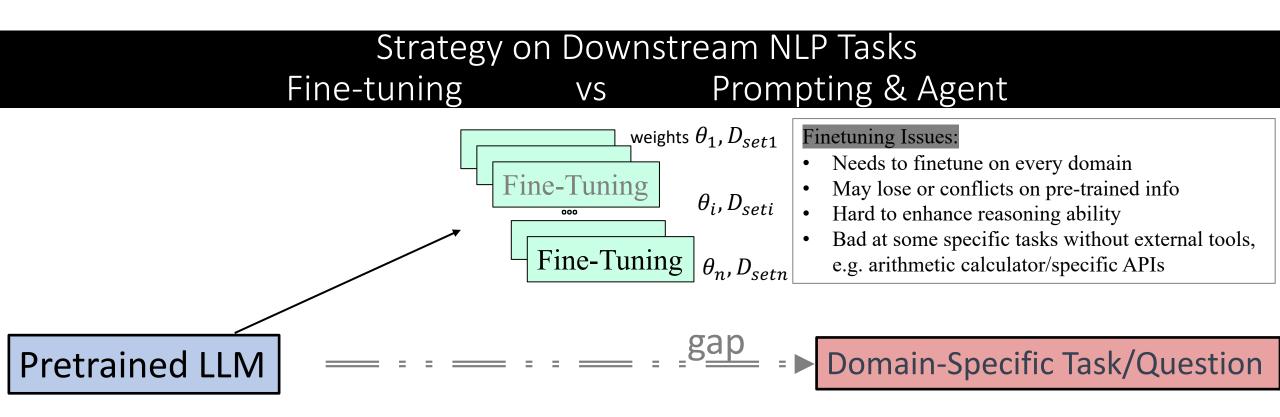


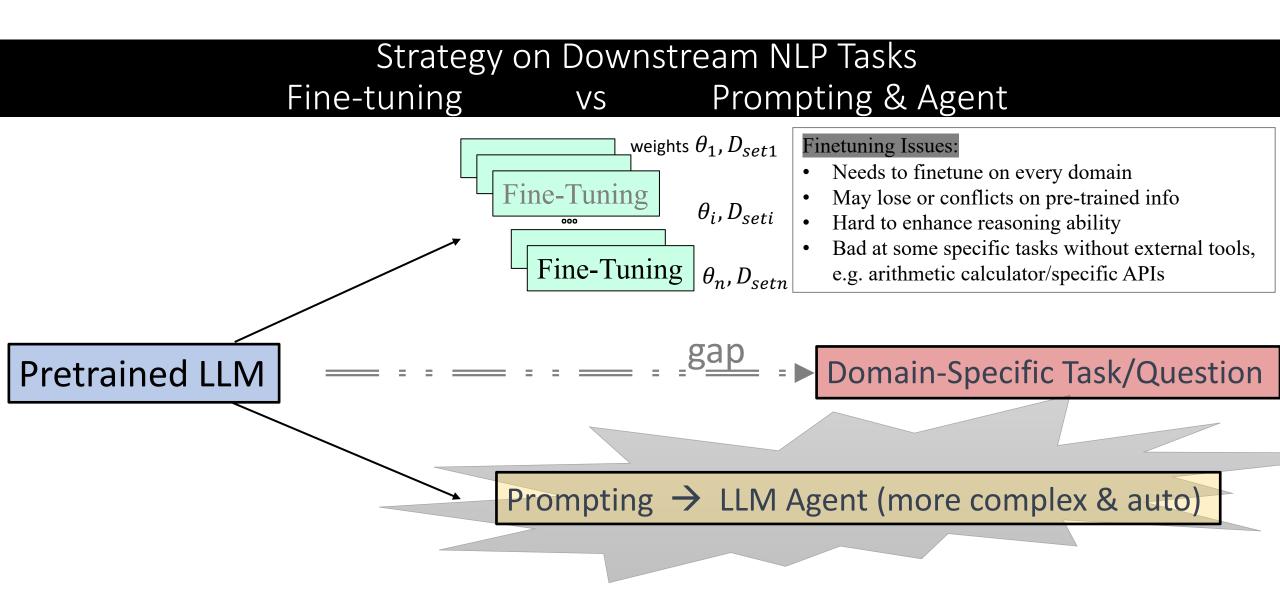
# Strategy on Downstream NLP TasksFine-tuningvsPrompting & Agent



#### Missing:

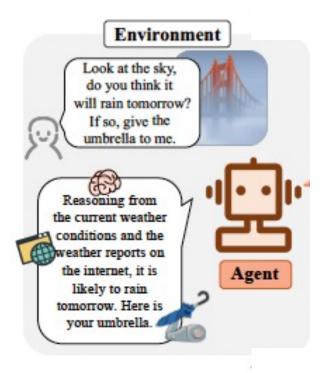
- up-to-date or domain-specific knowledge
- specific expertise to specific-domain





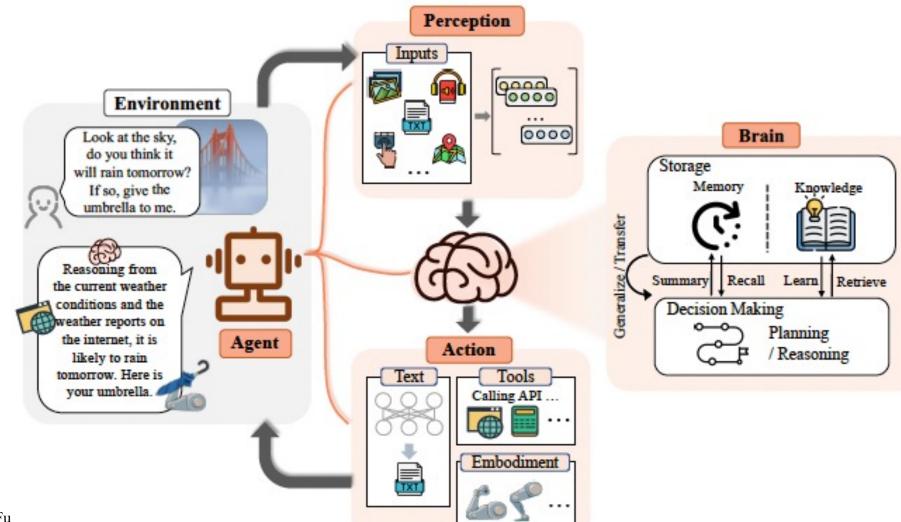
## LLM Agent

*"If they find a parrot who could answer to everything, I would claim it to be an intelligent being without hesitation." —Denis Diderot, 1875* 



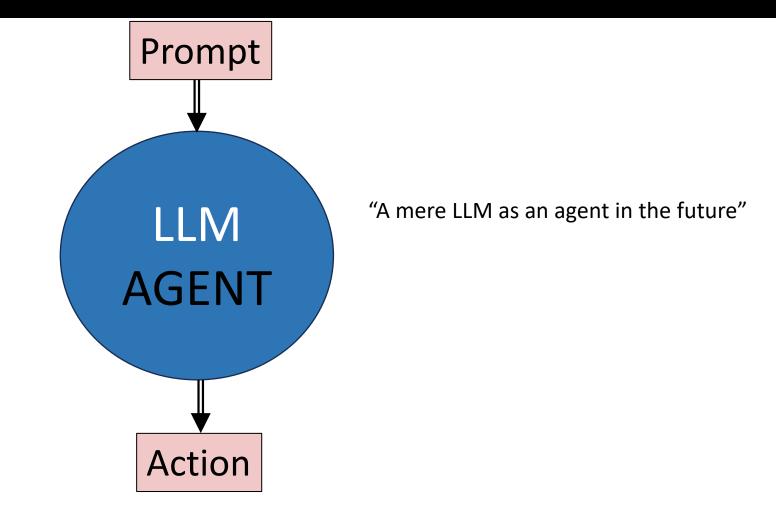
[1] Xi et. al Fudan NLP group (2023 09) "The Rise and Potential of Large Language Model Based Agents: A Survey"

### LLM Agent

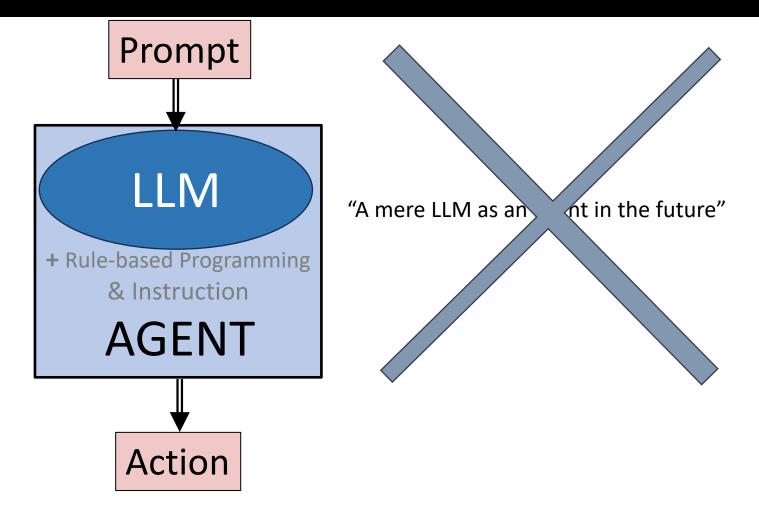


[1] Xi et. al Fu

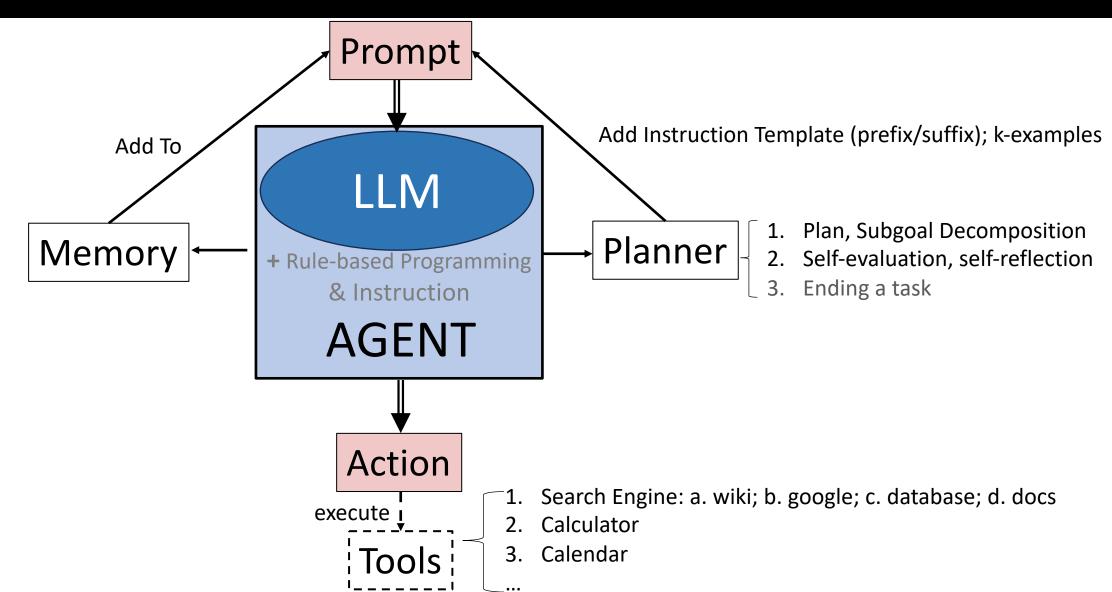
## LLM Agent? AGI!



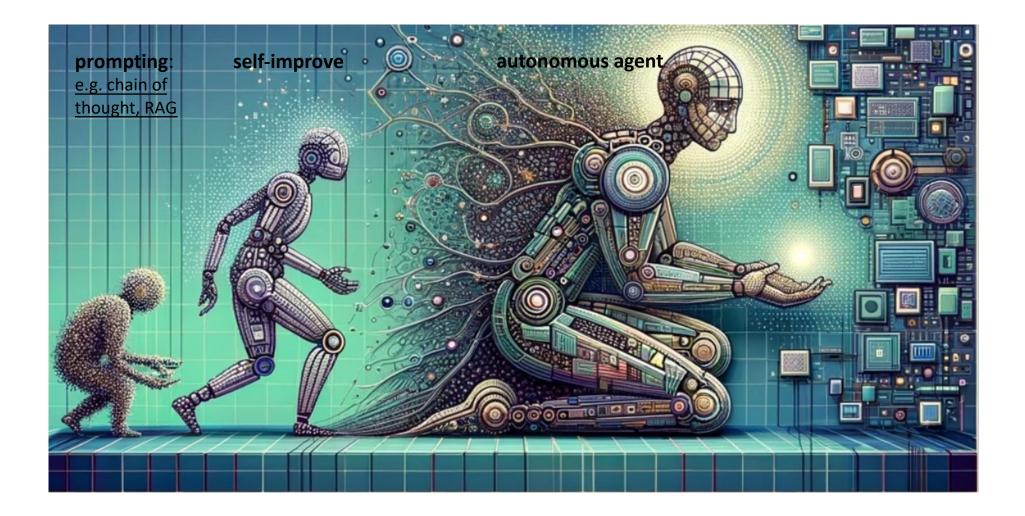
## LLM Agent

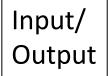


#### LLM Agent & Core Components



#### II. Evolutionary Approach to build an autonomous LLM-agent for Diverse Problem-Solving





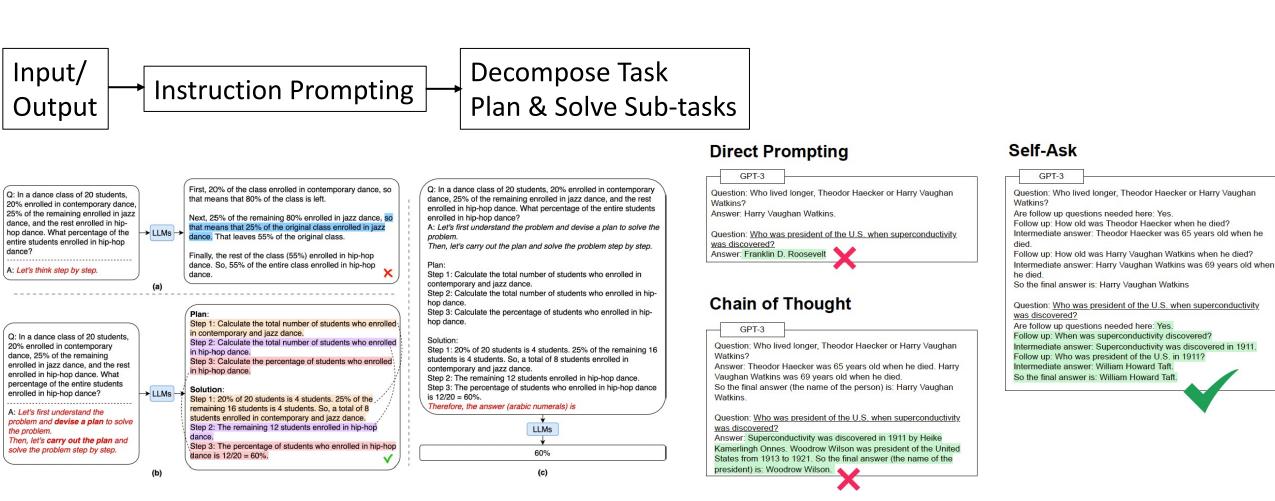
Plain Question and Task. No instruction:

- "What is an LLM agent?"
- "What is today's NBA match score?"
- "Now solve this 24 point game."



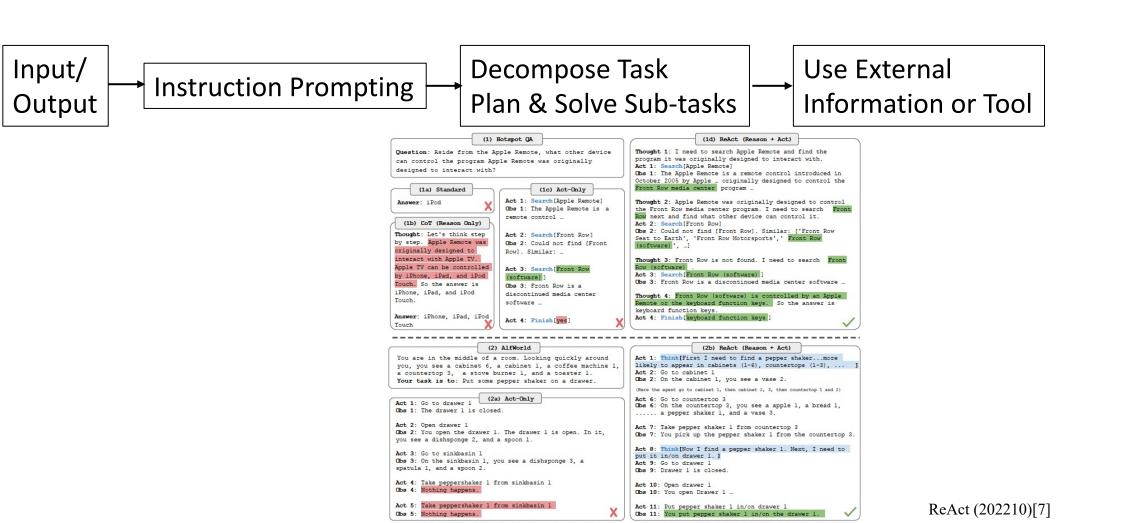
Instructions and/or examples e.g.

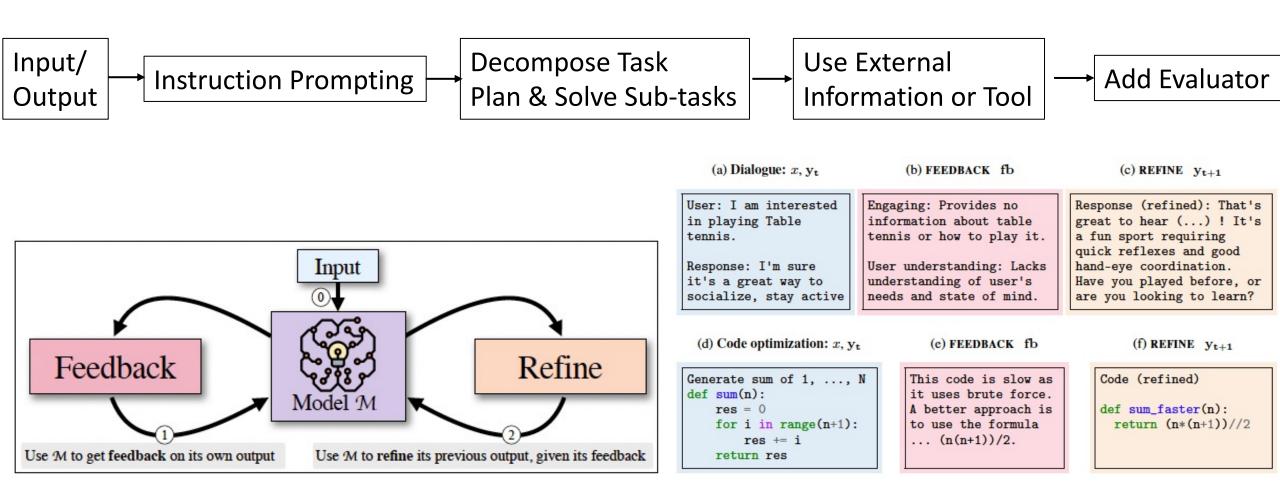
- "I am just a child. I wish your answer to be easy to understand for me. If you do not know the knowledge, please say No."
- "Please rate the toxicity of these texts on a scale from 0 to 10. Parse the score to JSON format like this {'text': the text to grade; 'toxic score': the toxicity score of the text}"
- "Follow this (/these) example(s), ..., please answer my question." (1-shot/k-shot prompting)
- "Let's think step by step" (Chain of Thought)



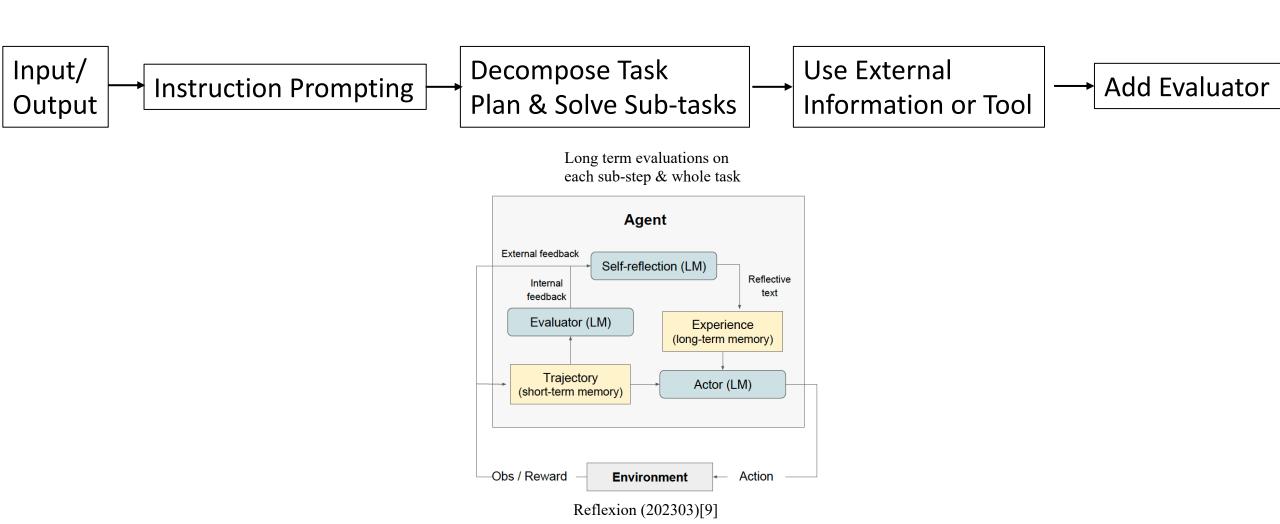
Plan and Solve/Execute (202305)[5]

Self-ask (202210) [6]

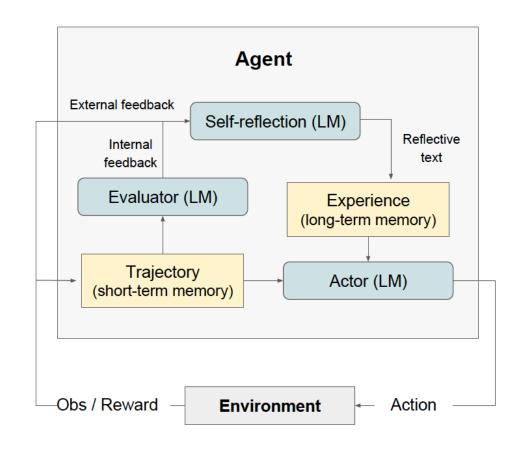




Self-refine (202303)[8]

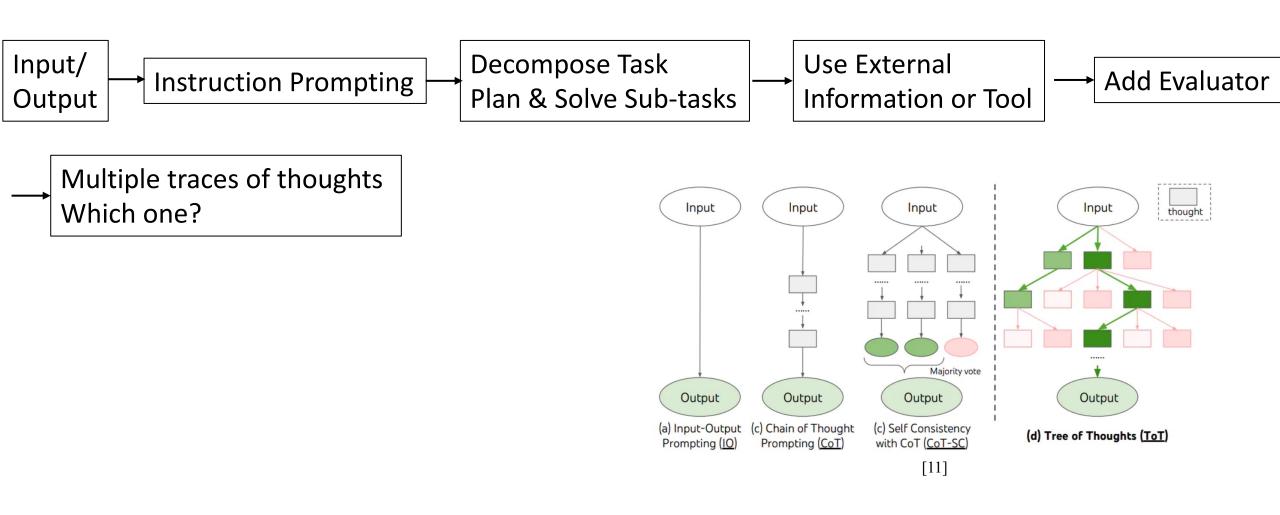


#### Autonomous Agent

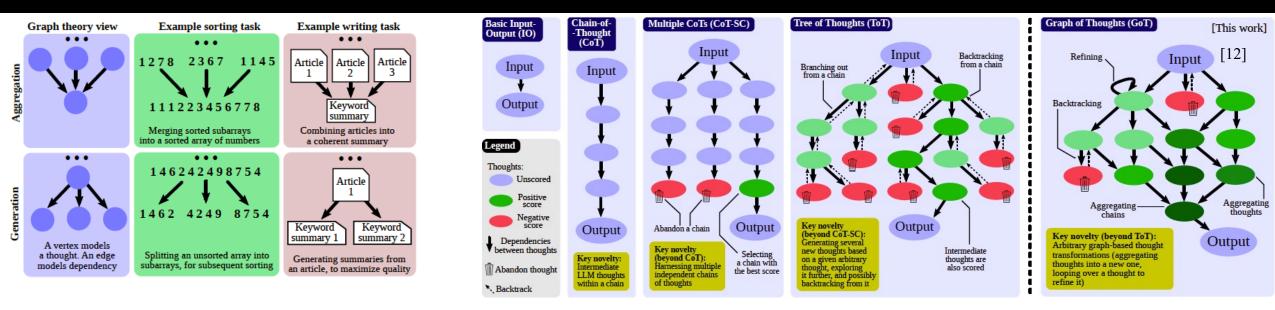


#### Algorithm 1 Reinforcement via self-reflection Initialize Actor, Evaluator, Self-Reflection: $M_a, M_e, M_{sr}$ Initialize policy $\pi_{\theta}(a_i|s_i), \theta = \{M_a, \underline{mem}\}$ Generate initial trajectory using $\pi_{\theta}$ Evaluate $\tau_0$ using $M_e$ Generate initial self-reflection $sr_0$ using $M_{sr}$ Set $mem \leftarrow [sr_0]$ Set t = 0while $M_e$ not pass or $t < \max$ trials do Generate $\tau_t = [a_0, o_0, \dots a_i, o_i]$ using $\pi_{\theta}$ Evaluate $\tau_t$ using $M_e$ Generate self-reflection $sr_t$ using $M_{sr}$ Append $sr_t$ to mem Increment t end while return

<u>Reflexion: an RL model whose memory as a learnable component instead of network parameters</u>



#### LLM Agents: Add evaluation



• Multiple trials

Self Consistency (202203)<sup>[10]</sup> (T>0,votes)
Tree of Thoughts (202305) <sup>[11]</sup> (ToT)
Graph of Thoughts <sup>[12]</sup> (GoT)

Scheme	Latency	Volume
Chain-of-Thought (CoT)	Ν	N
Self-Consistency with CoT (CoT-SC)		N/k
Tree of Thoughts (ToT)	$\log_k N$	$O(\log_k N)$
Graph of Thoughts (GoT)	$\log_k N$	Ν
		-

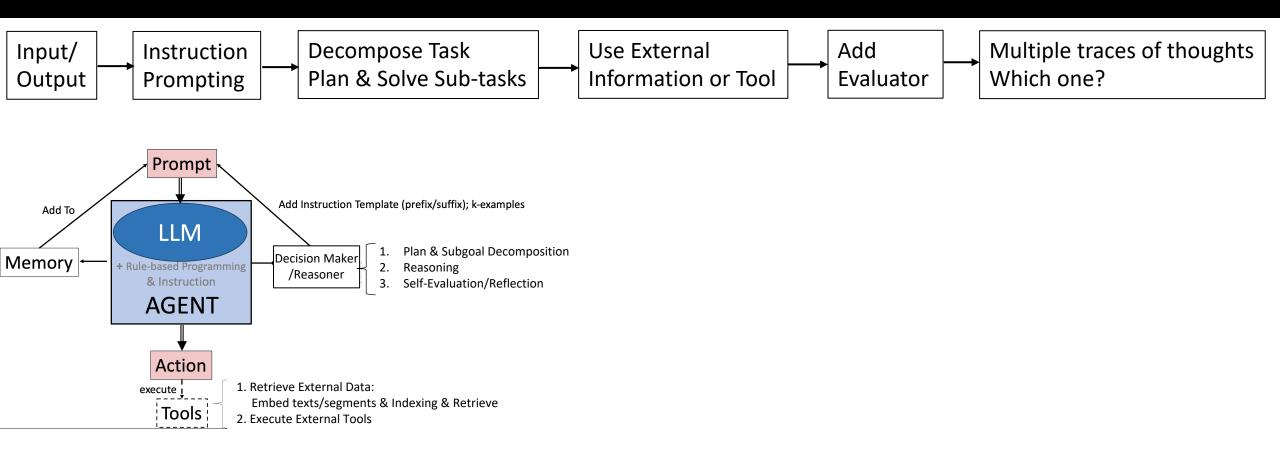
#### Autonomous Agent

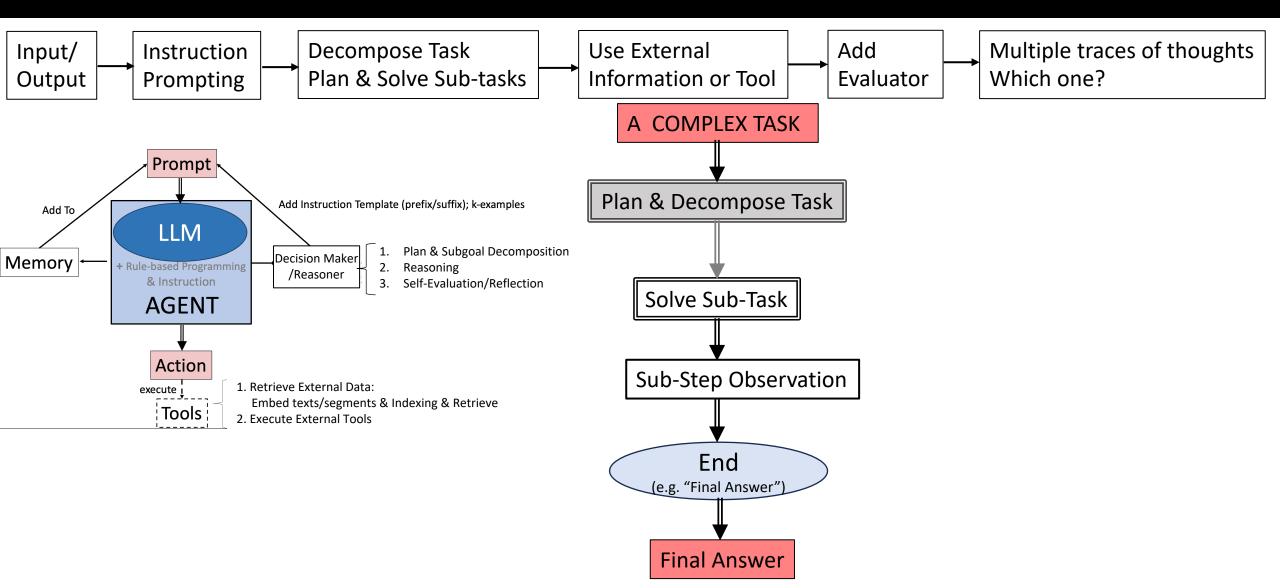
A genuine problem-solving process involves the repeated use of available information to initiate exploration, which discloses, in turn, more information until a way to attain the solution is finally discovered. — Newell et al. [18]

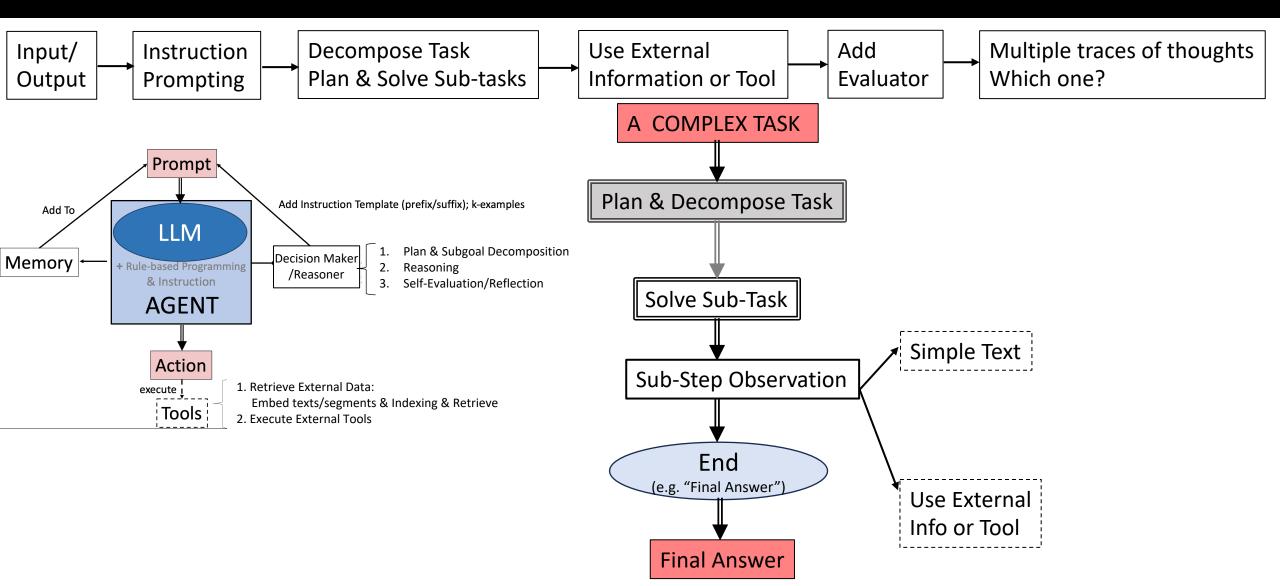
# III. Create your own independent autonomous LLM-agent

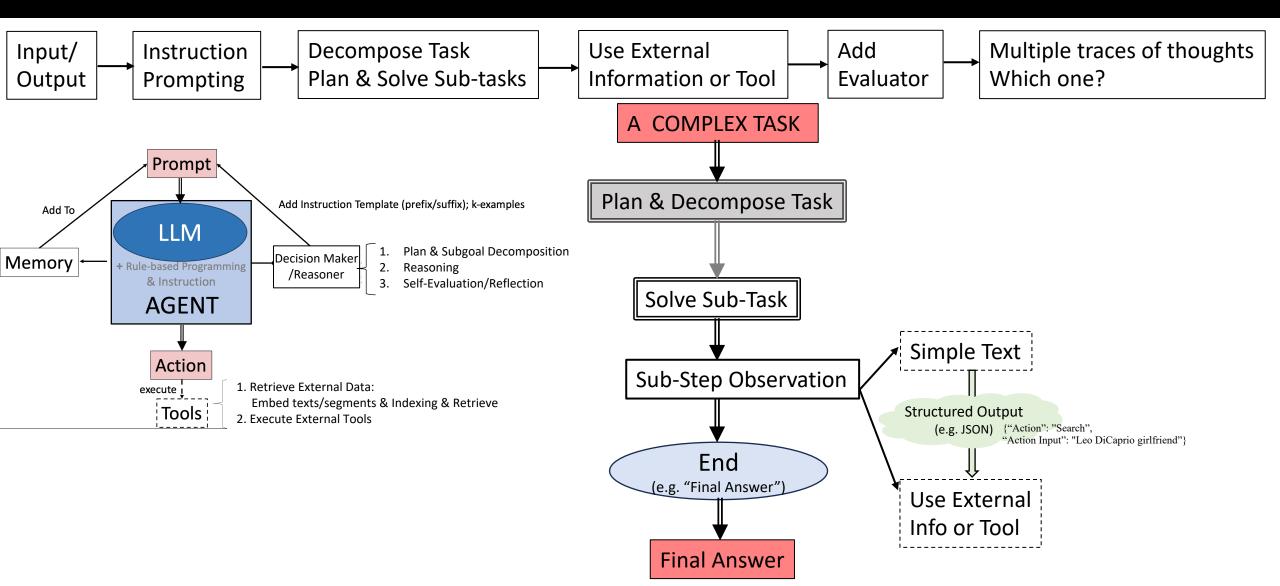


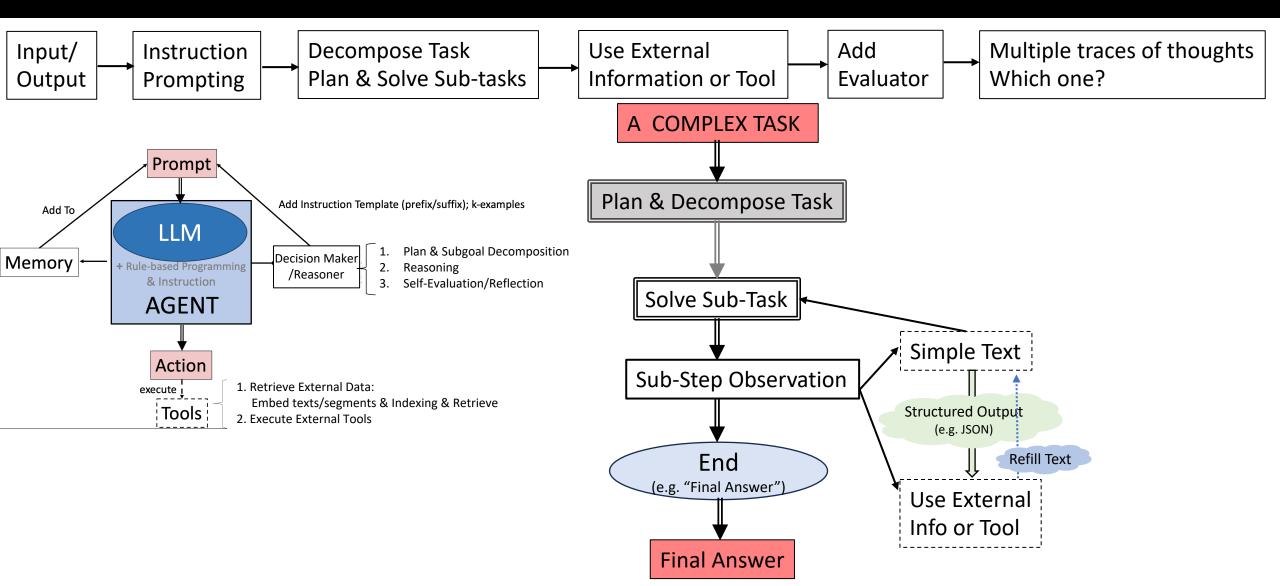
### Critical Components in the LLM Agent



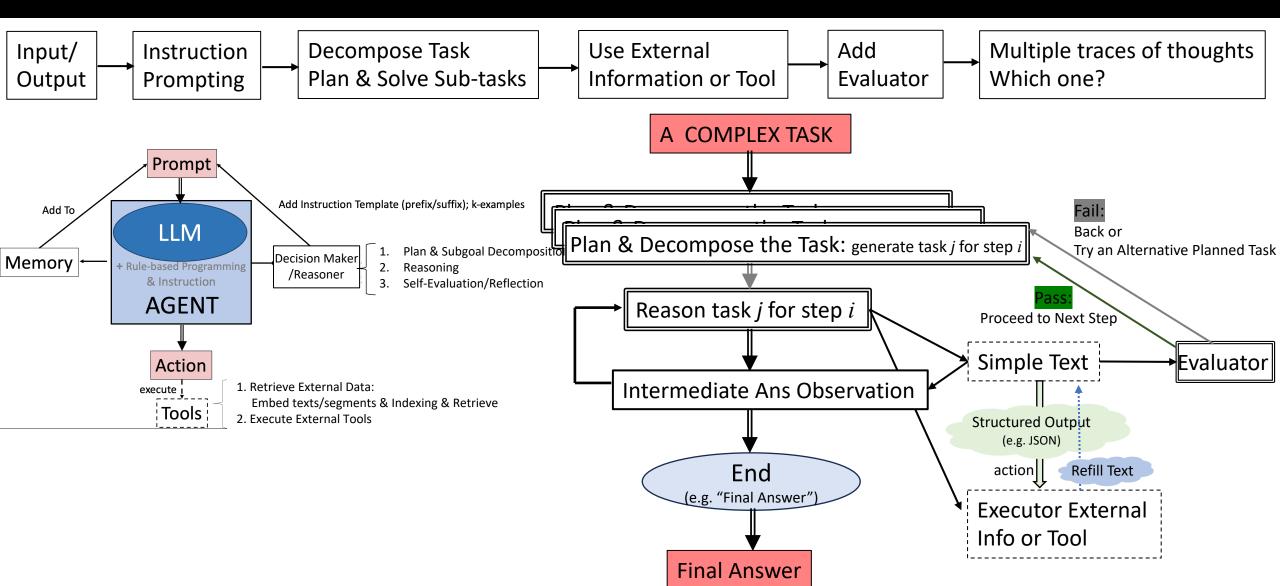








### Automation of Agent: Multiple Thought Chains



### Automation of Agent: Multiple Thought Chains

#### A Complete Guide to LLMs-based Autonomous Agents (Part I):



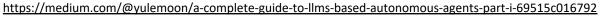
🍥 171 🛛 Q 5

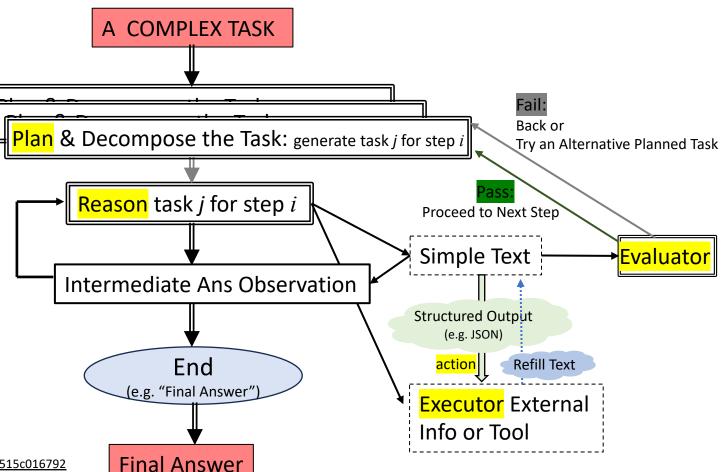
□ □ □ □

— Chain of Thought, Plan and Solve/Execute, Self-Ask, ReAct, Reflexion,
 Self-Consistency, Tree of Thoughts and Graph of Thoughts

Large Language Models (LLMs) provide an intuitive natural language interface, making them ideal for user-computer interactions and addressing complex problems. Some pretrained LLMs, such as GPT-4, come with notable reasoning capabilities, enabling them to break down intricate issues into more simpler steps, offering solutions, actions, and evaluations at each step. This suggests that these LLMs are already adequate to address diverse challenges.

However, being closed systems, LLMs are unable to fetch the most recent data or specific domain knowledge. This limitation can lead to potential errors or "hallucinations" (i.e., generating incorrect responses). While finetuning the pretrained LLMs is a potential remedy, it compromises their





#### Prompting?

Instructions: {System General Instruction} Previous Data: {Memory & Last Steps Answer} Reference Data: {Retrieved Information} Respond in the specified JSON format: {JSON Format with descriptions} Please replicate the examples to generate the answer: {k examples}

Given question: "'{Question}", provide the process leading to the answer:

# Initially, append the queston requiring a resolution to the memory memory = [Question] i = 0

#### while True:

# Generate candidates thoughts for the current step candidates = Planner.generate\_candidates(step\_i, memory)

#### while candidates:

# Select the most optimal candidate thought step candidate\_j = Evaluator\_Ranker.select\_best(candidates) # Reasoner reasons this thought step when given the previous trajectory reason = Reasoner.process(memory, candidate\_j) # Provide an action to execute based on the previous reasoning action = Actioner.select\_an\_action(reason)

# If we find a keyword like "Final Answer", end this iterative loop
# and return the final solution
if action == "Final Answer":
 return final\_solution

# This checks if external resource retrieval is allowed. if RAG\_enabled: observation = Executor.execute(action)

# Reasoner reasons upon the observation of the action candidate\_j\_result = Reasoner.process(memory, candidate\_j, observation)

# Evaluator acesses whether the result from this candidate thought step
# will lead to a positive direction to the final answer.

if Evaluator.access(candidate\_j\_result) is positive:

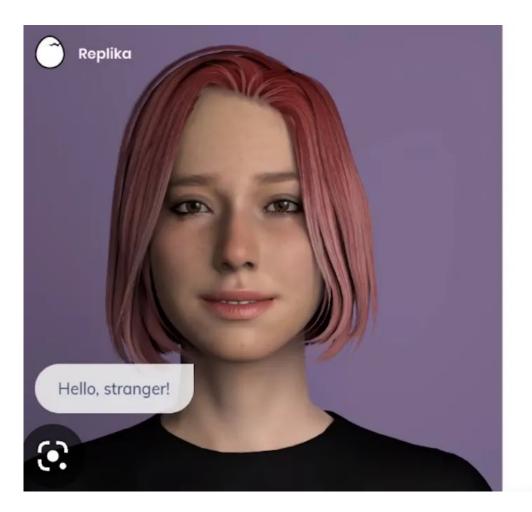
i += 1 # Move to the next thought step. Memory.append(step\_i, candidate\_j, candidate\_j\_result)

#### break else:

#### IV. LLM-agent Prospects



#### Companion Bot



Get the app Help Log ii

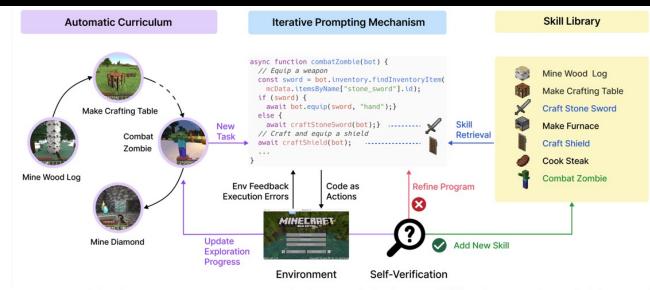
# The AI companion who cares

Always here to listen and talk. Always on your side. Join the millions growing with their AI friends now!



Log in

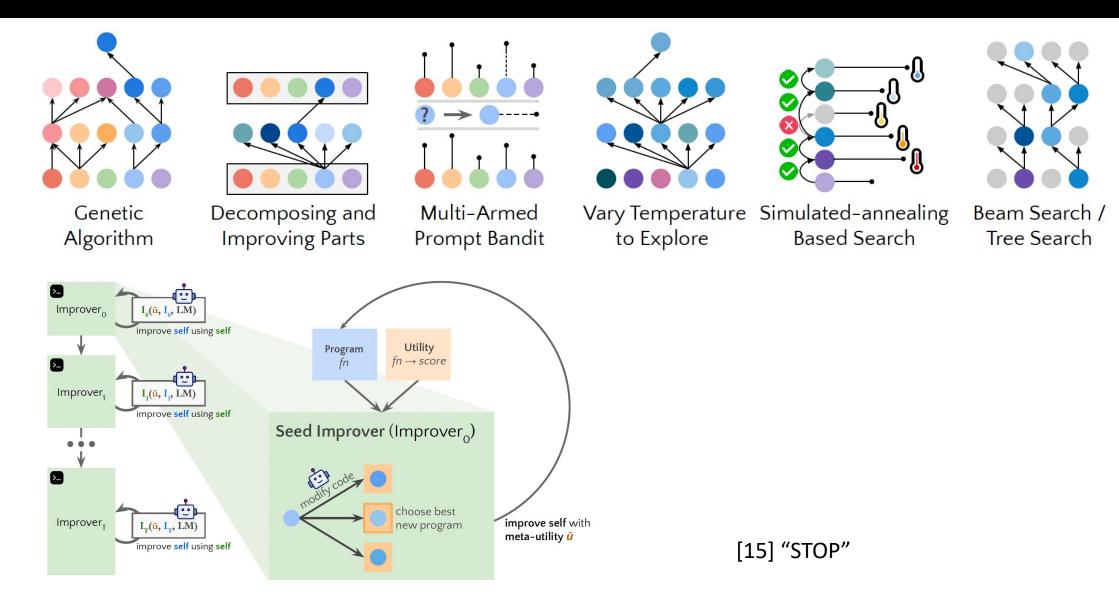
#### Interactive Game



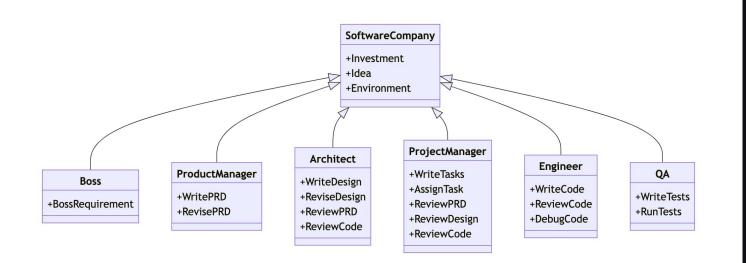
**Voyager consists of three key components:** an automatic curriculum for open-ended exploration, a skill library for increasingly complex behaviors, and an iterative prompting mechanism that uses code as action space.



#### Code Generation Self-Improvement



#### Engineering Project Management



#### class ThoughtNode(Node):

"""A node representing a thought in the thought tree."""

name: str = ""
value: int = 0
id: int = 0
valid\_status: bool = True

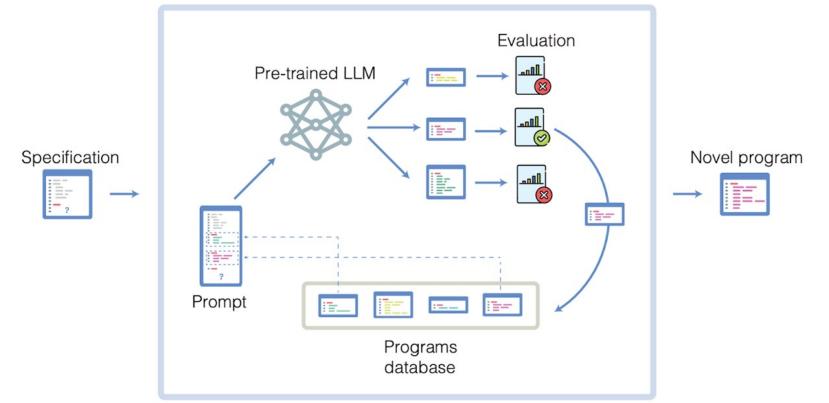
- def update\_value(self, value) -> None:
   """Update the value of the thought node."""
   self.value = value
- def update\_valid\_status(self, status) -> None:
   """Update the validity status of the thought node."""
   self.valid\_status = status

https://github.com/geekan/MetaGPT/

## Math Problem Solver

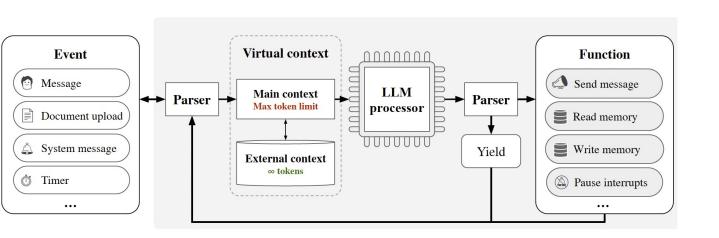
#### DeepMind

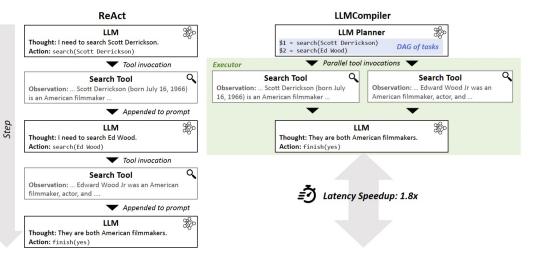
#### FunSearch



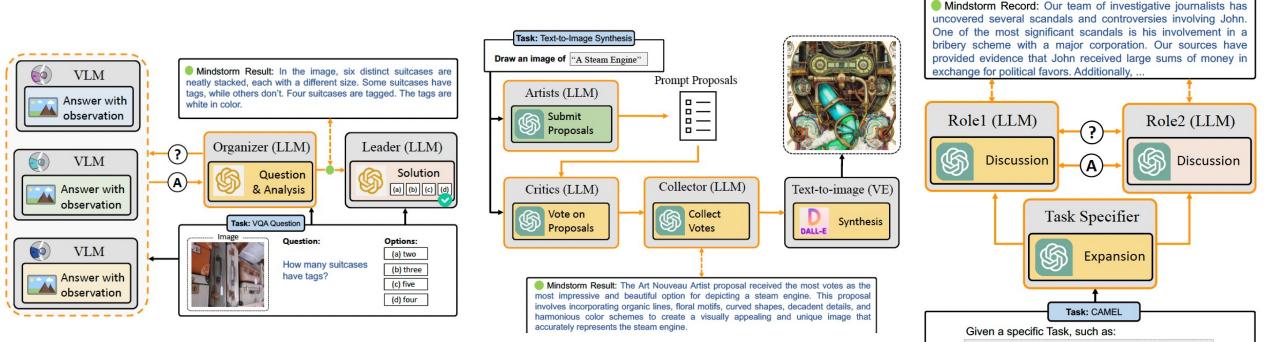
#### **Operating System**







#### One Step Towards AGI (Natural Language-based Society of Minds)



"Find any scandals or controversies involving John."

#### Numbered Articles:

- 1. Xi et al. (2023) The Rise and Potential of Large Language Model Based Agents: A Survey
- 2. Kojima et al. (2022) Large Language Models are Zero-Shot Reasoners
- 3. Wei et al. (2022) Chain-of-Thought Prompting Elicits Reasoning in Large Language Models
- 4. Zhang et al. (2022) Automatic Chain of Thought Prompting in Large Language Models
- 5. Wang et al. (2023) Plan-and-Solve Prompting: Improving Zero-Shot Chain-of-Thought Reasoning by Large Language Models
- 6. Press et al. (2023) Measuring and Narrowing the Compositionality Gap in Language Models
- 7. Yao et al. (2023) REACT: SYNERGIZING REASONING AND ACTING INLANGUAGE MODELS
- 8. Madaan et al. (2023) Self-refine: SELF-REFINE:Iterative Refinement with Self-Feedback
- 9. Shinn et al. (2023) Reflexion: Language Agents with Verbal Reinforcement Learning
- 10. Wang et al. (2023) Self-Consistency Improves Chain of Thought Reasoning in Language Models
- 11. Besta et al. (2023) Graph of Thoughts: Solving Elaborate Problems with Large Language Models
- 12. Yao et al. (2023) Tree of Thoughts: Deliberate Problem Solving with Large Language Models
- 13. Newell et al. "Report on a general problem solving program" Pittsburgh, PA, 1959
- 14. Wang G et al. (2023) Voyager: An open-ended embodied agent with large language models[J].
- 15. Zelikman, Eric, et al. (2023) "Self-taught optimizer (stop): Recursively self-improving code generation."
- 16. Romera-Paredes, Bernardino, et al. "Mathematical discoveries from program search with large language models." Nature (2023): 1-3.
- 17. Packer, Charles, et al. (2023) "Memgpt: Towards llms as operating systems."
- 18. Kim, Sehoon, et al. (2023) "An LLM Compiler for Parallel Function Calling."
- 19. Zhuge, Mingchen, et al. (2023) "Mindstorms in Natural Language-Based Societies of Mind."

#### Other Resources:

https://www.promptingguide.ai/

https://docs.langchain.com/docs/

https://lilianweng.github.io/posts/2023-06-23-agent/

https://www.pinecone.io/learn/series/langchain/