南京大学
NANJING UNIVERSITY

人工智能导论

智能体 (Agent)

郭兰哲

南京大学 智能科学与技术学院

https://www.lamda.nju.edu.cn/guolz

Email: guolz@nju.edu.cn

Recall

- 语言模型：基于概率预测下一个最有可能的词(Next-Token Prediction)
- 现代LLM架构：Transformer架构，核心机制Self-Attention
- ChatGPT：预训练 -> 监督微调 -> RLHF
- LLM推理：Chain-of-Thought
- DeepSeek-R1：监督微调 + 强化学习微调 （GRPO）

一些观点

SFT vs RLFT

- 对于形式化推理任务，例如math、code，更容易设计rule-based reward

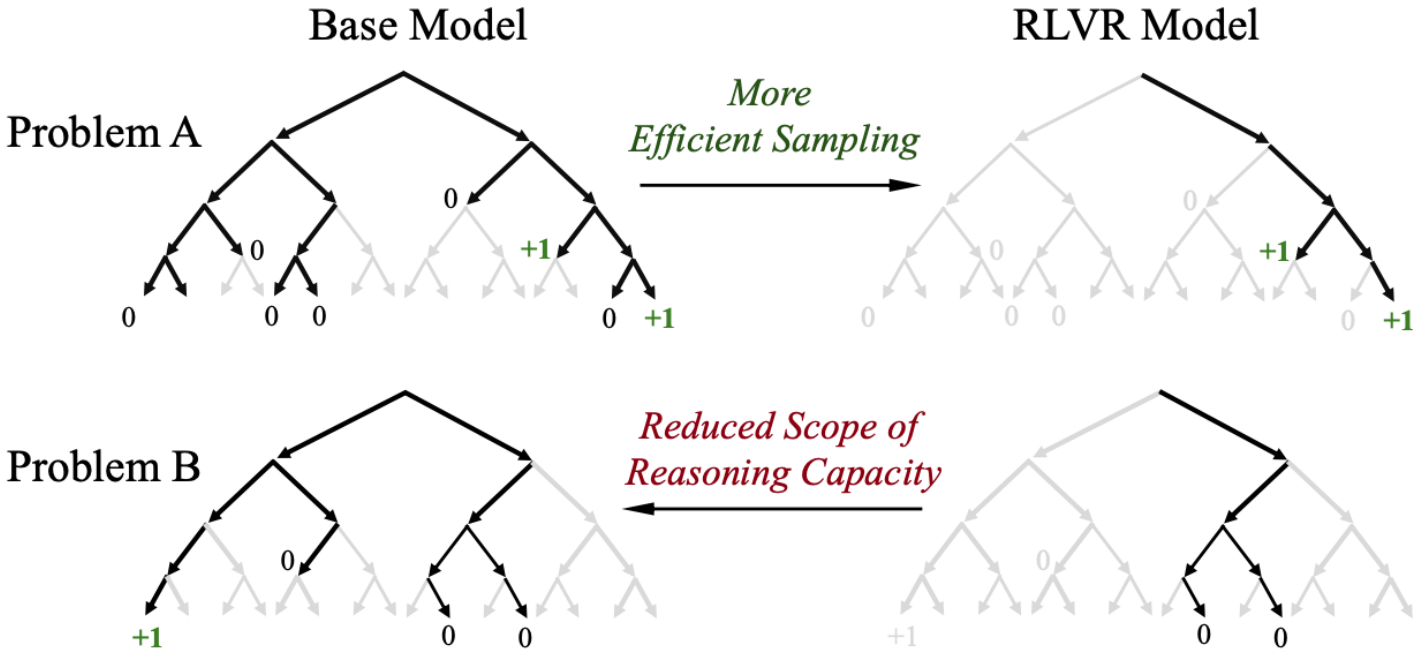
  - **SFT vs RL**

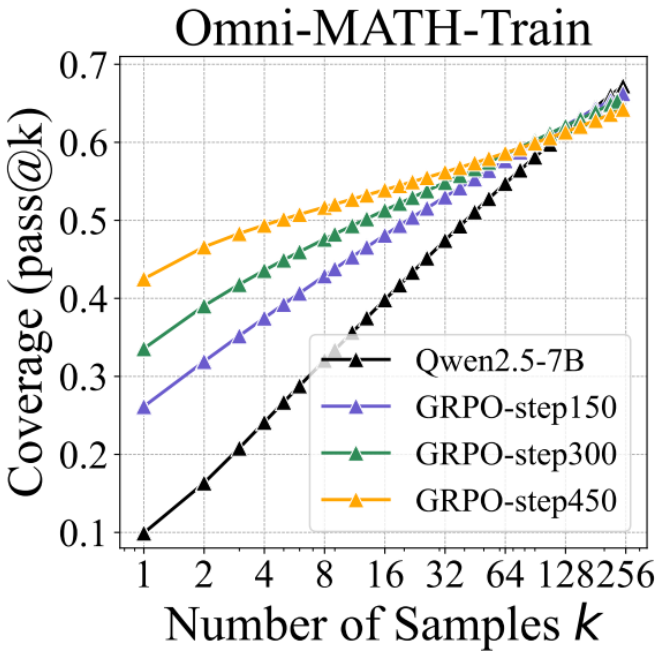
    - 直接利用SFT更多是去拟合数据中的pattern，难以学习到背后的规律；
    - RL则是通过鼓励模型在最大化reward的过程中学习到推理背后的规律，获得的泛化性和推理表现上界更高
    - SFT规范模型输出格式，使得后续的RL可以获得更高收益 [1]
    - 小模型RL不容易出现Long CoT [2]

[1] SFT Memorizes, RL Generalizes: A Comparative Study of Foundation Model Post-training. https://arxiv.org/pdf/2501.17161
[2] Demystifying Long Chain-of-Thought Reasoning in LLMs. https://arxiv.org/pdf/2502.03373

RL能否带来推理能力提升?

观点：RL并不一定真正扩展了大模型的推理能力，它更多是在提升采样效率、强化 base model 已经会的高奖励推理路径





Does Reinforcement Learning Really Incentivize Reasoning Capacity in LLMs Beyond the Base Model? https://arxiv.org/pdf/2504.13837

LLM是记忆还是推理?

GSM-NoOp

Oliver picks 44 kiwis on Friday. Then he picks 58 kiwis on Saturday. On Sunday, he picks double the number of kiwis he did on Friday, but five of them were a bit smaller than average. How many kiwis does Oliver have?

---

o1-mini: Oliver picks kiwis over three days as follows:
- Friday: 44 kiwis
- Saturday: 58 kiwis
- Sunday: Double the number he picked on Friday, which is $2 \times 44 = 88$ kiwis

However, on Sunday, 5 of these kiwis were smaller than average. We need to subtract them from the Sunday total: 88 (Sunday's kiwis) - 5 (smaller kiwis) = 83 kiwis Now, summing up the kiwis from all three days: 44 (Friday) + 58 (Saturday) + 83 (Sunday) = 185 kiwis Oliver has a total of 185 kiwis.

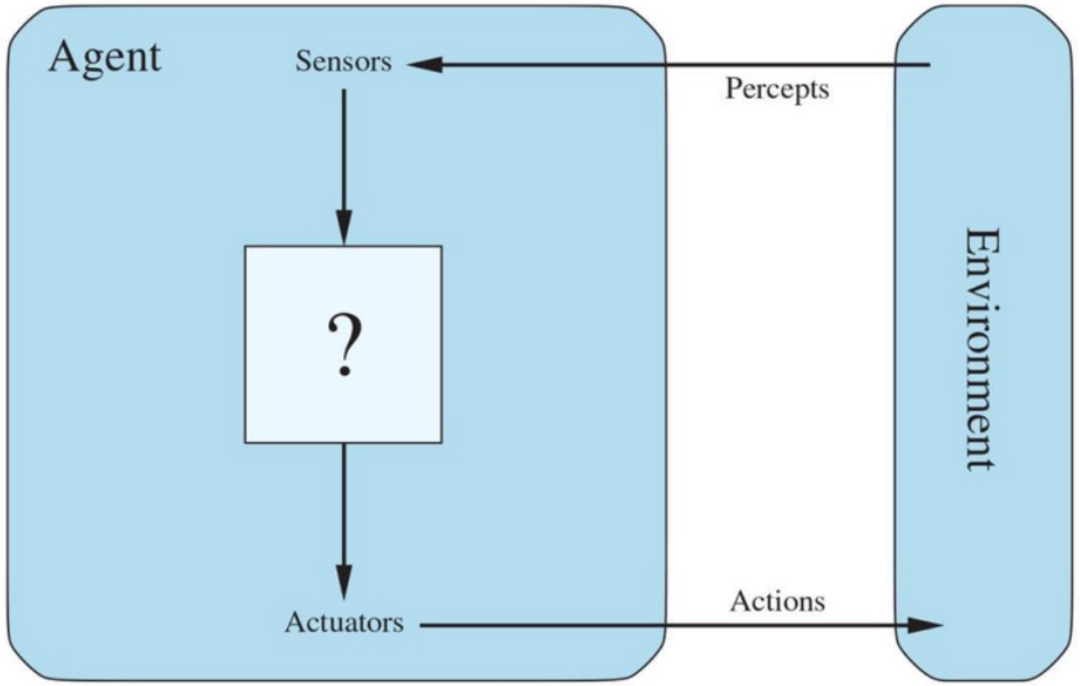
Llama3-8B: Let's break it down step by step:
Oliver picks 44 kiwis on Friday. He picks 58 kiwis on Saturday. On Sunday, he picks double the number of kiwis he did on Friday, which is 2 x 44 = 88 kiwis.
Five of the kiwis picked on Sunday are a bit smaller than average, so we subtract 5 from the total number of kiwis picked on Sunday: 88 - 5 = 83 kiwis. Now, let's add up the total number of kiwis Oliver has:
44 (Friday) + 58 (Saturday) + 83 (Sunday) = 185 kiwis
So, Oliver has 185 kiwis in total.

[1] GSM-Symbolic: Understanding the Limitations of Mathematical Reasoning in Large Language Models. ICLR 2024.

新趋势：智能体时代


1.0 对话工具时代
理解与生成
你好！
有什么可以帮你？
大语言模型
(LLM)
• 回答问题
• 生成文本
• 知识检索
2.0 决策助手时代
理解、分析与建议
• 数据分析
• 方案建议
• 辅助决策
3.0 智能体时代
规划、行动与执行
感知
(Perception)
记忆
(Memory)
规划
(Planning)
行动
(Action)
• 目标驱动
• 自主规划
• 工具使用
• 记忆与反思
• 持续学习
4.0 自主智能体时代
协作、创造与价值实现
多智能体协作
长程目标
创造与创新
Agent
与环境交互
价值落地
自主
智能
协作
创造
价值

回顾：什么是智能体？



"An **agent** is anything that can be viewed as **perceiving** its environment through sensors and **acting** upon that environment through actuators."

-- Russell & Norvig *AI: A Modern Approach*

智能体是一个能够感知环境，进行推理规划，并采取行动与环境进行交互的系统

回顾：什么是智能体？

Knowledge

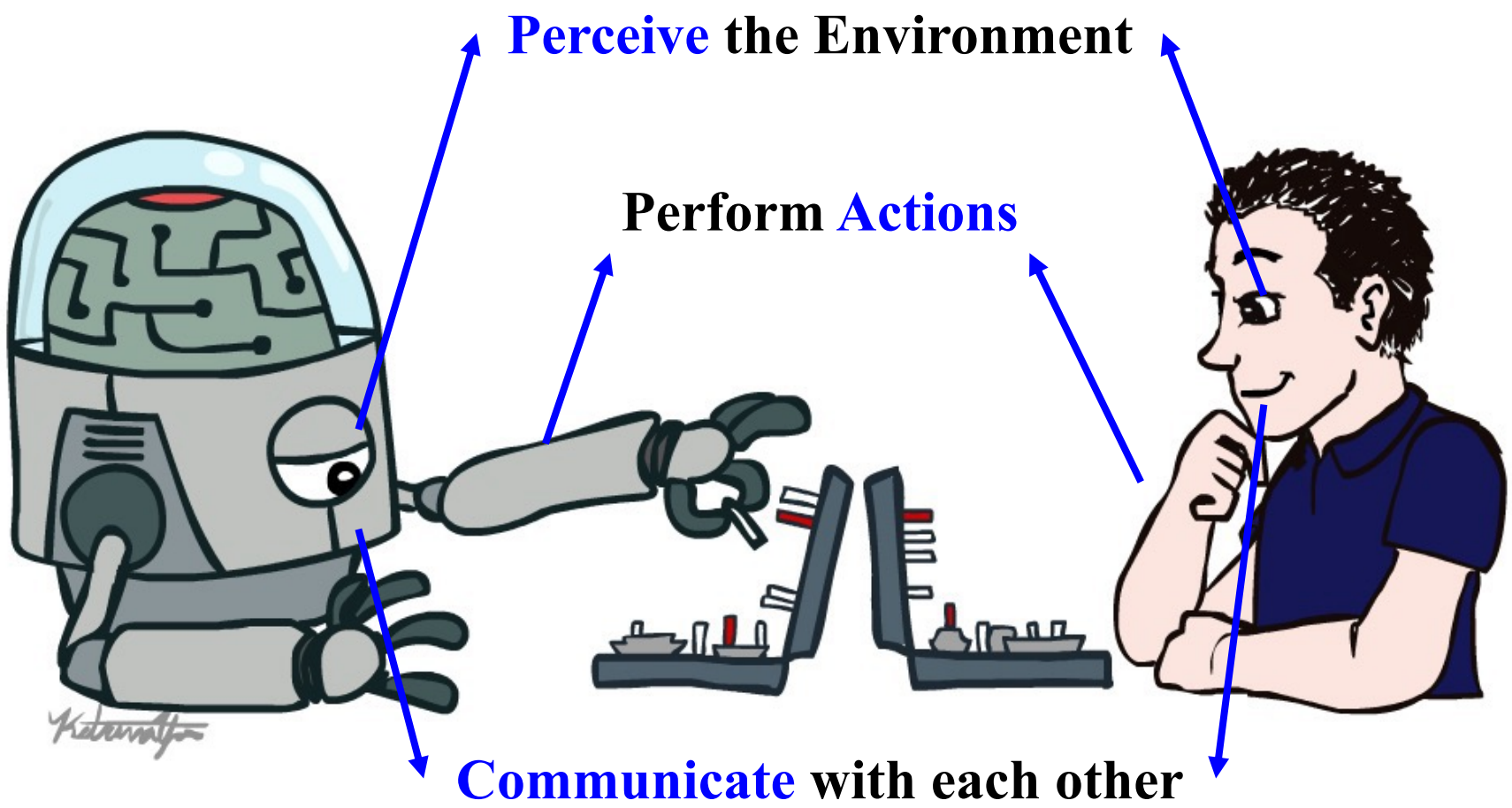
- 游戏规则
- 经验

Reasoning

- 下一步怎么操作？

Learning

- 玩的越多能力越强



Think like human

Act like human

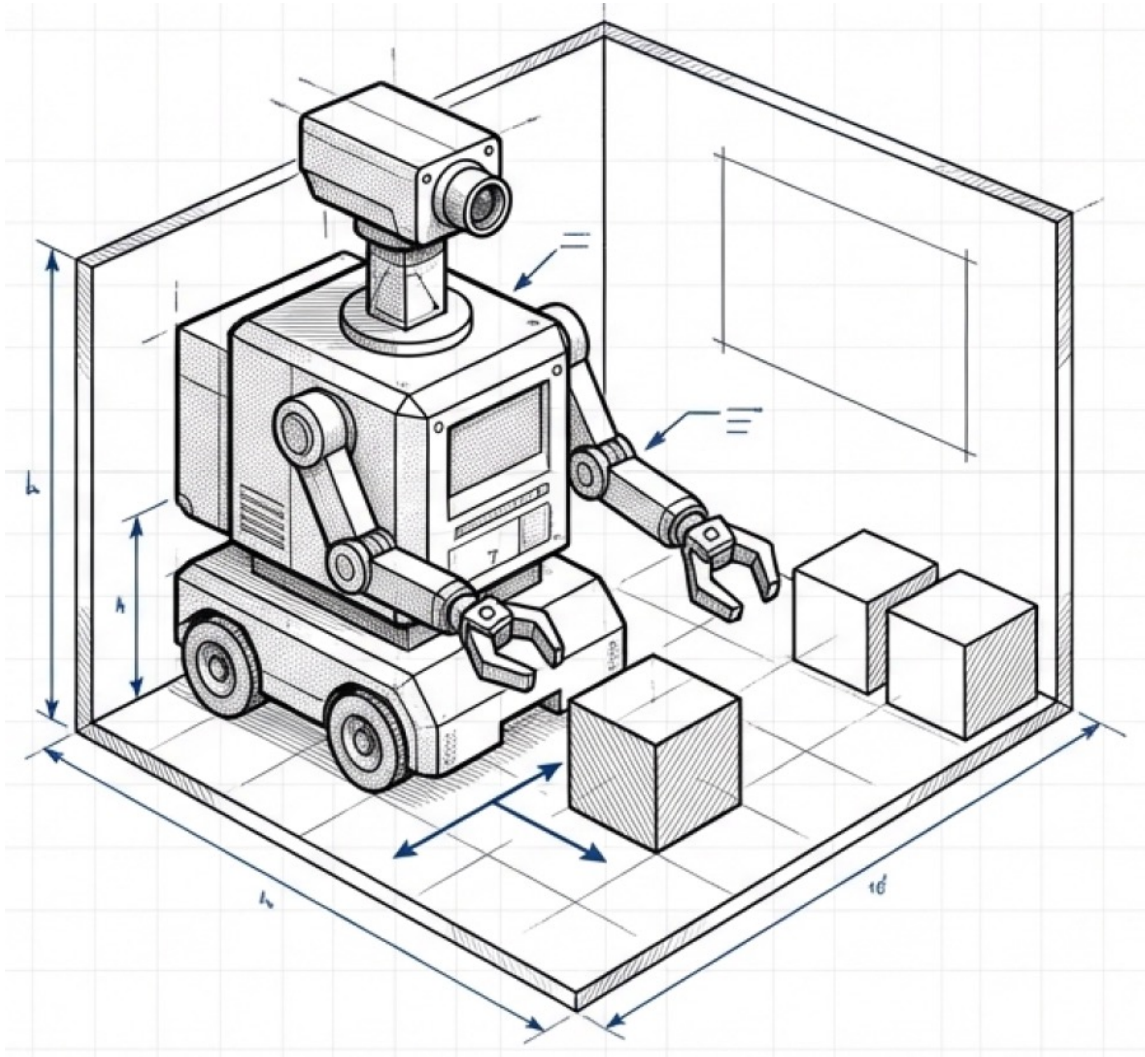
逻辑智能体

基于人工定义的符号与逻辑规则

关键案例

先驱：**Shakey the Robot (1969)**

第一个能够推理自身行为，并与物理世界交互的通用移动机器人，能够自主规划路径和动作完成“推箱子”任务



优势： 严谨的逻辑性、可解释性

局限： 缺乏泛化能力，感知能力弱

强化学习智能体

基于强化学习与环境海量交互试错

关键案例

- 围棋：AlphaGo
- 游戏智能体
  - Atari, Open-AI Five, AlphaStar…

优势：封闭环境中掌握超越人类的复杂技能

局限：样本效率低，难以在不同场景迁移

两个角度理解智能体

LLM-first view：让我们把LLM变成Agent

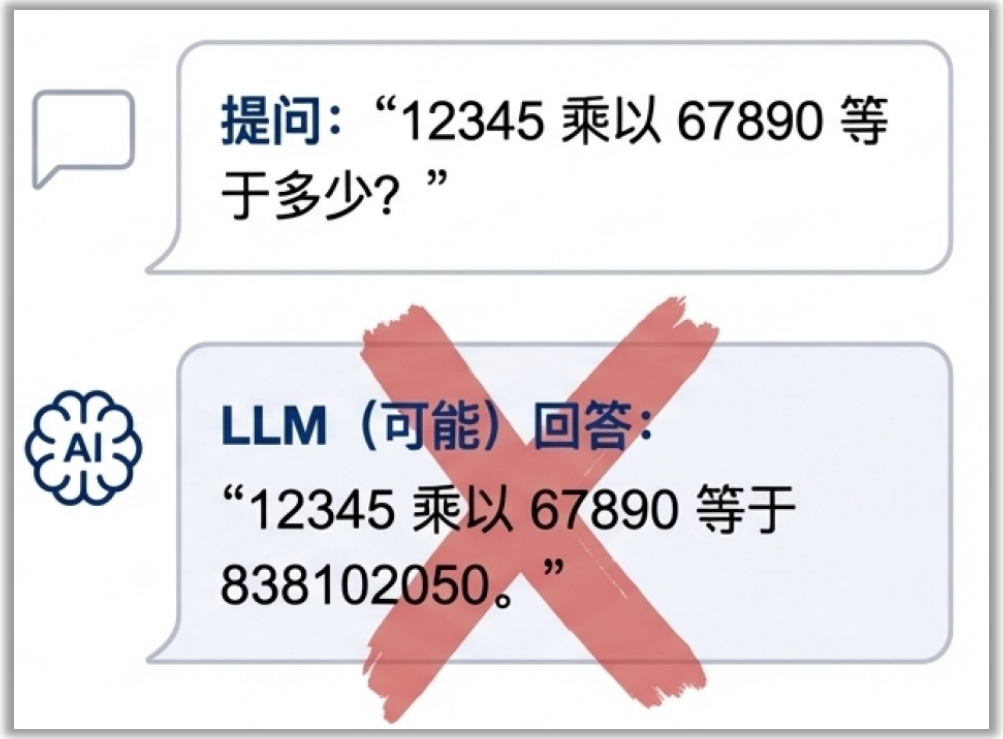
- 关键：如何在LLM的基础上一步步升级，从chatbot到reasoner再到Agent

Agent-first view：让我们把LLM放到Agent架构中

- 关键：Agent本身有哪些挑战？LLM的引入可以帮助缓解哪些挑战，又引入了哪些新的挑战？

LLM-First View：从LLM到Agent，是如何发展的？

大模型推理的局限



可靠性不足，模型幻觉

概率近似正确本质，难以保障严谨性

Human + Tool Use

- As humans, we have limited time and memory, feel tired, and have emotions.
- **Human + tool use**
  - Enhanced scalability
  - Improved consistency
  - Greater interpretability
  - Higher capacity and productivity

LLM + Tool Use

- Just like humans, LLMs suffer from the similar limitations. But in the same way,
- **LLMs + tool use**
  - Enhanced scalability
  - Improved consistency
  - Greater interpretability
  - Higher capacity and productivity

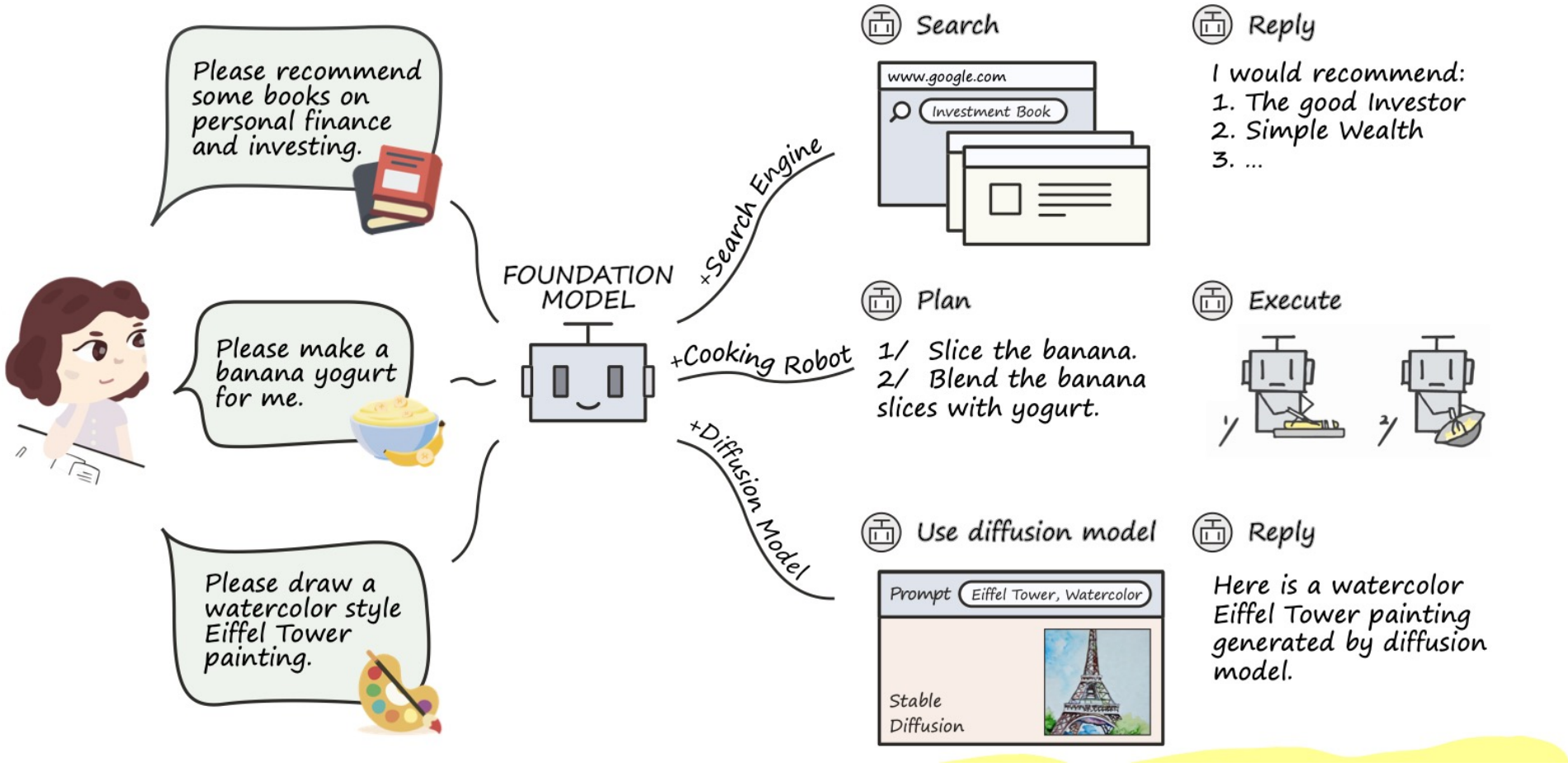
scikit learn

Hugging Face

matplotlib

Search Google or type a URL

LLM + Tool Use



Neuro-Symbolic Learning思想的体现：不再只是依赖单一神经网络，而是通过神经网络大模型 + 外部工具，构建更强大的AI系统

LLM + Tool Use

模型怎么知道有哪些工具，什么时候该调用工具？

纯 Prompt 工程

```
你可以使用以下工具：
- search(query)：搜索网页
- calculator(expr)：计算数学表达式

请按照 Thought → Action → Observation 的格式回答
```

模型并没有真正“学会”调用工具，只是在**模式匹配**，见过类似格式就照着输出

LLM + Tool Use： Prompt

模型怎么知道有哪些工具，什么时候该调用工具？

```
tools = [
    {
        "name": "get_weather",
        "description": "查询指定城市的当前天气情况，包括温度、天气状况和湿度",
        "input_schema": {
            "type": "object",
            "properties": {
                "city": {
                    "type": "string",
                    "description": "城市名称，例如：上海、北京、广州"
                },
                "unit": {
                    "type": "string",
                    "enum": ["celsius", "fahrenheit"],
                    "description": "温度单位，默认摄氏度"
                }
            },
            "required": ["city"]
        }
    },
```

用户输入

↓

大模型推理：是否需要工具？选哪个？

↓

输出结构化工具调用指令

↓

外部系统执行工具，返回结果

↓

大模型接收结果，继续推理或生成最终回答

↓

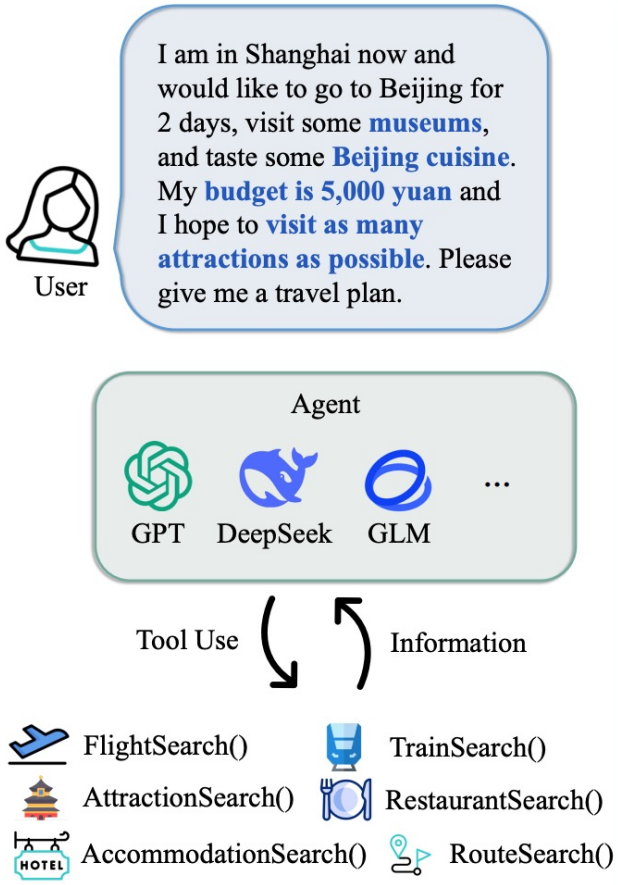
用户输出

ReAct框架：推理→调用→观察→再推理

ReAct: Synergizing Reasoning and Acting in Language Models. ICLR 2023. https://arxiv.org/abs/2210.03629

LLM + Tool Use： Prompt

复杂任务不能一步完成，需要拆解成多个子任务，模型需要决定**先做什么、后做什么、哪一步需要什么工具、出错后如何调整**



Planning

[1] **visit some museums…**

There are some museums in Beijing:
- The Palace Museum
- National Museum of China
- Beijing Capital Museum

…

[2] **taste some Beijing cuisine…**

There are some restaurants:
- Dadong Duck
- Siji Minfu
- Xiaodiao Litang

…

[3] **budget is 5000 yuan…**

The cross-city transportation costs about 1,500, and the accommodation costs about 500, leaving me with a budget of about 3,000.
- The budget is sufficient to try different foods

[4] **visit as many attractions as possible**
- select adjacent attractions
- choose convenient transportation

…

Itinerary Plan

[Day 1, Activity 1]
Train, G104, 06:27 → 13:12, cost: 693
Shanghai Hongqiao Railway Station → Beijingnan Railway Station

[Day 1, Activity 2]
The Palace Museum, 14:00 → 17:30
Transports: Metro, Beijingnan Railway Station→ The Palace Museum, cost 3, 13:15 → 13:50, walking: 1.5km

[Day 1, Activity 3]
Siji Minfu, 17:45 → 18:45, cost 180,
Transports: Walking, The Palace Museum → Siji Minfu, cost 0, 17:30 → 17:45, walking: 0.8km

[Day 1, Activity 4]
Wangfujing Street, 17:45 → 18:45,
Transports: Taxi, The Palace Museum → Wangfujing Street, cost 16, 17:30 → 17:45,

…

[Day 1, Activity 6]
Beijing XX hotel, room: 1, cost: 580
Transports: …

[Day 2, Activity 1]
Chenji century-old Luzhu, 08:10 → 08:40, cost: 32
Transports: Walking, Beijing XX hotel → Chenji century-old Luzhu, 0.4km 08:00 → 08:06

[Day 2, Activity 2]
National Museum of China, 09:15 → 11:45, cost: 0
Transports: Metro, Chenji century-old Luzhu → National Museum of China, cost 3, 08:40 → 09:15, walking: 1.2km

…

[Day 2, Activity 4]
Beijing Capital Museum

…

[Day 2, Activity 5]
Train, G153, 16:30 → 22:27, cost: 576
Beijingnan Railway Station→Shanghai Hongqiao Railway Station
Transports: Metro, Beijing Capital Museum → Beijingnan Railway Station, cost: 4, 15:30 → 16:02, walking: 0.8km

[1] ChinaTravel: An Open-Ended Benchmark for Language Agents in Chinese Travel Planning. Shao et al., 2025.

LLM + Tool Use： Prompt

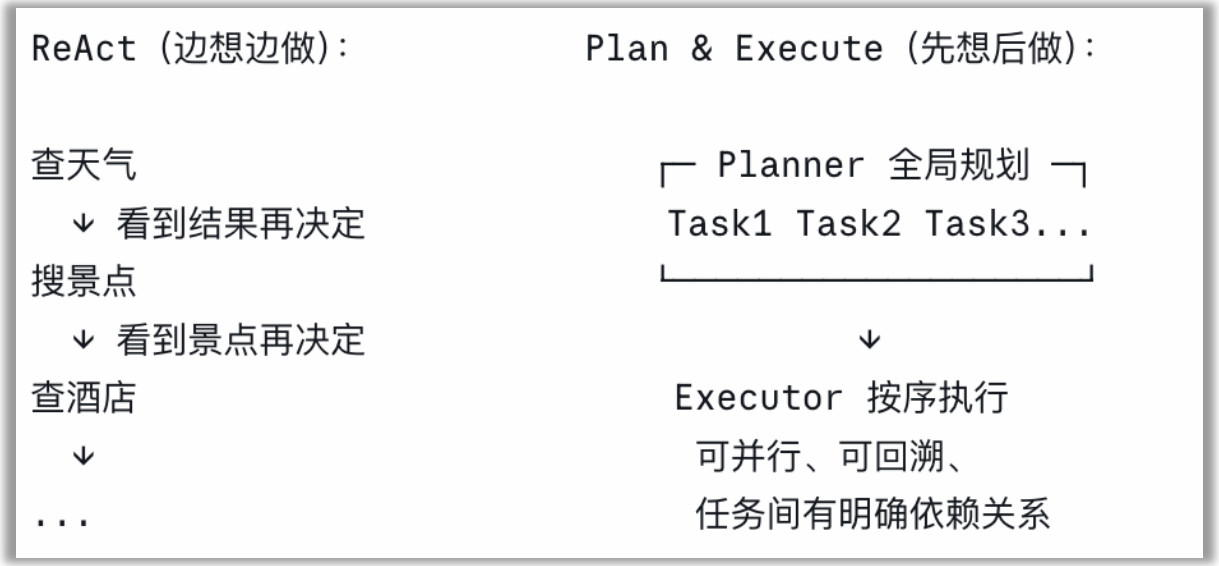
帮我规划一个五天的京都旅行，我喜欢历史文化，预算中等，下个月出发

【Planner 输出】

分析用户需求:
- 目的地: 京都
- 时长: 5天
- 偏好: 历史文化
- 预算: 中等
- 时间: 下个月

生成执行计划:
Task 1: 查询下个月京都天气与最佳游览时段
Task 2: 搜索京都历史文化类核心景点
Task 3: 查询中等预算酒店选项（距核心景区步行可达）
Task 4: 查询北京→京都往返机票价格
Task 5: 根据景点地理位置，规划5天合理游览路线
Task 6: 整合所有信息，生成完整旅行方案

ReAct v.s. Plan & Solve



Plan-and-Solve Prompting: Improving Zero-Shot Chain-of-Thought Reasoning by Large Language Models. https://arxiv.org/abs/2305.04091

LLM + Tool Use：SFT

模型怎么知道有哪些工具，什么时候该调用工具？

监督微调

构造训练数据：
用户："上海今天天气？"
标准输出：{
"tool": "get_weather",
"parameters": {"city": "上海"}
}

用户："1加1等于几？"
标准输出：直接回答"2"，不调用任何工具

训练数据来源主要有三类：

- **人工标注**：人工写出"什么情况调什么工具"的示范数据
- **合成数据**：用强模型（GPT-4）自动生成大量工具调用轨迹，再用弱模型学习
- **真实使用日志**：收集用户实际使用工具的成功案例

LLM + Tool Use： SFT

The New England Journal of Medicine is a registered trademark of [QA("Who is the publisher of The New England Journal of Medicine?") → Massachusetts Medical Society] the MMS.

Out of 1400 participants, 400 (or [Calculator(400 / 1400) → 0.29] 29%) passed the test.

The name derives from "la tortuga", the Spanish word for [MT("tortuga") → turtle] turtle.

The Brown Act is California's law [WikiSearch("Brown Act") → The Ralph M. Brown Act is an act of the California State Legislature that guarantees the public's right to attend and participate in meetings of local legislative bodies.] that requires legislative bodies, like city councils, to hold their meetings open to the public.

Your task is to add calls to a Question Answering API to a piece of text. The questions should help you get information required to complete the text. You can call the API by writing "[QA(question)]" where "question" is the question you want to ask. Here are some examples of API calls:

Input: Joe Biden was born in Scranton, Pennsylvania.

Output: Joe Biden was born in [QA("Where was Joe Biden born?")] Scranton, [QA("In which state is Scranton?")] Pennsylvania.

Input: Coca-Cola, or Coke, is a carbonated soft drink manufactured by the Coca-Cola Company.

Output: Coca-Cola, or [QA("What other name is Coca-Cola known by?")] Coke, is a carbonated soft drink manufactured by [QA("Who manufactures Coca-Cola?")] the Coca-Cola Company.

Input: x

Output:

[1] Toolformer: Language Models Can Teach Themselves to Use Tools. Schick et al., NeurIPS 2023.

LLM + Tool Use：RL

模型怎么知道有哪些工具，什么时候该调用工具？

强化微调

✅ 调用了正确工具，参数合法，最终答对 → 高奖励

⚠️ 调用了工具但参数错误，答案偏差 → 低奖励

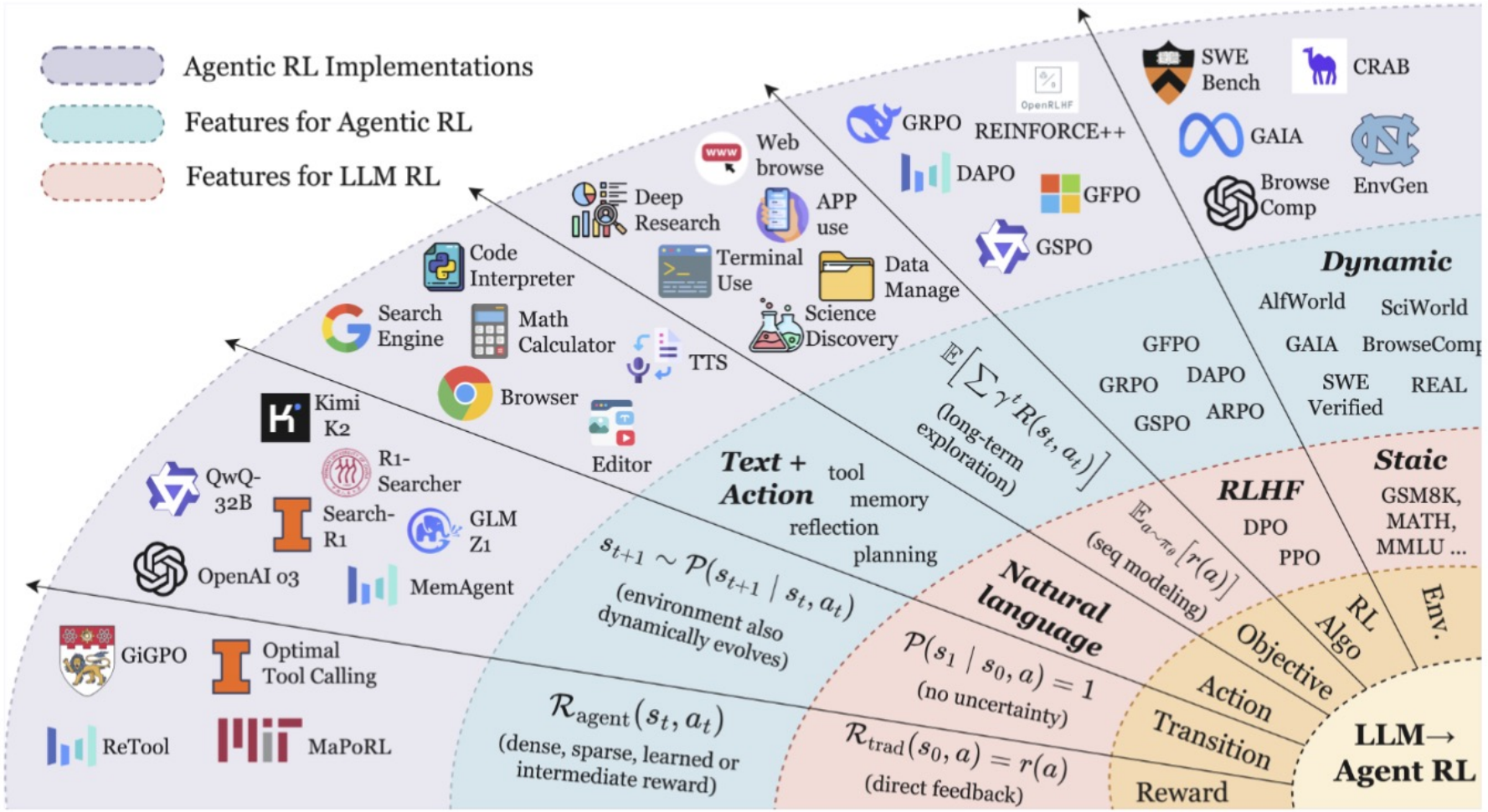
❌ 不该调用工具却调了，浪费 token → 负奖励

❌ 该调工具却没调，靠胡编蒙混 → 负奖励

目前主流趋势：监督微调+强化微调

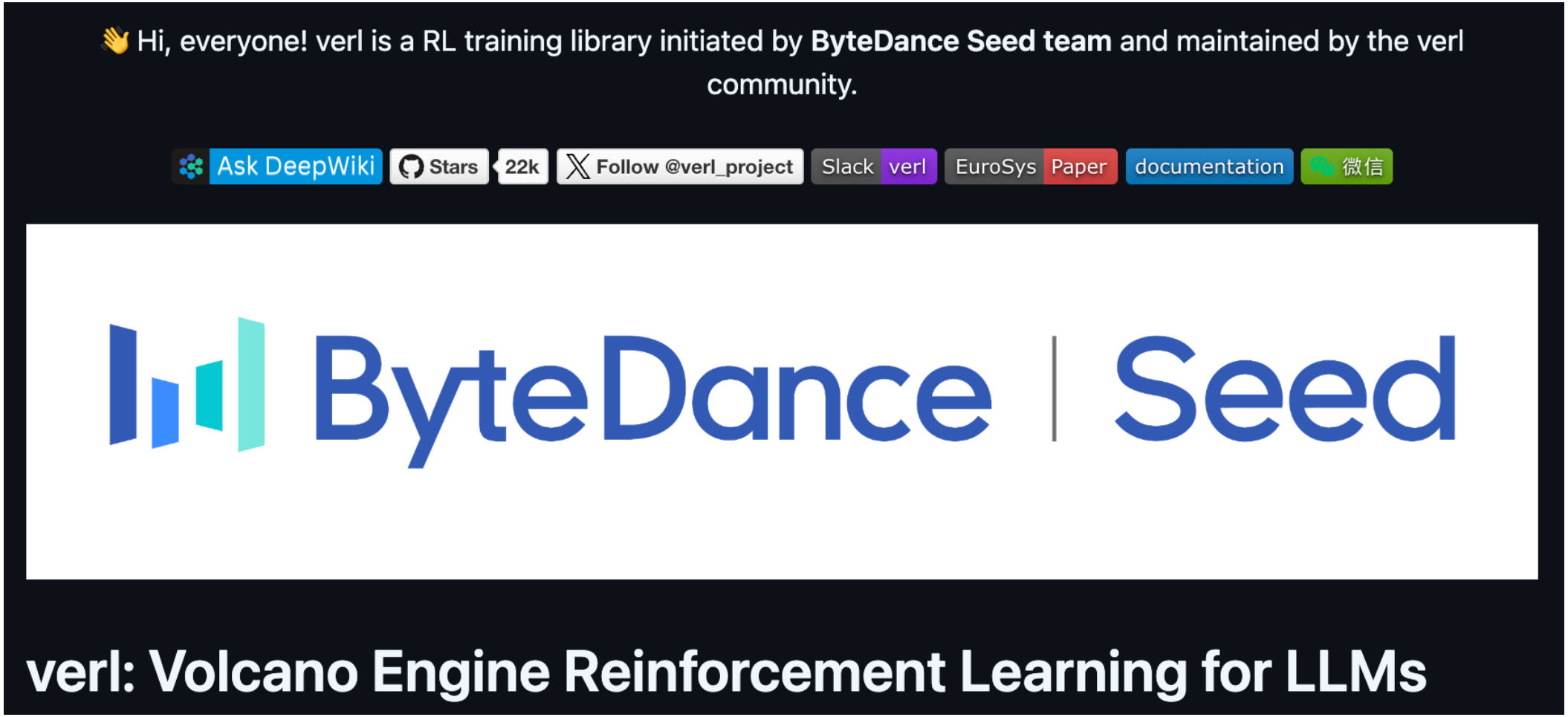
Agentic RL

The Landscape of Agentic Reinforcement Learning for LLMs: A Survey
https://www.alphaxiv.org/abs/2509.02547



Agentic RL

VERL: https://github.com/verl-project/verl

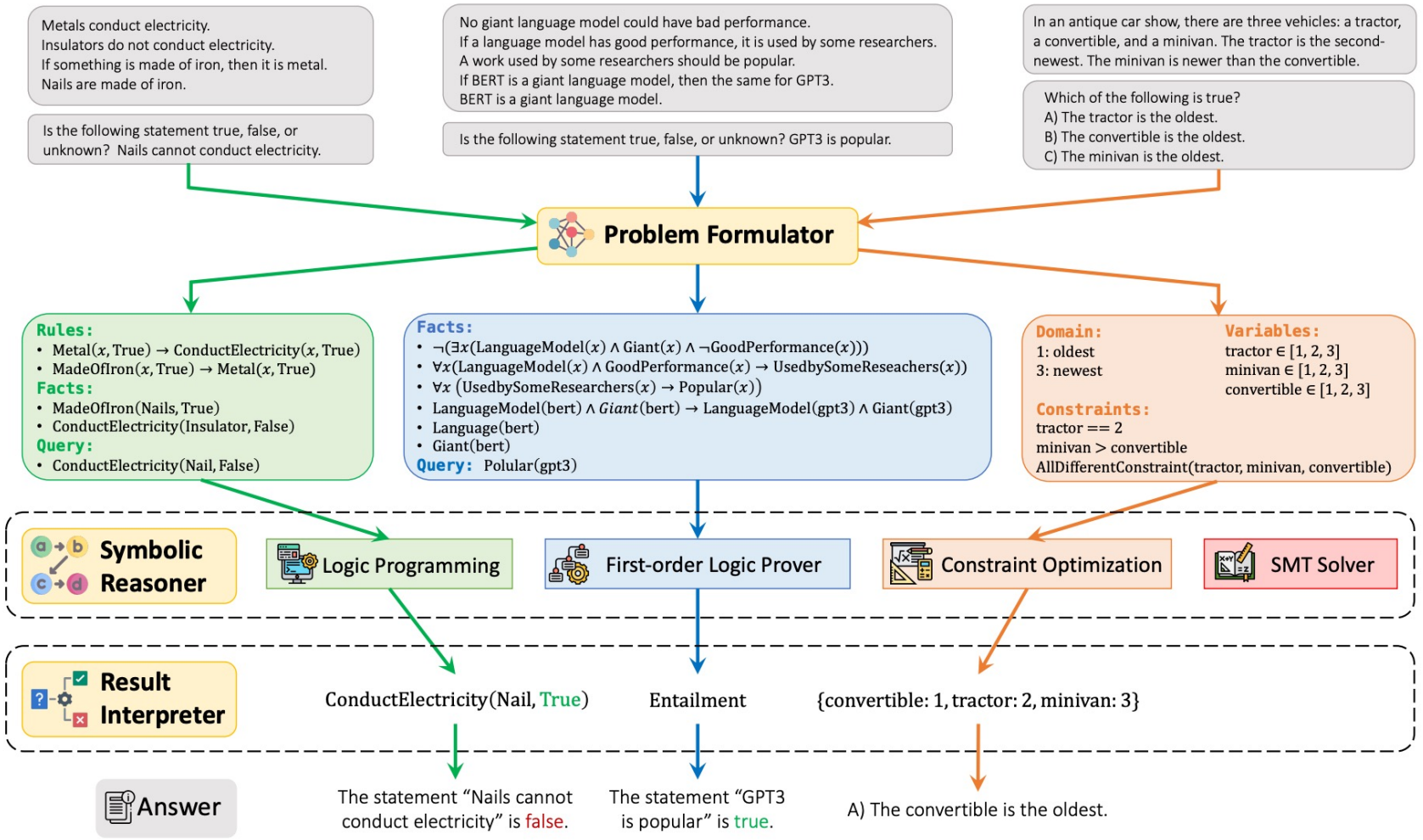


例子： Logical Reasoning

Convert **Natural Language** into **Formal Language**, then call a **symbolic solver**, such as

- First-order Logic Prover
- SMT Solver
- Constraint Optimizer

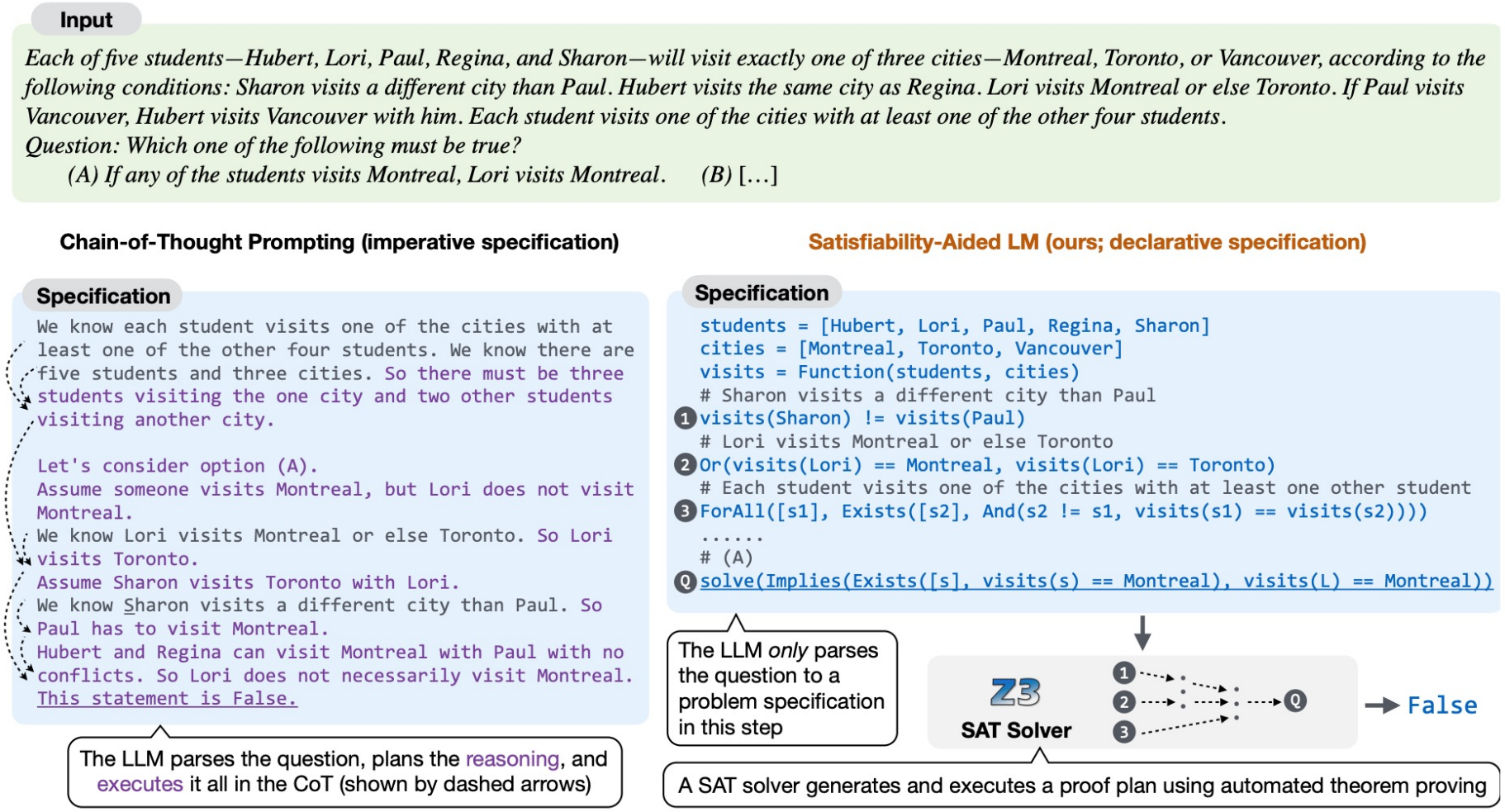
…



[1] LOGIC-LM: Empowering Large Language Models with Symbolic Solvers for Faithful Logical Reasoning. Pan et al., EMNLP 2023.

例子： Math Reasoning

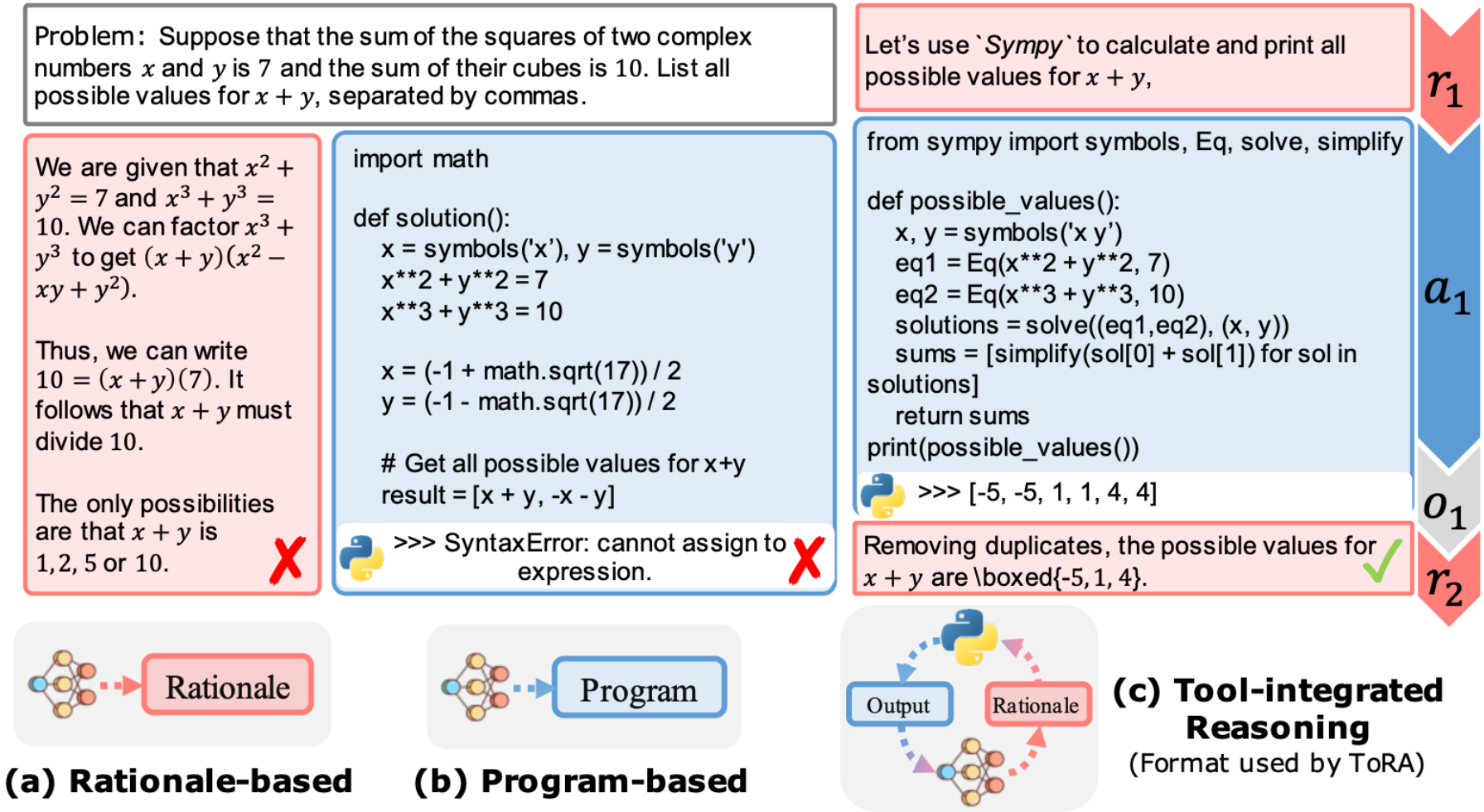
Parse an **natural language** input into a declarative task specification (a set of logical constraints) , then use a SAT solver (e.g., Z3) to solve the problem



[1] SATLM: Satisfiability-Aided Language Models Using Declarative Prompting. Ye et al., NeurIPS 2023.

例子： Math Reasoning

Integrate natural language reasoning with the utilization of external tools (e.g., computation libraries, symbolic solvers)



[1] ToRA: A Tool-Integrated Reasoning Agent for Mathematical Problem Solving. Gou et al., ICLR 2024.

例子： Math Reasoning

Question

Raymond and Samantha are cousins. Raymond was born 6 years before Samantha. Raymond had a son at the age of 23. If Samantha is now 31, how many years ago was Raymond's son born?

Chain of Thought

Samantha is 31 - 6 = 25 years old.
Raymond's son was born 25 - 23 = 2 years ago.

Answer: 2

Ground Truth

When Raymond's son was born Samantha was *23 - 6 = 17* years old. Thus it has been *31 - 17 = 14* years since Raymond's son was born.

Answer: 14

Prolog Generation

```
:- use_module(library(clpq)).

age_diff(raymond, samantha, 6).

age(raymond, 23).
age(samantha, 31).

solve(Years_ago) :-
    age_diff(raymond, samantha, Age_diff),
    age(raymond, Raymond_age),
    age(samantha, Samantha_age),
    {Raymond_son_age = Raymond_age - Age_diff},
    {Years_ago = Samantha_age - Raymond_son_age}.
```

Prolog Interpreter

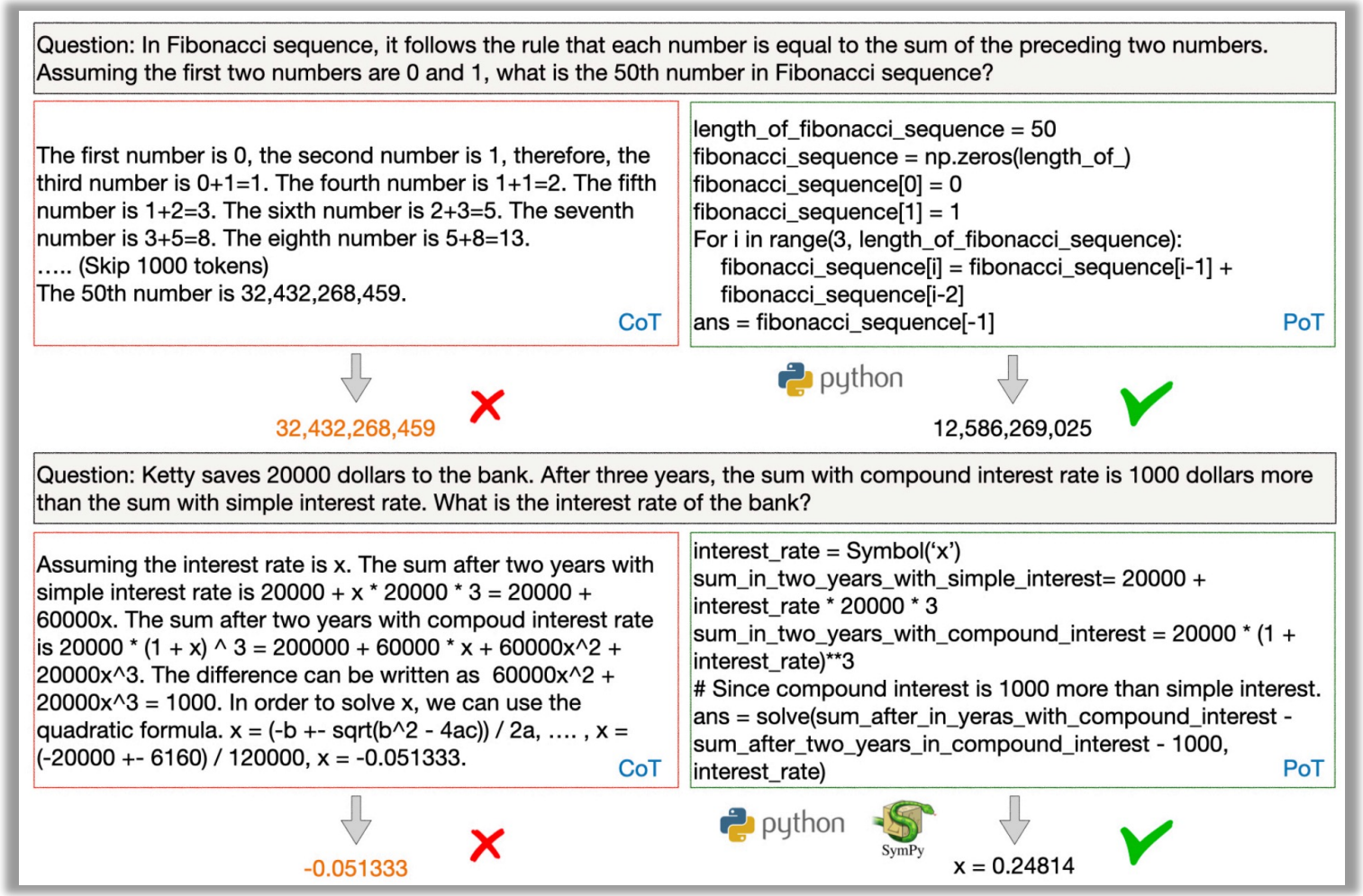
Answer: 14

[1] Arithmetic Reasoning with LLM: Prolog Generation & Permutation. Yang et al., ACL 2024.

例子： Math Reasoning

Program of Thought

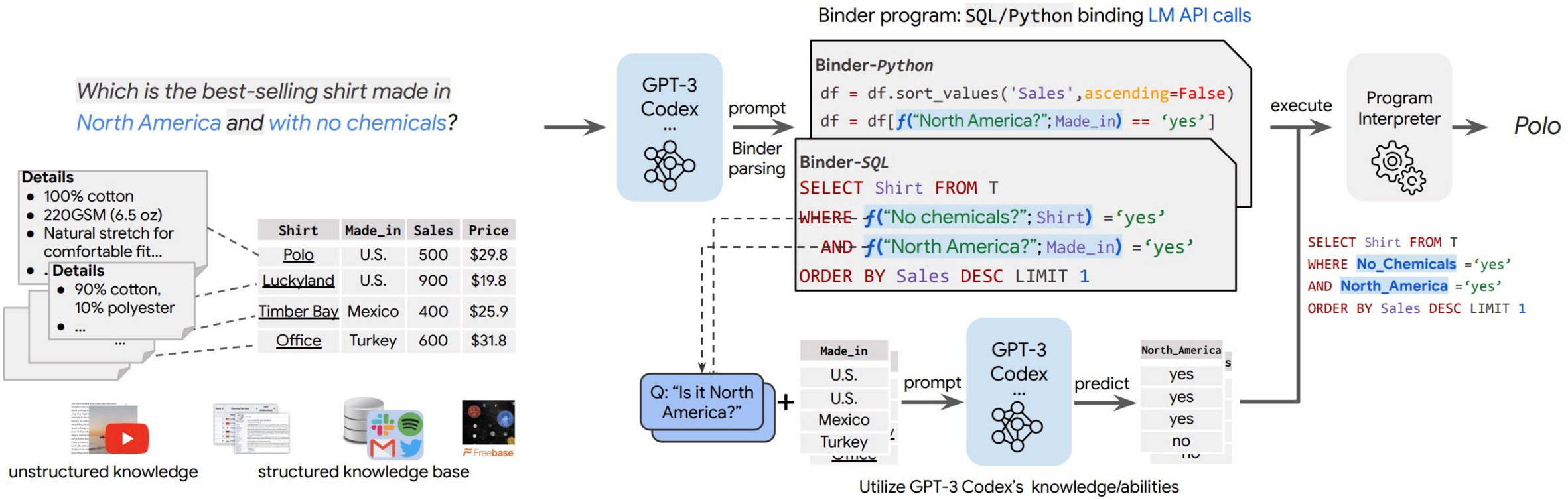
Convert the reasoning process expressed in natural language into a **programming language** (e.g., Python, etc.), and then **execute the program interpreter**



[1] PAL: Program-aided Language Models. Gao et al., ICML 2023.
[2] Program of Thoughts Prompting: Disentangling Computation from Reasoning for Numerical Reasoning Tasks. Chen et al., TMLR 2023.

例子：表格推理

- **Parse Stage**: LLM maps input to **Python/SQL** algorithm
- **Execution Stage**: A program interpreter executes the program to derive the answer

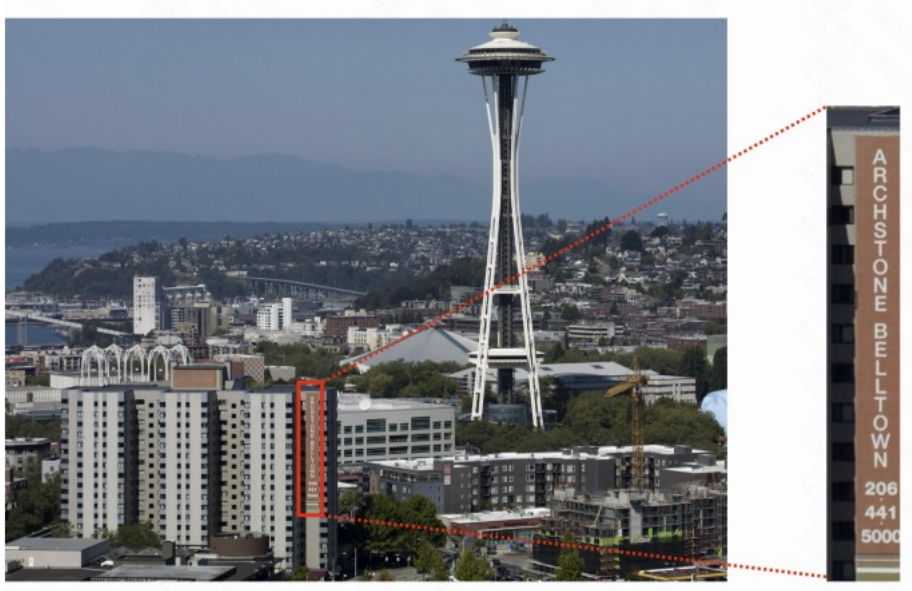


[1] Binding Language Models in Symbolic Languages. Cheng et al., ICLR 2023.

例子：多模态推理

Multi-Modal Reasoning

LLMs generate code to manipulate images for visual reasoning




```
# Define the cropping coordinates (x1, y1, x2, y2)
x1, y1, x2, y2 = 1750, 1950, 1850, 2600

# Crop the image
cropped_image = image[y1:y2, x1:x2]

# Apply zoom (resize the cropped image to enhance details)
zoom_factor = 2
zoomed_image = cv2.resize(cropped_image, None,
fx=zoom_factor, fy=zoom_factor,
interpolation=cv2.INTER_CUBIC)

# Save the processed image with a random suffix
random_suffix = random.randint(1000, 9999)
processed_filename = f"224_{random_suffix}.jpg"
processed_path = "/mnt/data/temp_processed_images/" +
processed_filename
cv2.imwrite(processed_path, zoomed_image)
```

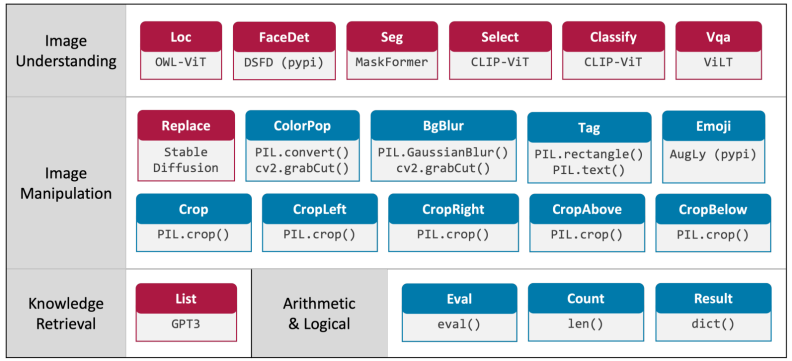
[1] Thyme: Think Beyond Images. Zhang et al., Arxiv 2025.

例子：多模态推理

LLMs generate a program to compose a diverse set of modules for visual reasoning

Question: Are there both ties and glasses in the picture?

LLM

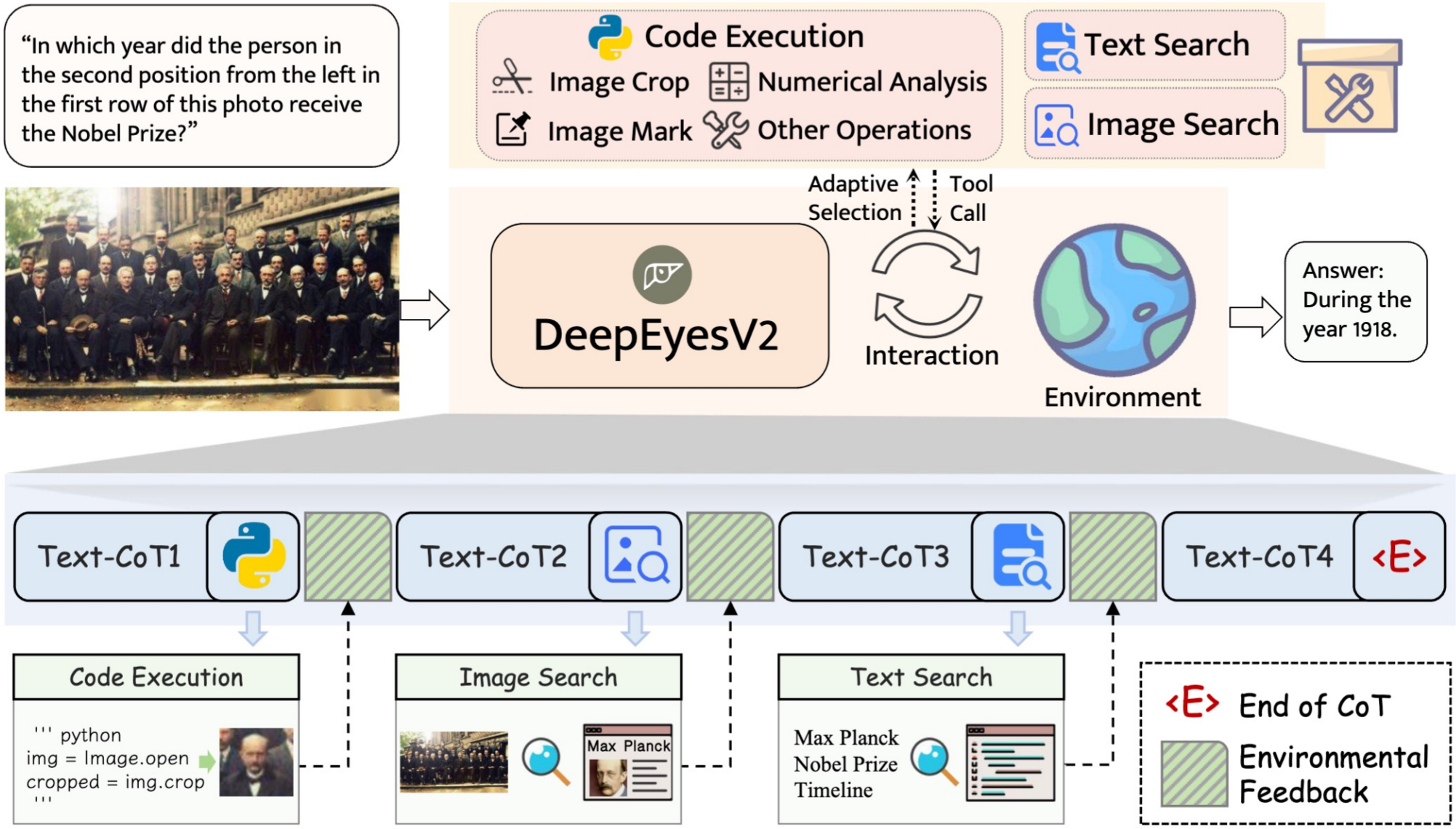


Model Zoo

```
BOX0=Loc(image=IMAGE, object='ties')
ANSWER0=Count(box=BOX0)
BOX1=Loc(image=IMAGE,
objects='glasses')
Answer1=Count(box=BOX1)
ANSWER2=Eval("'yes' if {ANSWER > 0) and
{ANSWER1)>0 else 'no'")
RESUL=ANSWER2
```

[1] Visual Programming: Compositional visual reasoning without training. Gupta et al., **CVPR 2023 Best Paper**.

例子：多模态推理



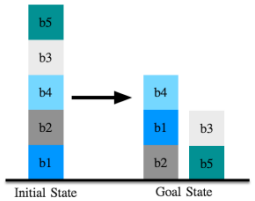
[1] DeepEyesV2: Toward Agentic Multimodal Model. https://www.alphaxiv.org/abs/2511.05271

例子： Embodied Planning

For planning tasks, first **generate the PDDL descriptions**, then use a **PDDL Planner** (e.g., FastDownward) to produce the plan

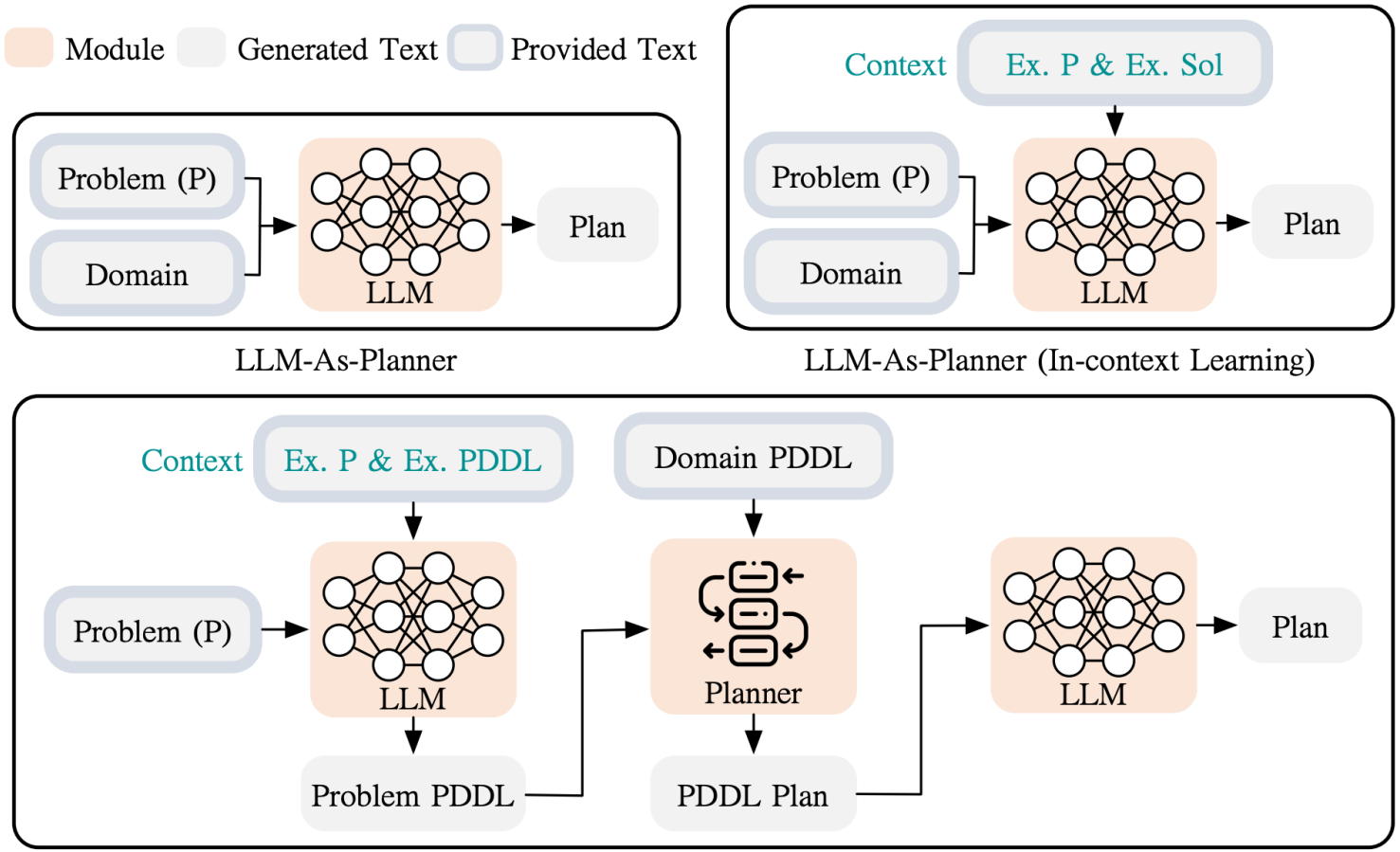
A Failure Example of GPT-4 in Planning

Problem (P1): You have 5 blocks. One cannot place more than one block on another block. b5 is on top of b3. b4 is on top of b2. b2 is on top of b1. b3 is on top of b4. b1 is on the table. b5 is clear. Your arm is empty.
Your goal is to move the blocks.
b1 should be on top of b2.
b3 should be on top of b5.
b4 should be on top of b1.



GPT-4:

```
1. Move b5 from b3 to the table.
2. Move b3 from b4 to b5.
3. Move b4 from b2 to the table.
4. Move b2 from b1 to b5.
5. Move b1 from the table to b2.
6. Move b4 from the table to b1.
```

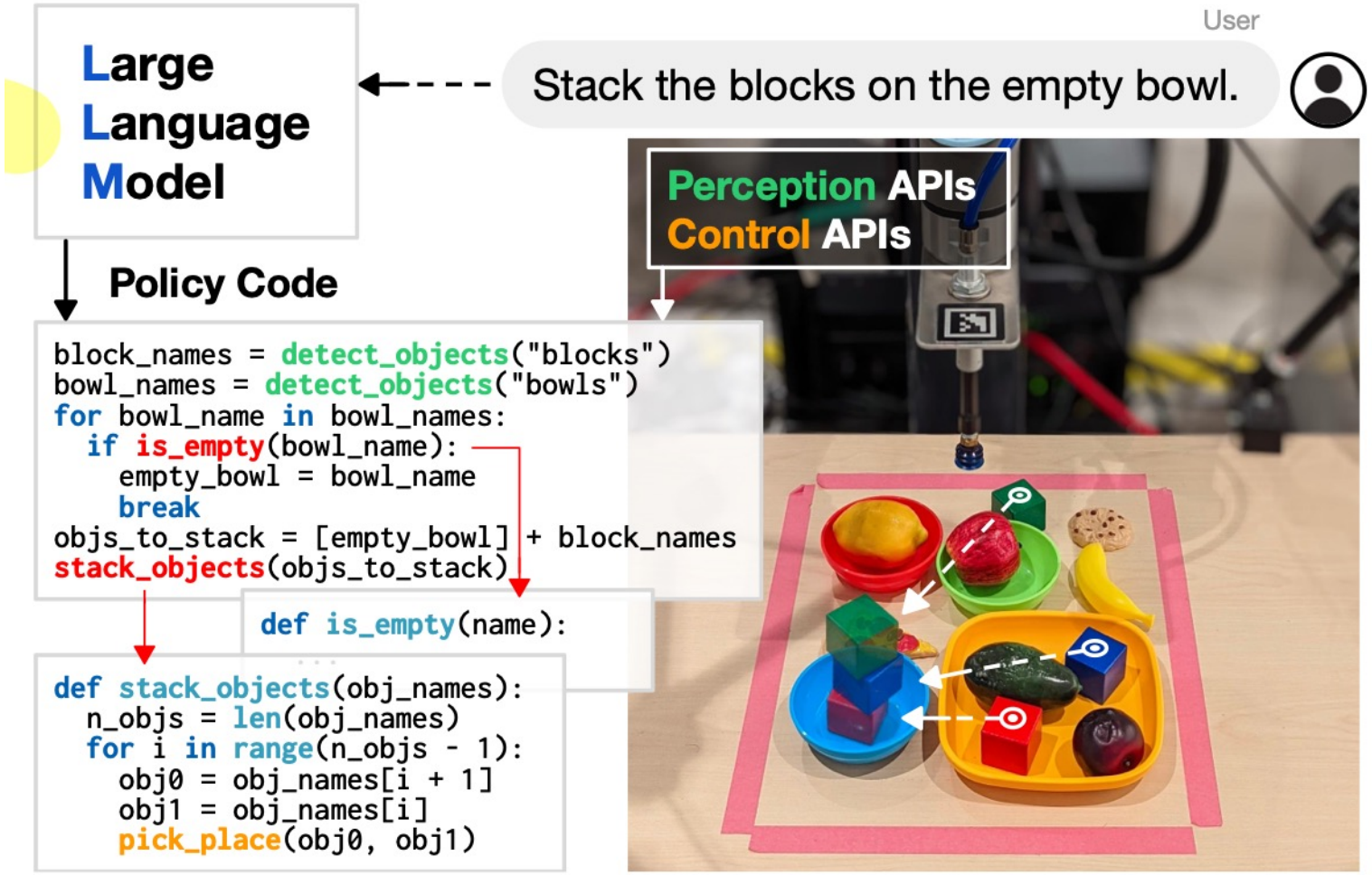


[1] LLM+P: Empowering Large Language Models with Optimal Planning Proficiency. Arxiv 2023.

例子： Embodied Planning

Code as Policy

Robots can use LLMs to translate natural language commands into robot policy code which process perception outputs, parameterize control primitives, recursively generate code for undefined functions, and generalize to new tasks



[1] Code as Policies: Language Model Programs for Embodied Control. J. Liang et al. CoRL 2022.

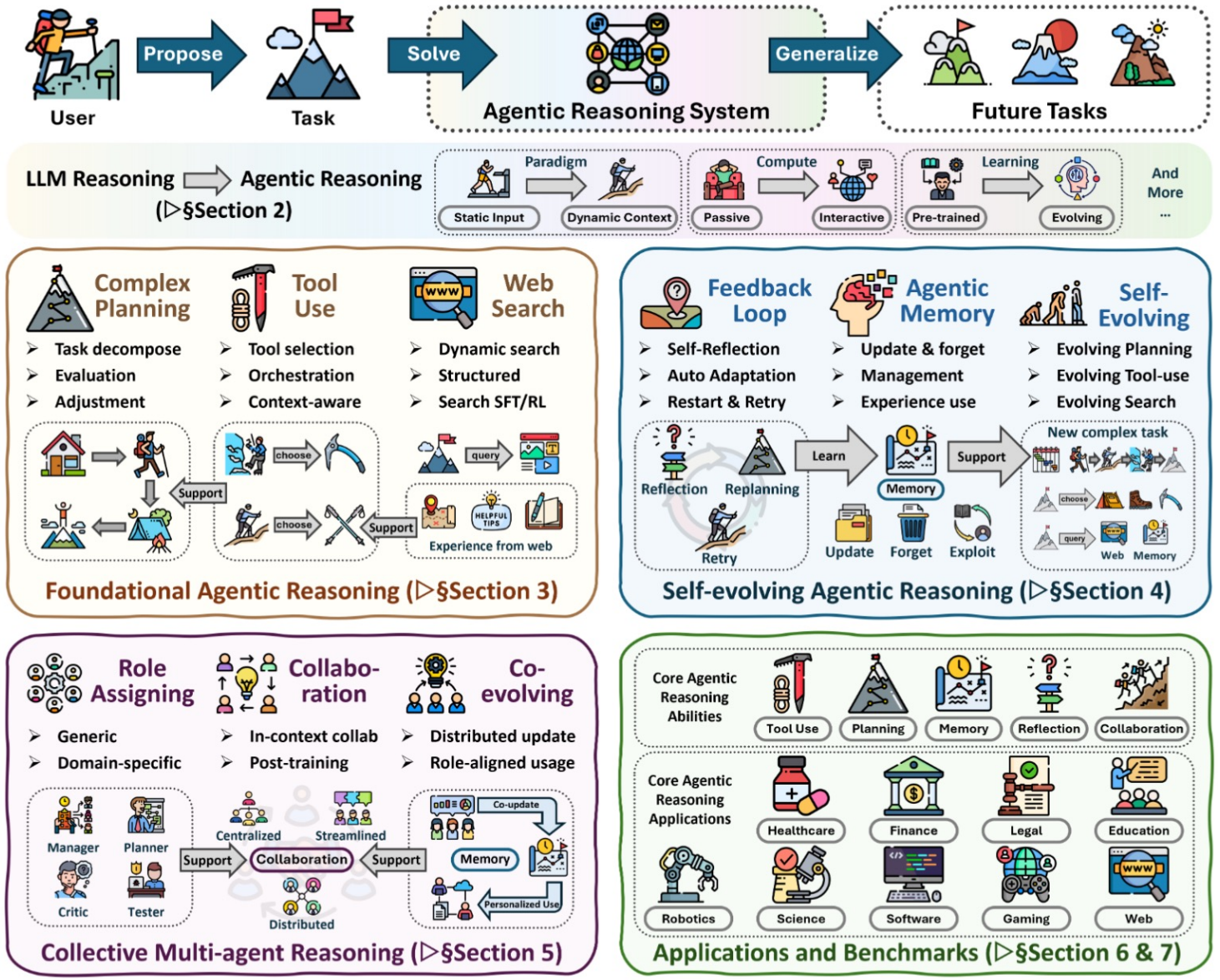
例子： Embodied Planning

[1] Gemini Robotics: Bringing AI into the Physical World. https://arxiv.org/abs/2503.20020

Agentic Reasoning

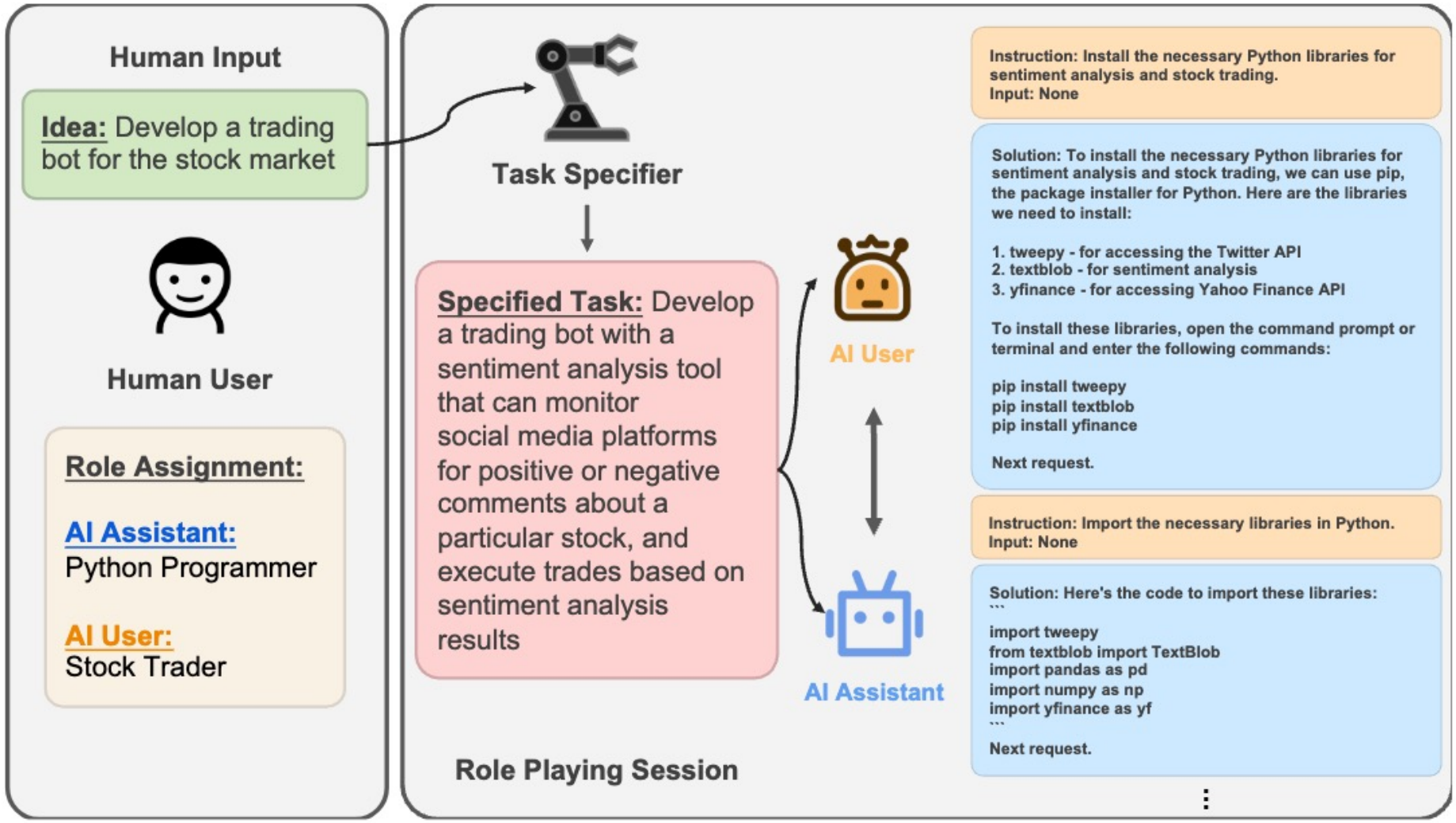
Agentic Reasoning for Large Language Models

https://www.alphaxiv.org/abs/2601.12538



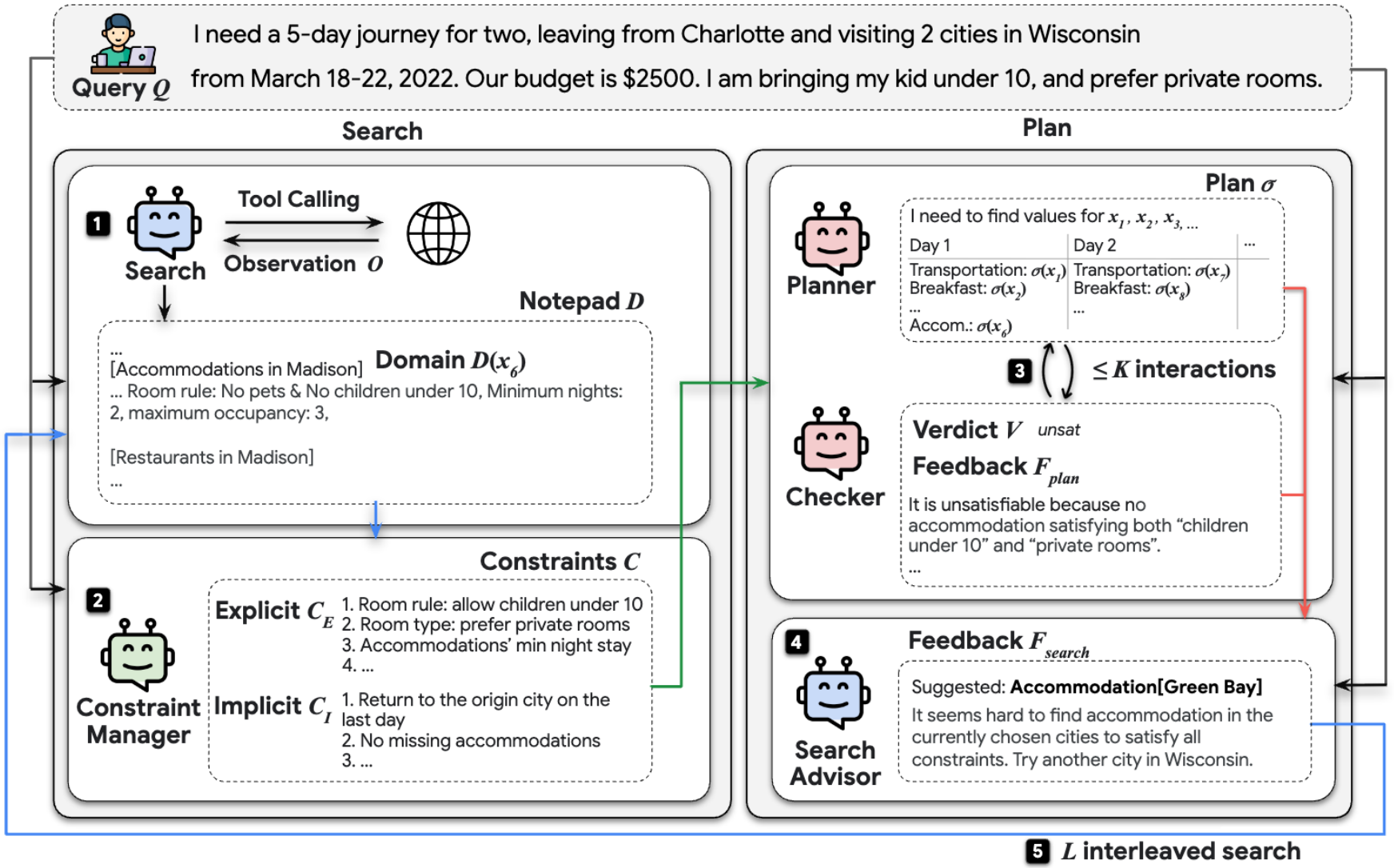
一个Agent不一定能解决问题

从单一Agent到Multi-Agent



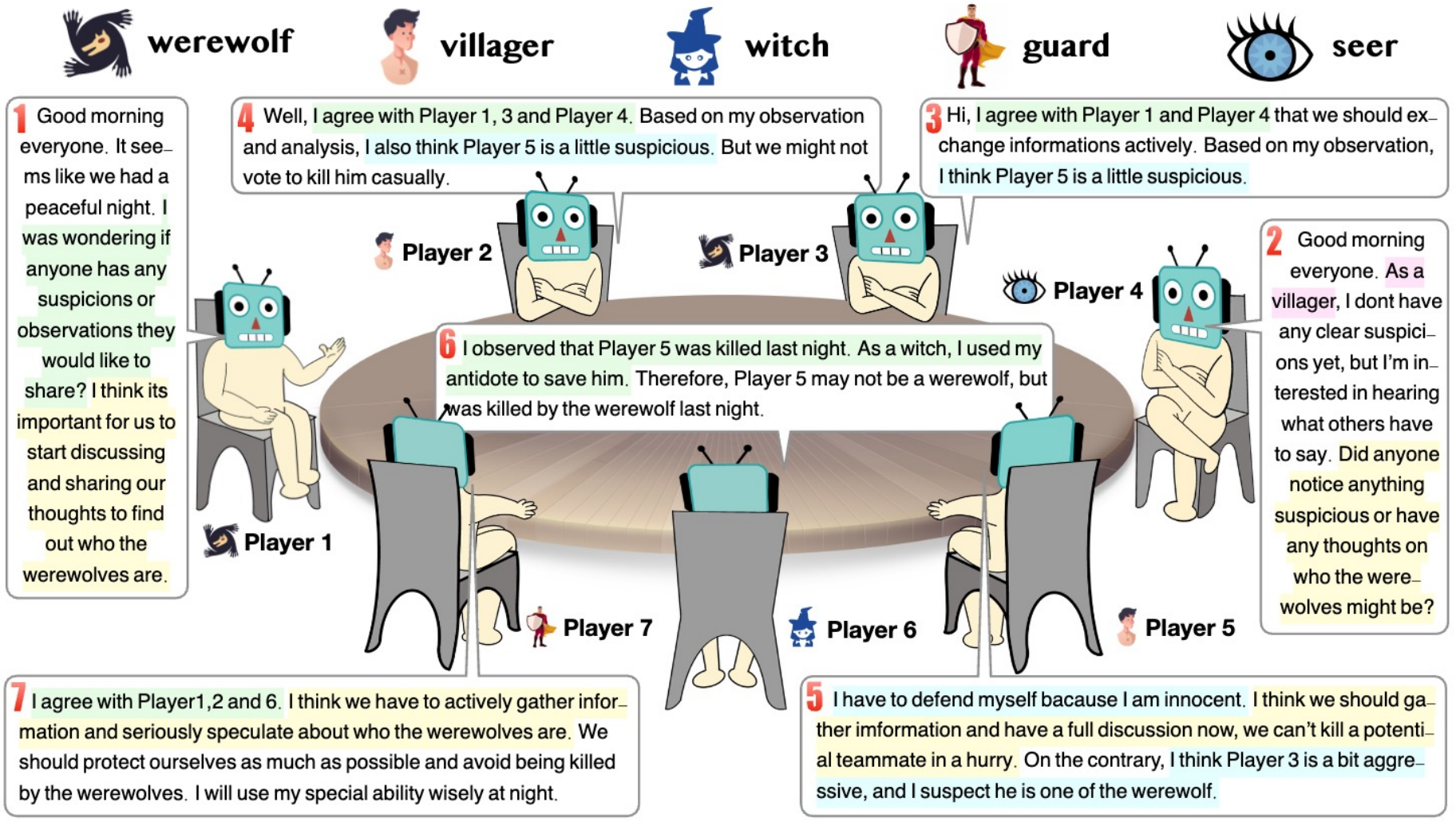
CAMEL: Communicative Agents for "Mind" Exploration of Large Language Model Society. https://www.alphaxiv.org/abs/2509.25586

从单一Agent到Multi-Agent



ATLAS: Constraints-Aware Multi-Agent Collaboration for Real-World Travel Planning. https://www.alphaxiv.org/abs/2509.25586

从单一Agent到Multi-Agent



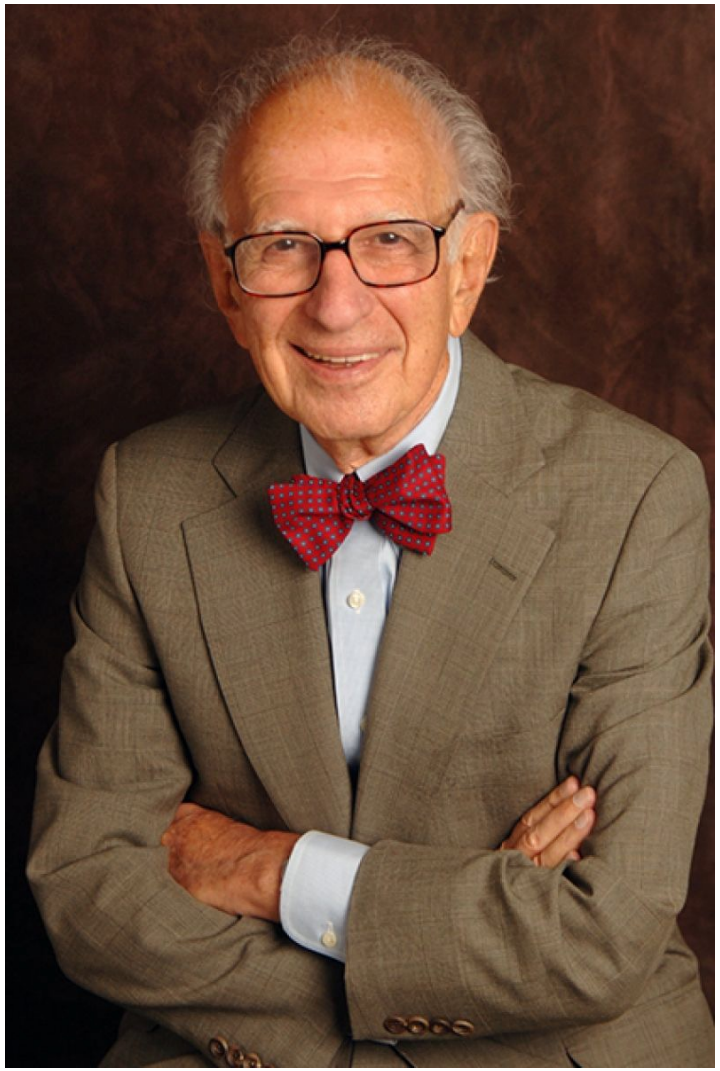
Exploring Large Language Models for Communication Games: An Empirical Study on Werewolf. https://www.alphaxiv.org/abs/2309.04658

Memory

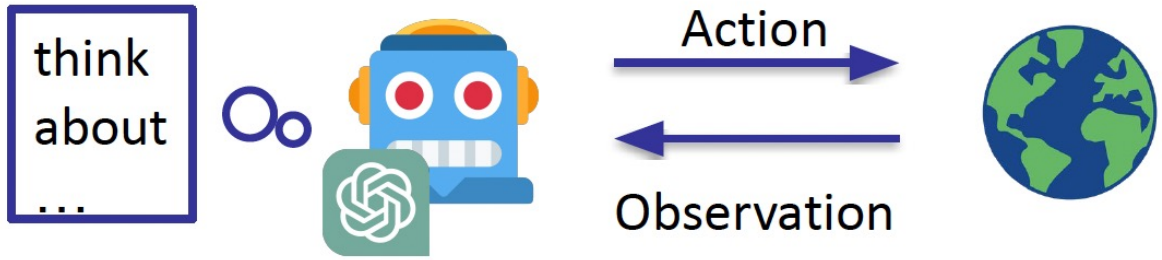
Memory is everything. Without it

we are nothing.

—— Eric Kandel

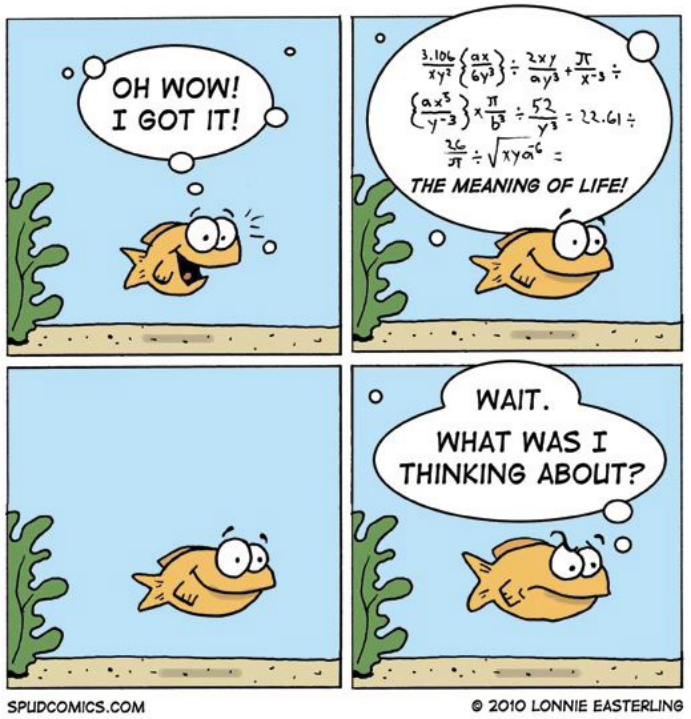


Memory



Memory

- Read and write
- Stores experience, knowledge, skills, …
- Persist over new experience



Memory

类比人类记忆，Agent的记忆分类

Type by content	Definition
Working Memory （工作记忆）	当前任务上下文 （Context）
Episodic Memory （情景记忆）	具体事件的记忆 (Experience)
Semantic Memory (语义记忆）	存储知识 (Knowledge)
Procedural Memory (程序记忆）	存储技能 (Skill)

Skill

Skill 是从历史经验中提炼出的、**可复用的任务执行单元**，封装了"在什么情况下、执行什么操作、达到什么效果"的完整知识

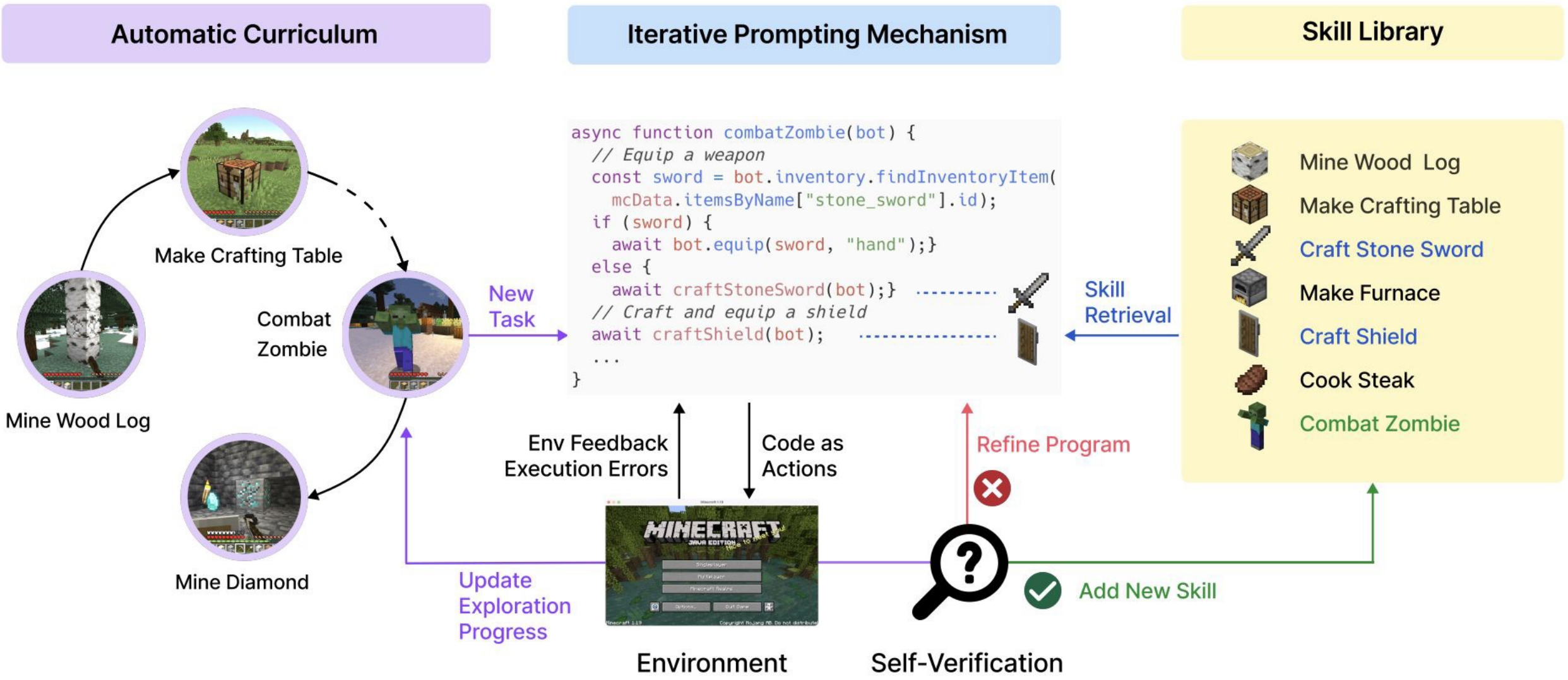
一个Skill

触发条件：什么情况下使用该技能

执行过程：具体怎么操作

预期效果：成功的标志是什么

Skill



Voyager: An Open-Ended Embodied Agent with Large Language Models. https://arxiv.org/abs/2305.16291

Skill

Coding Agent

Skill: 读取CSV并清洗数据

触发条件: 用户上传CSV文件，要求数据分析

执行过程:

1. 用 pandas 读取文件
2. 检测并处理缺失值
3. 检测并删除重复行
4. 输出清洗后的数据概览

预期效果: 返回干净的 DataFrame + 清洗日志

Skill: 生成数据可视化报告

触发条件: 用户要求"画图"或"可视化"

执行过程:

1. 判断数据类型（时序/分类/数值）
2. 选择合适图表类型
3. 用 matplotlib 生成图表
4. 自动添加标题、坐标轴标签、图例

预期效果: 返回清晰美观的图表文件

Skill

Research Agent

Skill: 快速定位领域核心论文

触发条件: 用户提出某个研究方向，需要了解背景

执行过程:

1. 用领域关键词搜索 arxiv 和 Google Scholar
2. 按引用数筛选出 top 10 论文
3. 提取每篇论文的：问题、方法、结论、局限性
4. 识别引用关系，找出奠基性工作
5. 按时间线梳理技术演进脉络

预期效果: 输出“领域地图” - 关键论文 + 演进时间线

Skill 生态

全部 自媒体 金融 法律 互联网 科研 教育 健康医疗 生活服务 通用工具 其它

技能包 数据集 开发辅助 办公效率 数据分析 影音娱乐

行业技能包 | 官方严选优质技能组合

查看更多 >

A股投资分析技能包

基于深度量化策略与多维数据雷达，全方位洞察A股板块热度、...

技能包 | 3.2w

一键添加

包含以下技能

板块热度分析 科技股分析 量化股票分析 红利股分析 查看更多

自媒体创作技能包

提供集小红书与公众号图文创作、多平台改写及违禁词查询于一...

技能包 | 3.9w

一键添加

包含以下技能

小红书笔记创作 公众号文案创作 今日头条爆文操盘手 查看更多

全能法务助理技能包

专为法务从业者、律师与企业合规团队打造的智能法务工具箱。...

技能包 | 1.1w

一键添加

包含以下技能

法律咨询报告 诉讼大师 法律类案检索 法律备忘录 查看更多

调研分析技能包

融数据挖掘、商业咨询与市场洞察于一体的超级分析技能包，一...

技能包 | 1.7w

一键添加

包含以下技能

超级分析师 行业趋势深度调研 竞品/公司调研报告 查看更多

Skill 生态

科研严选技能

arXiv 论文数据搜索
数据集 免费

arxiv 论文搜索技能

1.2w人在用 添加

训练平台研究员，检索「Frontier Tuning」技术论文。

Semantic Scholar论文搜索
数据集 免费

学术论文知识图谱查询技能，精准检索关联研究内容与脉络。

1.1w人在用 添加

筛选生物医学RAG幻觉评估研究

OpenAlex 学术数据库
数据集 免费

OpenAlex 学术数据库查询技能

1.3w人在用 添加

科研助理，筛多模态医学报告高被引研究。

Crossref 文献引用溯源
数据集 免费

学术文献元数据查询技能，助力快速检索文献关键信息

1w人在用 添加

研究生，查询「大学生一旦过了13周」学业压力论文DOI。

「毕导」的学术雷达
免费

「毕导」为科研人员量身定制，追踪研究领域最新论文，生...

2.6w人在用 添加

生物信息PI，盯空间转录组分析方法的学术热点与选题建议。

PubMed 生物医学文献搜索
数据集 免费

PubMed 医学文献查询技能，助力医学领域文献检索与研究...

6.2K人在用 添加

检索GLP-1用于MASH临床文献

bioRxiv 论文搜索
数据集 免费

bioRxiv 论文检索技能

1.9K人在用 添加

发育生物学博士，查类器官与胚胎轴建立的生物医学预印本。

OpenCitations 开放引文库
数据集 免费

论文引用关系数据查询技能

9.7K人在用 添加

心理老师，梳理「大学生一旦过了13周」焦虑研究的高被引论文。

文献引用格式转换
免费

论文引用格式智能识别与互转工具，支持 11 种主流学术 / 文...

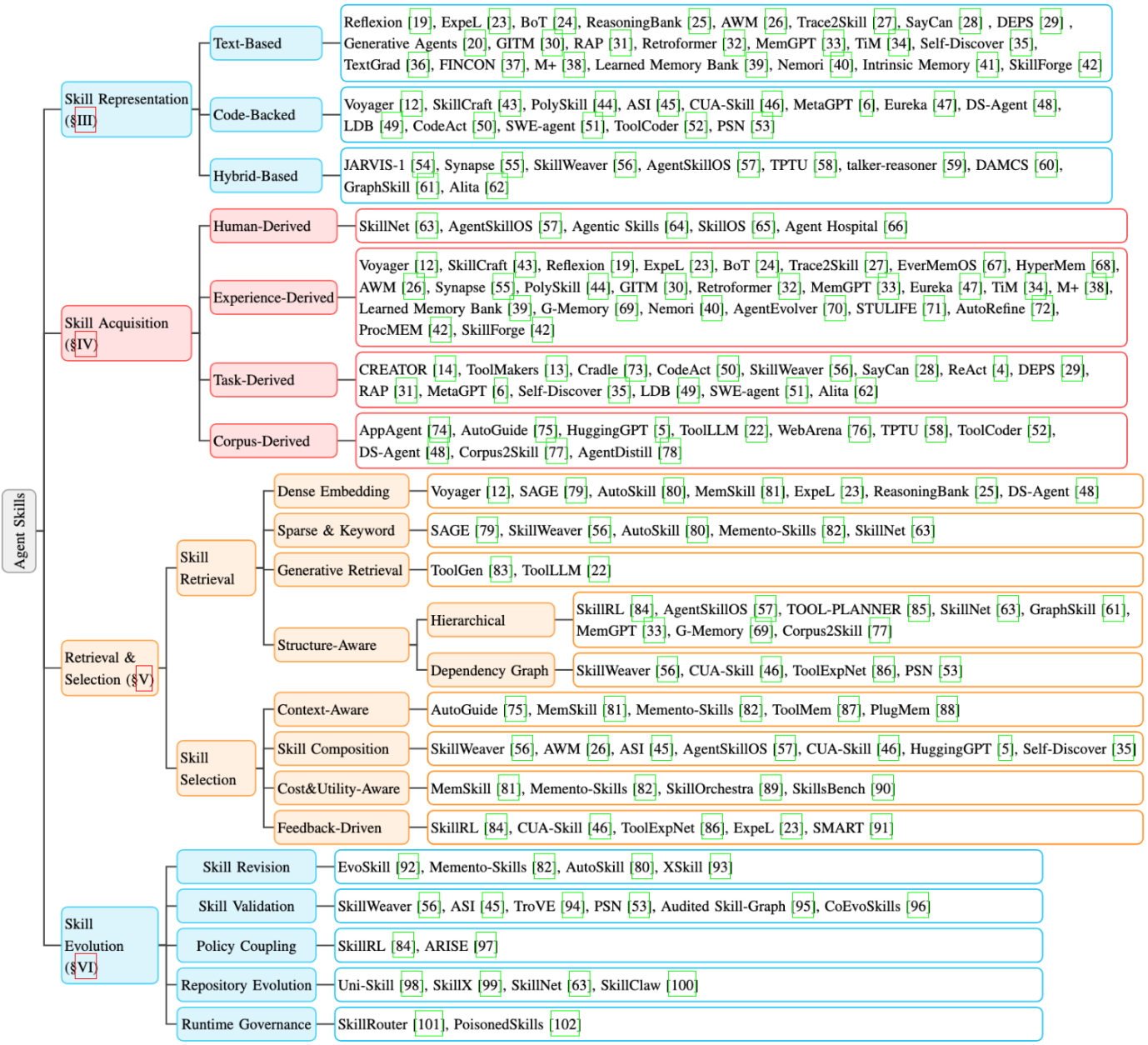
6.3K人在用 添加

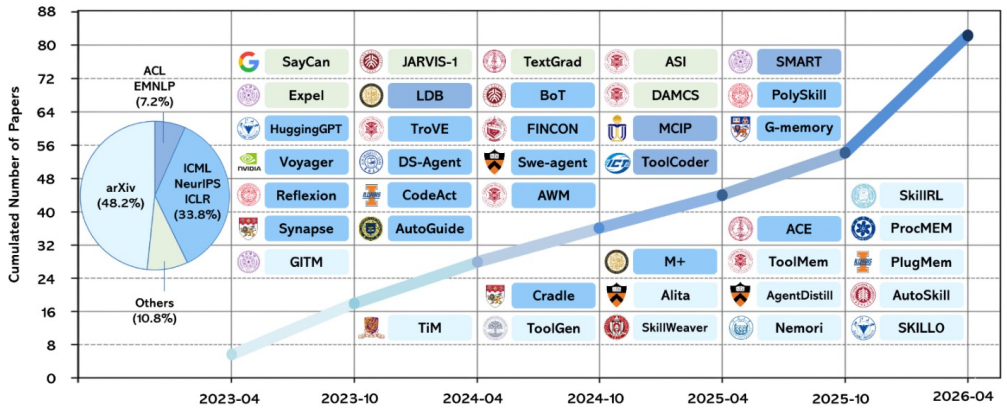
识别「Cochrane」导出记录，改成Vancouver投稿格式。

前沿科学问题

- Skill如何表示：文本？代码？逻辑语言？
- Skill如何生成：专家写？自动获取？
- Skill如何检索：从Skill库中找到和当前任务相关的Skill
- Skill如何演进：自主进化智能体
- ……

前沿科学问题

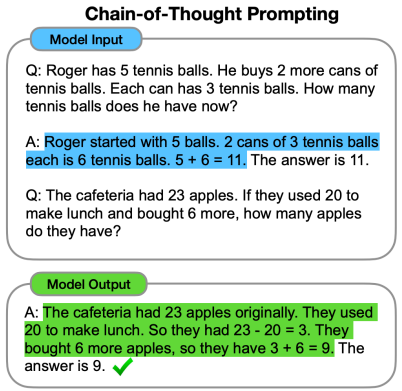


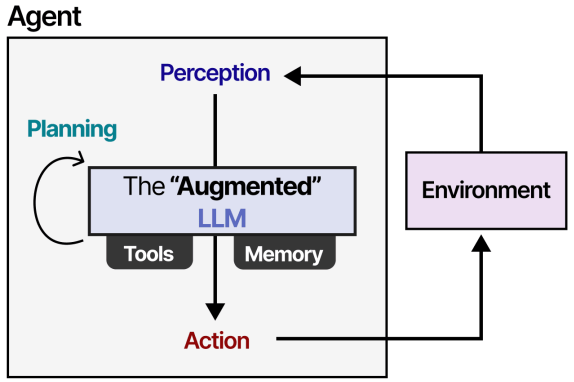


A Comprehensive Survey on Agent Skills: Taxonomy, Techniques, and Applications

https://www.alphaxiv.org/abs/2605.07358?utm_source=chatgpt.com

Evolution of AI Agents： LLM-First View

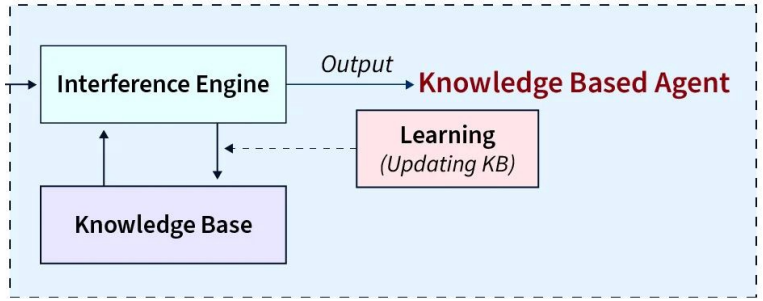




Chatbot **Reasoner** **Tool User** **Agent**

核心能力	自然语言对话	分步思考、思维链	搜索、计算、调用API	规划、执行、观察、反馈、记忆
主要局限	只能回答、不能执行	仍局限于文本空间	需要外部工具编排	长程任务、物理世界？

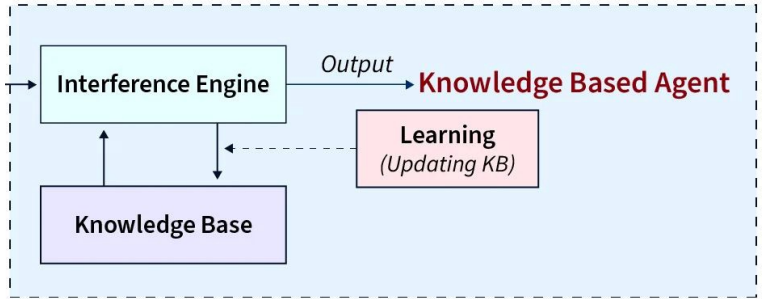
Evolution of AI Agents： Agent-First View

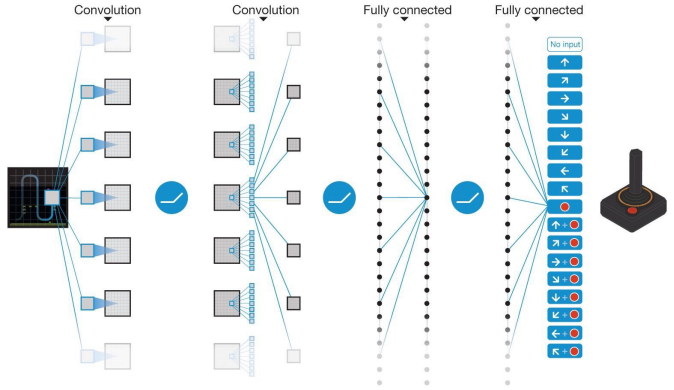


Symbolic Agent

感知能力	缺乏符号接地能力		
推理能力	严谨符号逻辑推理		
适应能力	依赖预先定义的符号空间		

Evolution of AI Agents： Agent-First View

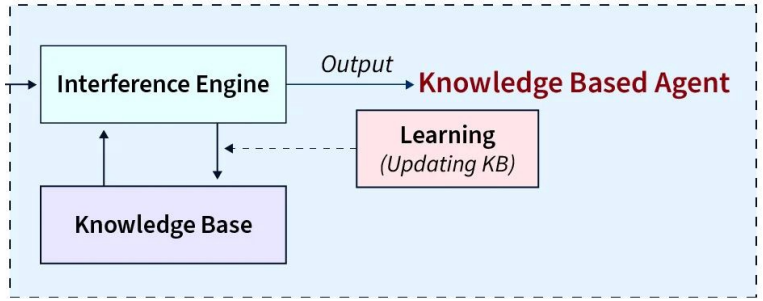


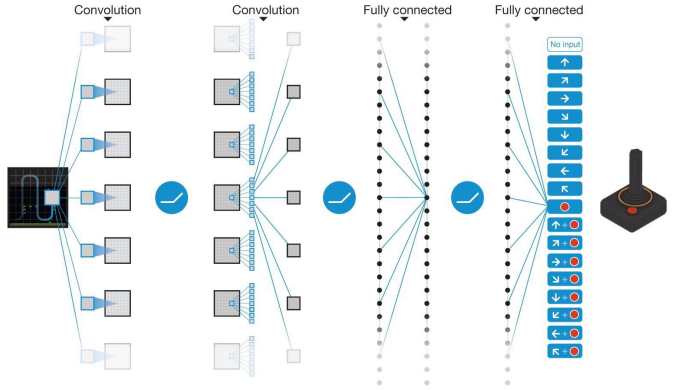


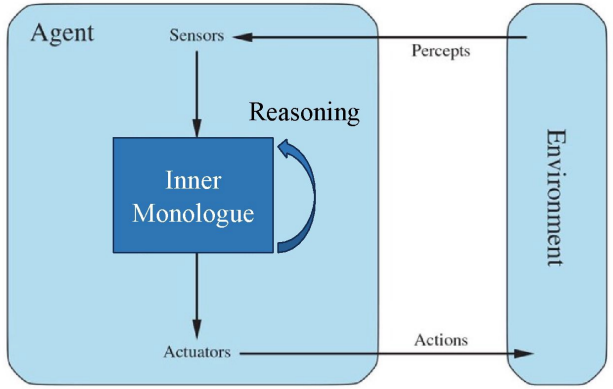
Symbolic Agent **Neural Agent**

感知能力	缺乏符号接地能力	神经网络的感知能力	
推理能力	严谨符号逻辑推理	缺乏推理能力	
适应能力	依赖预先定义的符号空间	样本效率低，难以在不同场景迁移	

Evolution of AI Agents： Agent-First View







Symbolic Agent **Neural Agent** **LLM Agent**

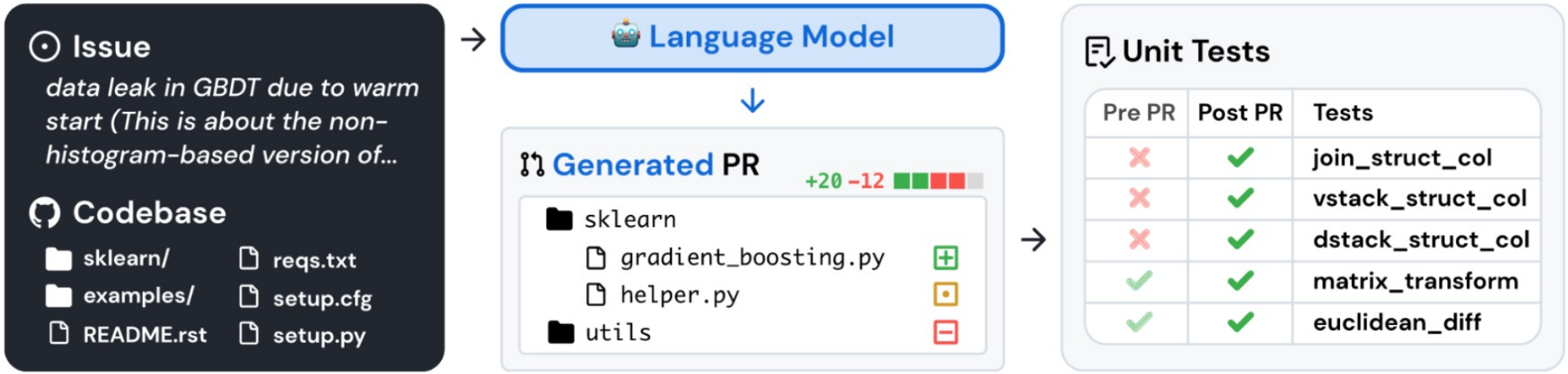
感知能力	缺乏符号接地能力	神经网络的感知能力	高，几乎任意模态任意数据
推理能力	严谨符号逻辑推理	缺乏推理能力	基于语言的思维链推理
适应能力	依赖预先定义的符号空间	样本效率低，难以在不同场景迁移	大模型自身的通用性

Applications

- Digital World
  - Coding Agents
  - Mobile Agents
  - Web/App Agents
  - Computer Agents
- Physical World
  - Gaming Agents
  - Robotics Agents

Coding Agents

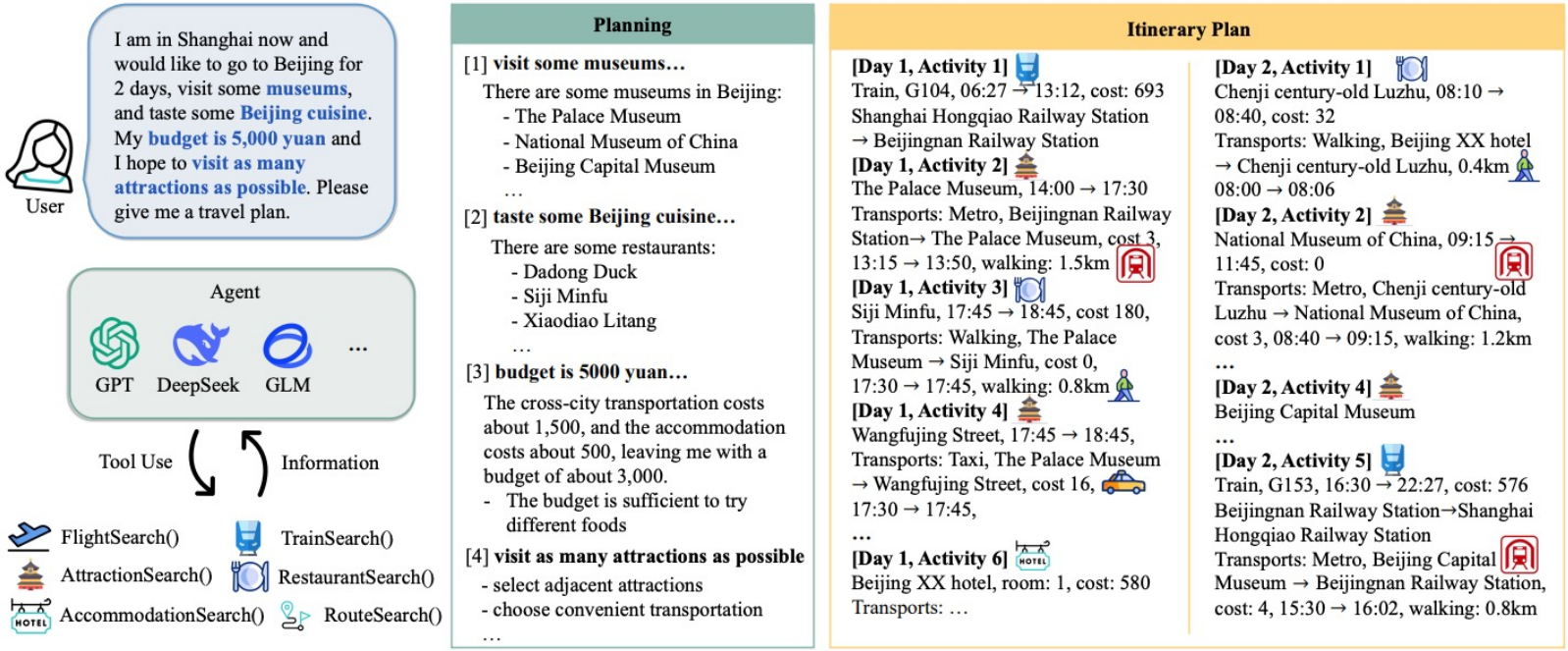
- 环境(Environments)： Project code repo, file systems, IDEs, ……
- 观察(Observation): Code files, outputs, docs, errors, commit history,……
- 动作(Action Space)： Coding edits, File search/view, test updates,……



Web/Tool-Use Agents

Web/App Use

- Environment: web browsers/apps
- Observation space: screenshots, DOM trees, HTML, historical actions…
- Action space: browser/app controls (e.g., click, type, scroll, drag, hover…)

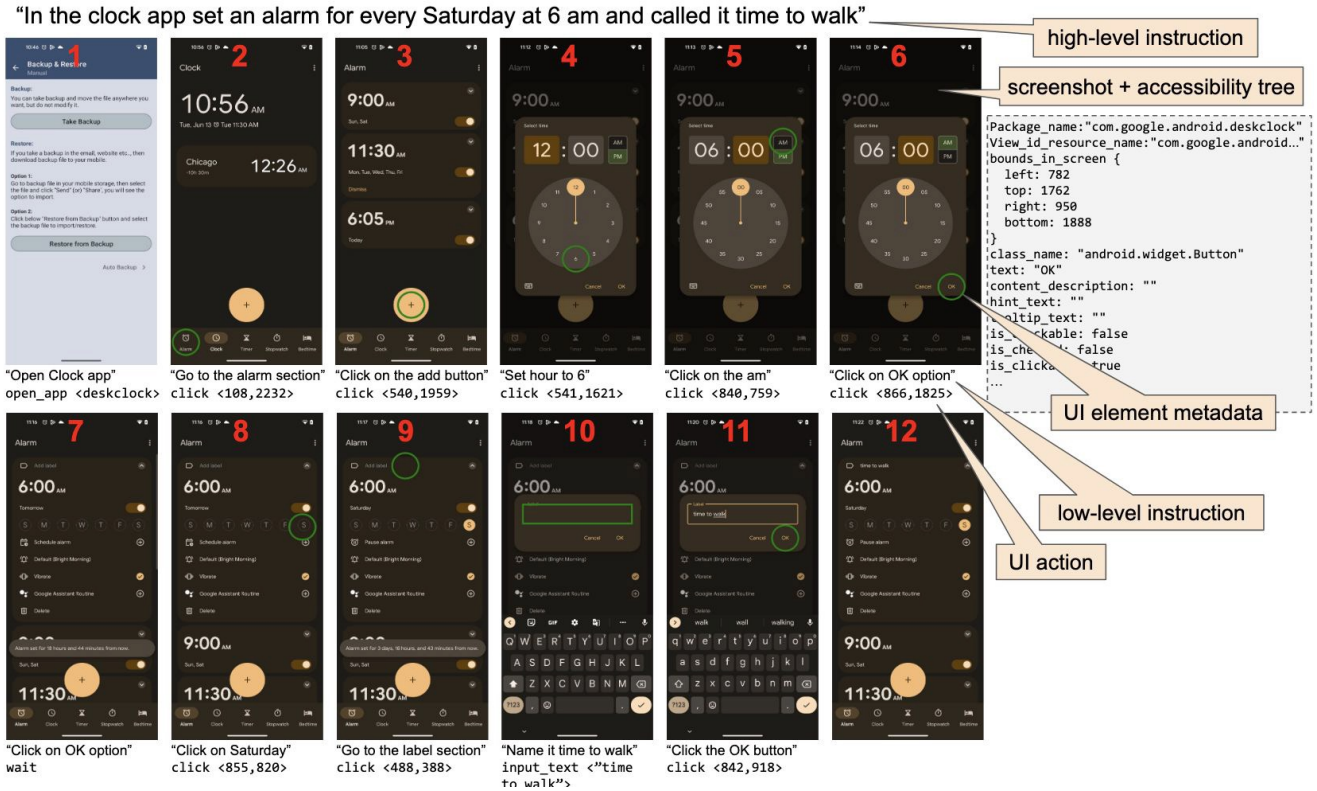


ChinaTravel: An Open-Ended Benchmark for Language Agents in Chinese Travel Planning

Mobile Use Agents

Mobile Use

- Environment: mobile device systems
- Observation space: screenshots, a11y trees, HTML, historical actions…
- Action space: mobile controls (e.g., tap, type, swipe…)



On the Effects of Data Scale on Computer Control Agents, (Li et al., 2024)

Education Agent

教学智能体

AI写作助手
@梁春龙

通过鲁迅的写作风格，进行文章的编写

1 0

计划书评分智能体
@黄裕强

计划书评分智能体

147 0

计划书点评智能体
@黄裕强

创意组、创业组、公益组计划书点评智能体

64 0

涉海口语陪练
官方
@官方

六大海事场景，练就涉海英语口语功底

54 2

文书生成助手
官方
@官方

能够准确识别用户需求，完成复杂的文书生成工作。

590 3

操作系统原理课程智能体
官方
@官方

面向《操作系统原理》课程，能够帮助学生通过知识点问答、学习路径规划，实现自主课程学习。

28 0

计算机组成原理与系统结...
官方
@官方

面向《计算机组成原理与系统结构》课程，能够帮助学生通过知识点问答、学习路径规划，实现自主课...

27 0

程序设计课程智能体
官方
@官方

面向《C语言程序设计》课程，能够提供知识问答、代码分析、作业解析等能力。

334 4

海法通译
官方
@官方

智能海法翻译助手，精准传递法理要义

145 9

儿童绘画点评
官方
@官方

上传你独一无二的绘画作品，为你解读画作的创意与想象力，助力发现大师潜力。

17K 1

创意探究课题生成
官方
@官方

基于多领域知识，智能生成新颖课题，帮助教师生成创意探究案例。

398 11

学习搭子
官方
@官方

一位温暖耐心的学习搭子，用鼓励和陪伴点亮你的学习之路。

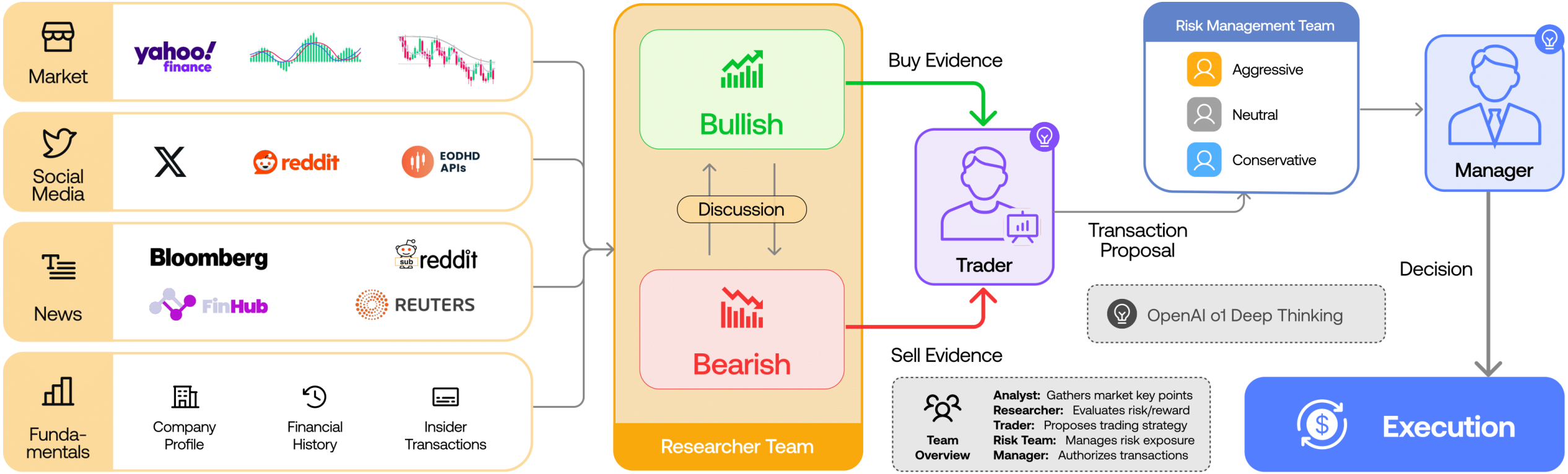
2K 19

Research Agents

https://github.com/wanshuiyin/Auto-claude-code-research-in-sleep

Financial Agents

TradingAgents: Multi-Agents LLM Financial Trading Framework
https://github.com/tauricresearch/tradingagents

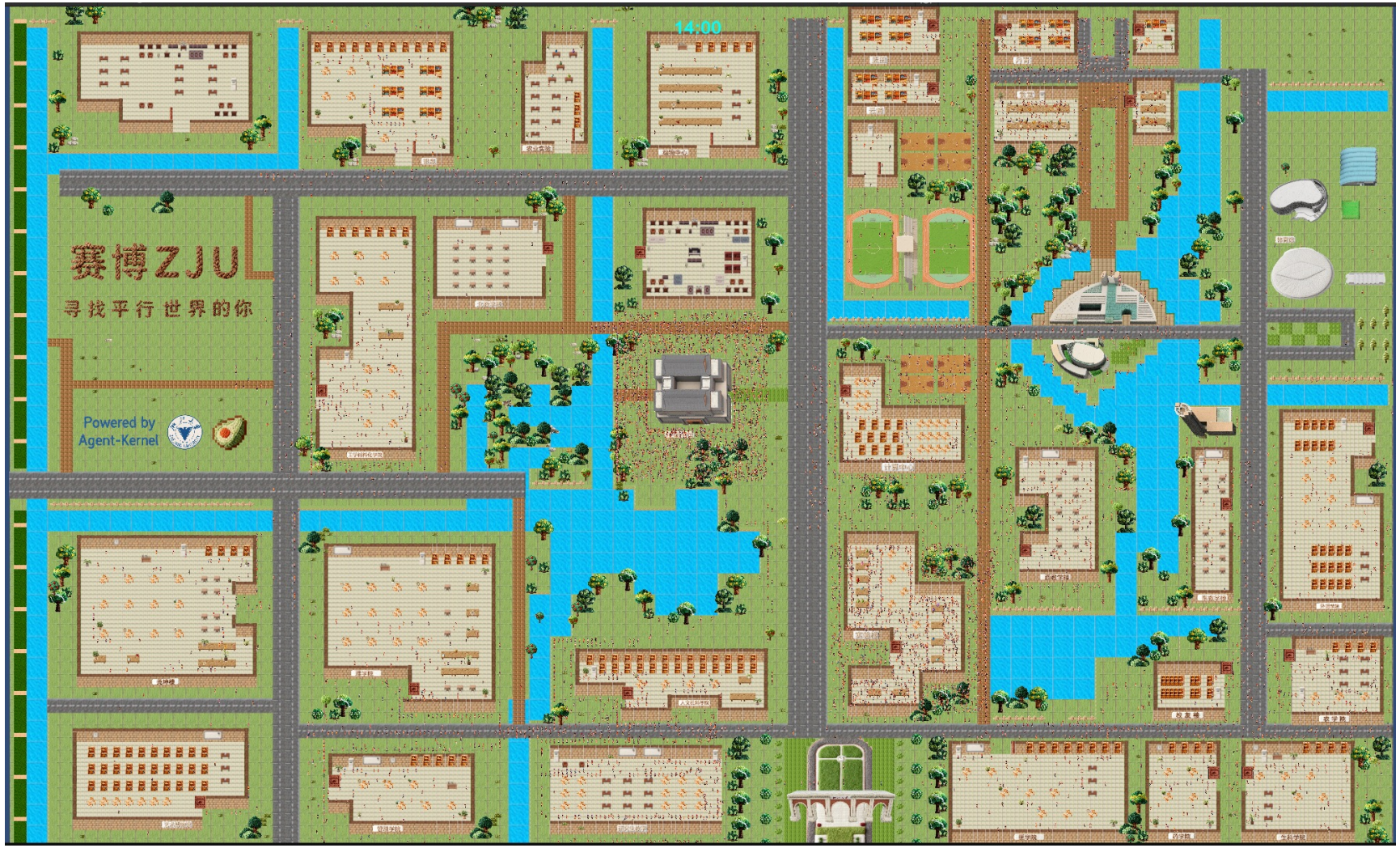


Generative Agents

Generative Agents: Interactive Simulacra of Human Behavior
https://arxiv.org/pdf/2304.03442

Generative Agents

https://www.bilibili.com/video/BV1xamQBuEgS?t=0.7



Generative Agents

https://github.com/666ghj/MiroFish

Game Agents

Digital Games

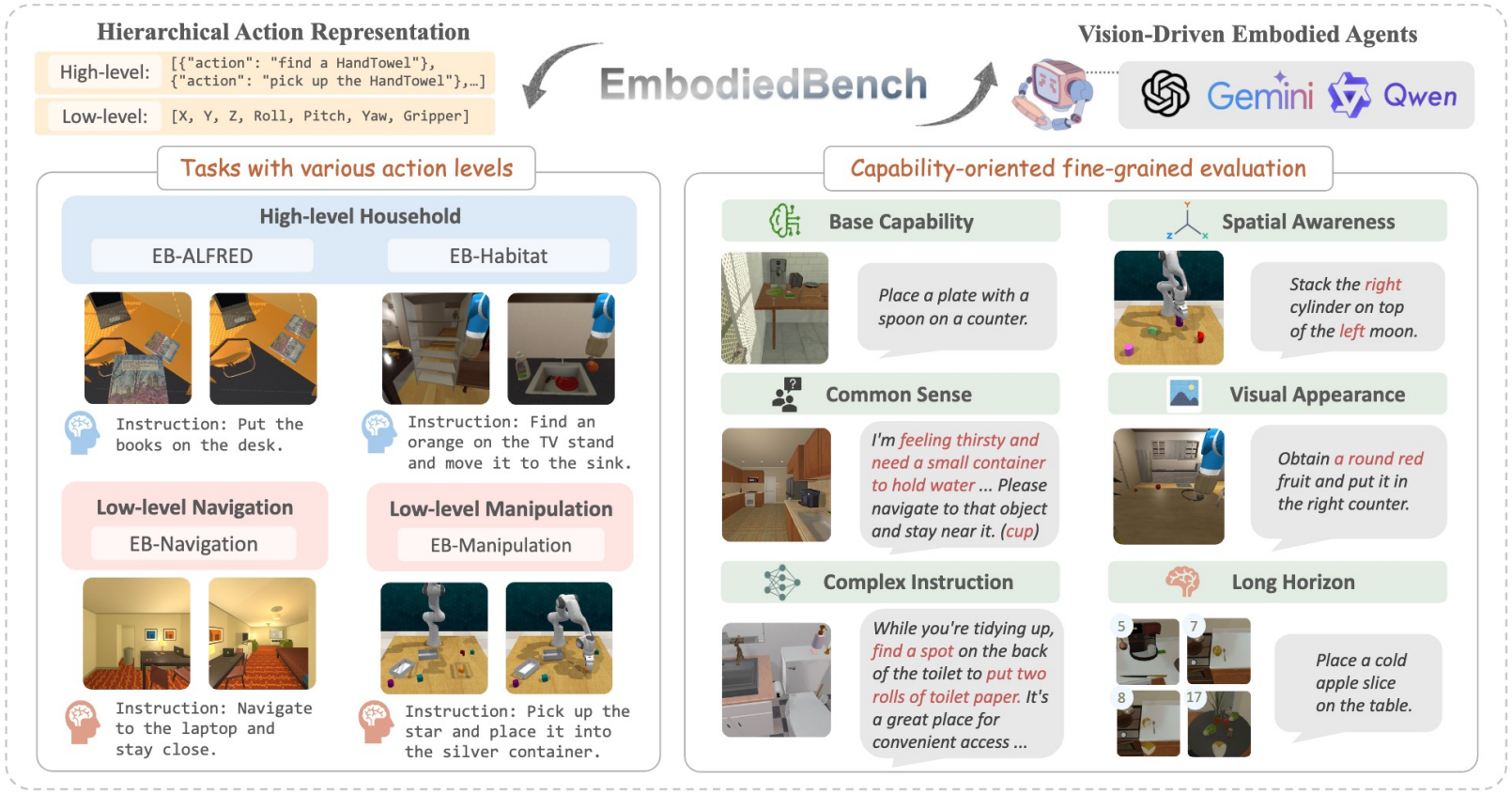
- Environment: game worlds/levels…
- Observation space: screenshots of game states, inventory, location…
- Action space: game controls (e.g., drop, move, attack, resource management…)

MineDojo: Building Open-Ended Embodied Agents with Internet-Scale Knowledge, (Fan et al., 2022)

Robotics Agents

Robotics for physical interaction

- Environment: physical world spaces
- Observation space: visual input, sensor readings, physical states, proprioception…
- Action space: motor controls (e.g., move, grasp, manipulate…)



EMBODIEDBENCH: Comprehensive Benchmarking Multi-modal Large Language Models for Vision-Driven Embodied Agent.