



Neuro-Symbolic Agent:

从反应式决策到可验证决策

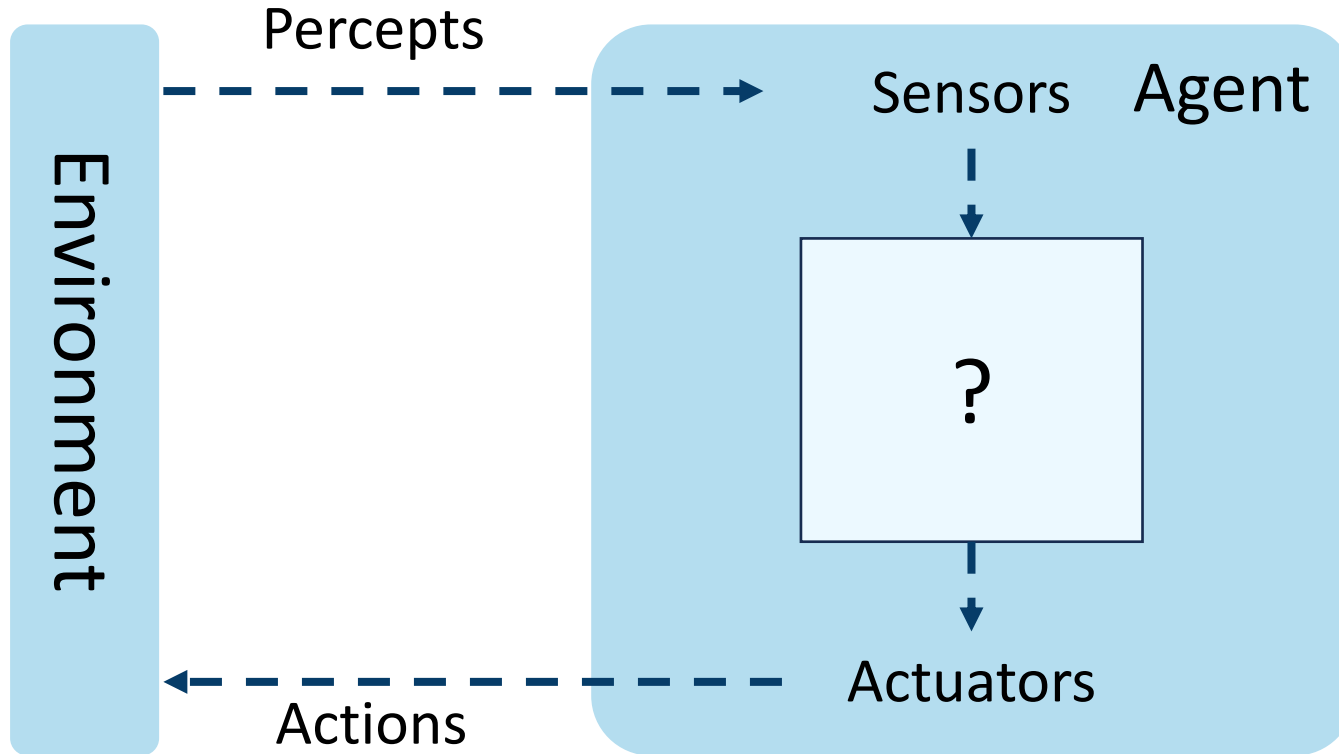
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<https://www.lamda.nju.edu.cn/guolz/>

2026.06.13 @ 智源大会

Agent



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

Two Views of Agent

LLM-first view

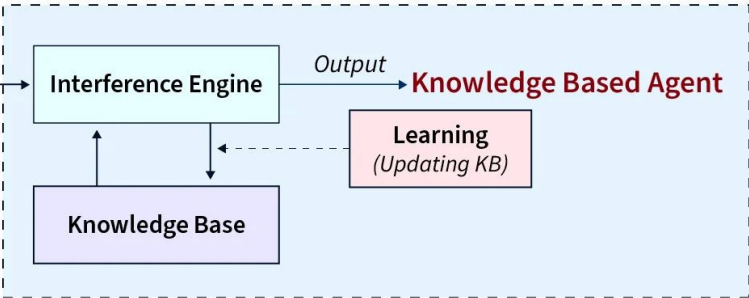
- Idea: 让我们把LLM变成Agent
- 关键：如何在LLM的基础上一步步升级，从Chatbot到Reasoner再到Agent？

Agent-first view

- Idea: 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，还存在哪些新的挑战？

Evolution of AI Agents: Agent-First View

Symbolic Agent

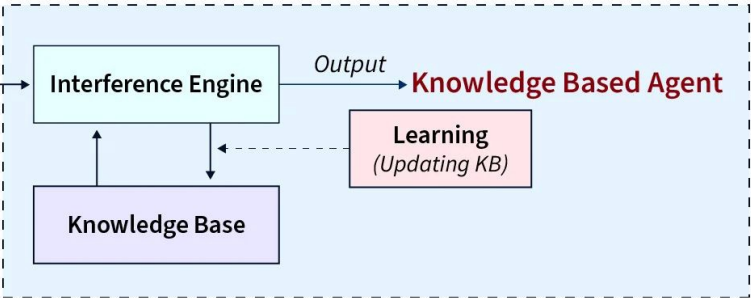


显式符号规则+推理规划算法

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		

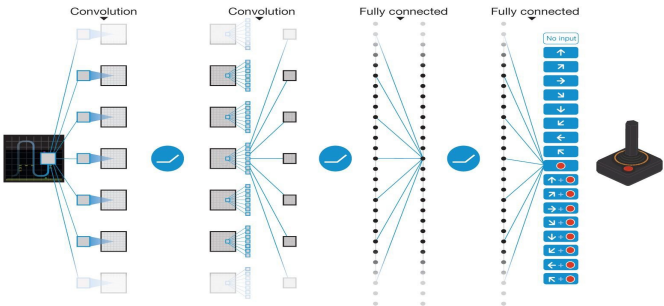
Evolution of AI Agents: Agent-First View

Symbolic Agent



显式符号规则+推理规划算法

Neural & RL Agent

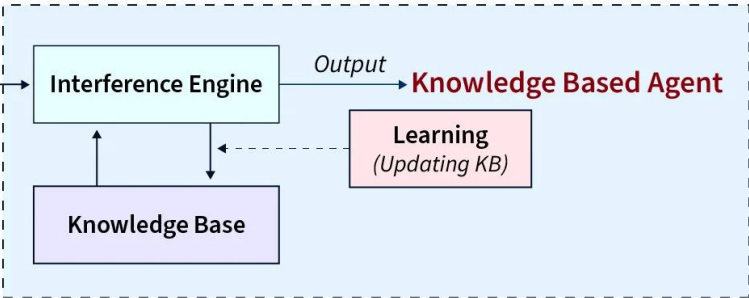


神经网络感知+强化学习策略

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	强化学习策略	
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	

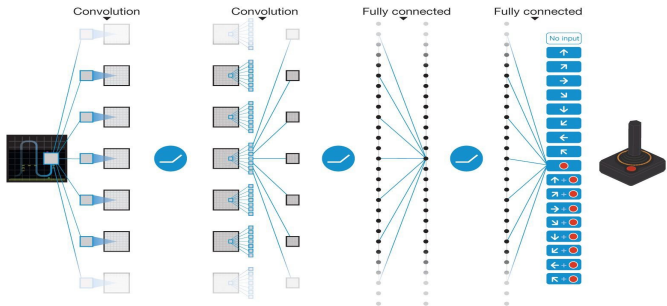
Evolution of AI Agents: Agent-First View

Symbolic Agent



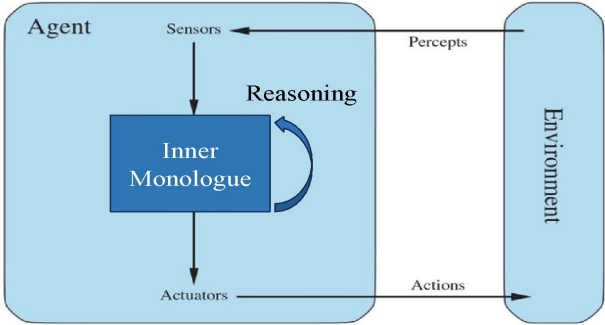
显式符号规则+推理规划算法

Neural & RL Agent



神经网络感知+强化学习策略

LLM Agent

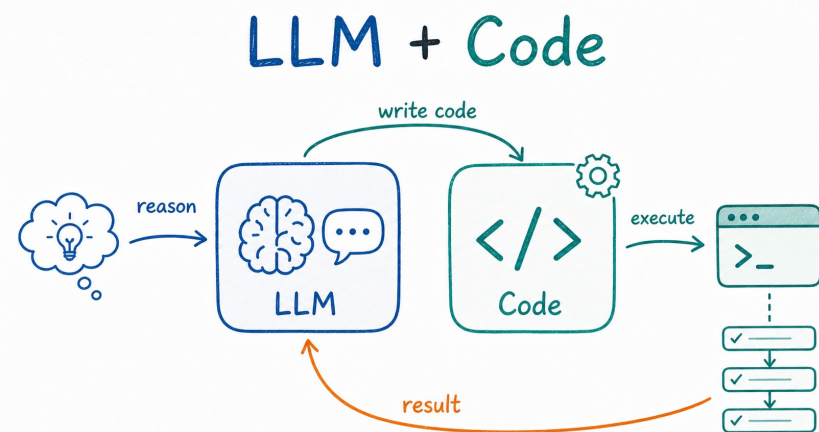


LLM通用感知与推理

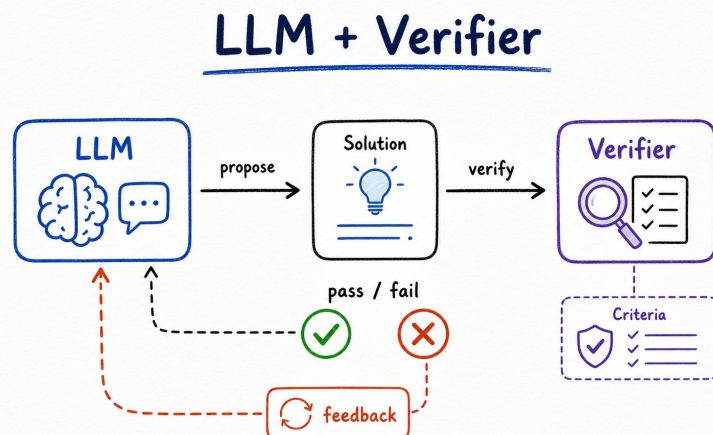
感知能力	缺乏符号接地能力	神经网络的感知能力	高，几乎任意模态数据
推理能力	严谨符号逻辑推理	强化学习策略	基于语言的思维链推理
适应能力	依赖预先定义的符号空间	样本效率低，难以在不同场景迁移	大模型自身的通用性

Is LLM All We Need?

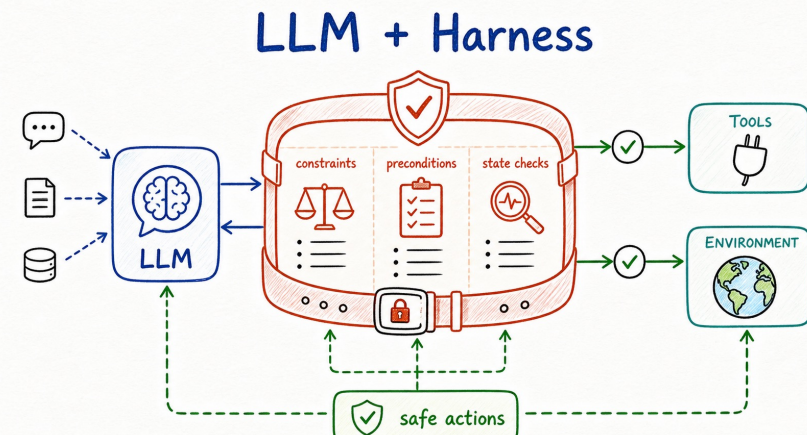
单纯依赖 LLM 驱动的 Agent 面临长程规划不可靠、动作不可验证、经验难以复用等问题，将 LLM 与形式化语言、求解器、验证器、Graph等符号系统结合，已成为提升 Agent 可靠、可控性的重要共识



借助形式化语言的
严谨推理能力



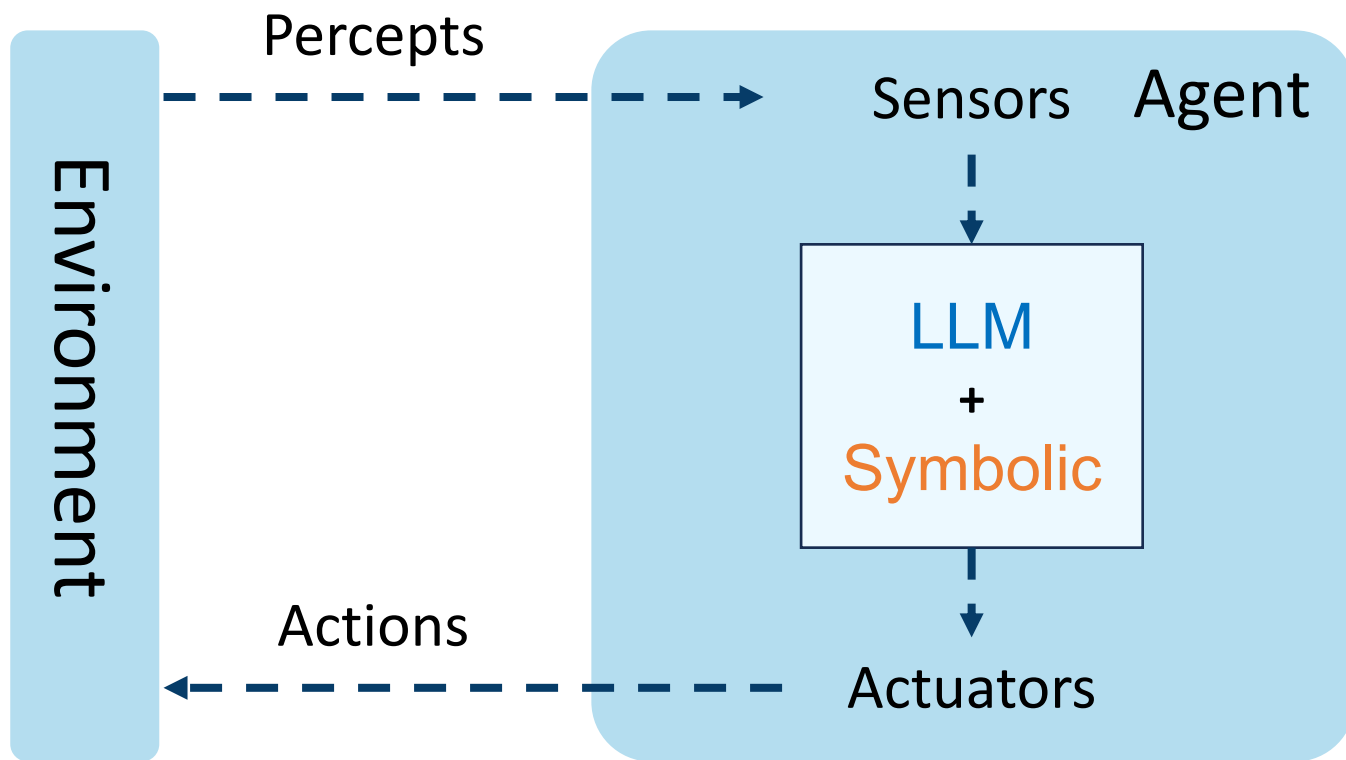
求解器、验证器的
约束与反馈



从交互经验中归纳
规则与技能

Neuro-Symbolic Agent

Neuro-Symbolic Agent是在 LLM-Agent框架中，融合形式化逻辑推理、可验证的状态/动作约束、可归纳的规则技能、可组合的符号记忆等，使 Agent 从反应式决策走向可验证、可持续进化的可靠智能体



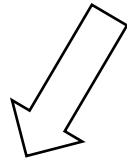
Where Symbolic Helps

- 辅助生成规划
- 验证动作执行
- 归纳可复用技能

LLM + Symbolic = Powerful Planning, Reliable Execution

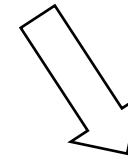
Outline

Neuro-Symbolic Agent



for Travel Planning

Symbolic helps planning



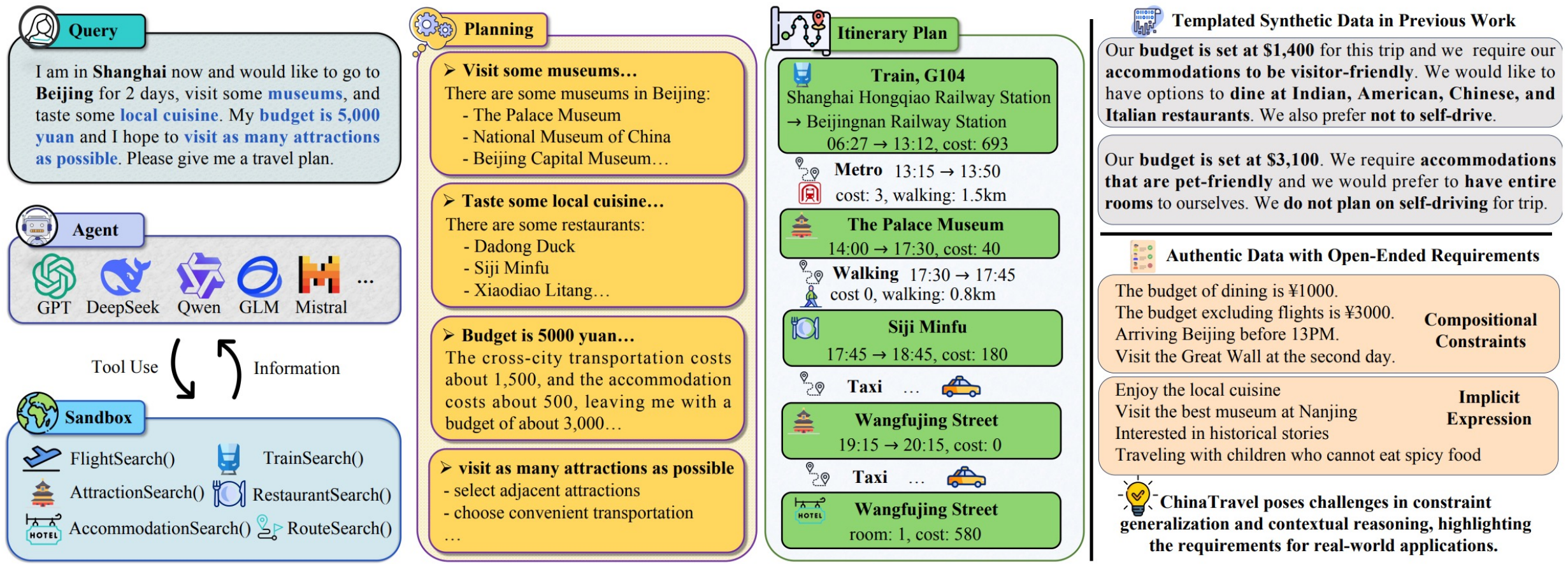
for Embodied Planning

Symbolic helps execute action

Neuro-Symbolic Agent for Travel Planning

Travel Planning Tasks

挑战：意图理解、工具调用、长程规划、约束满足

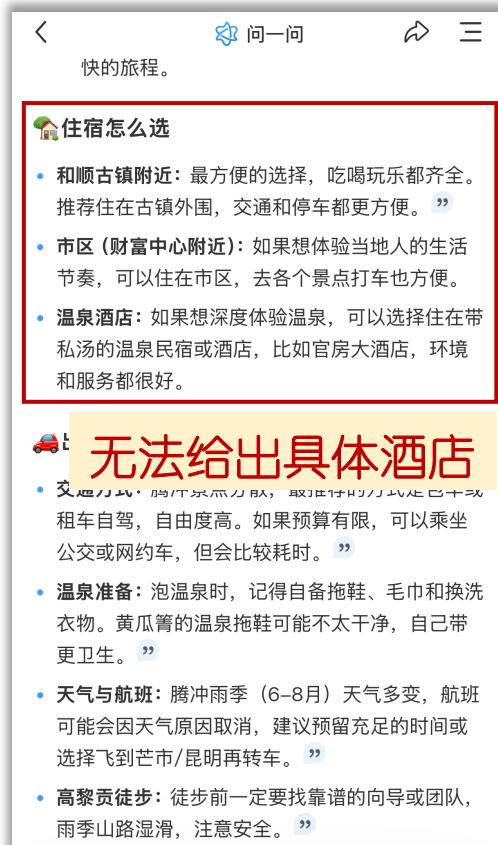
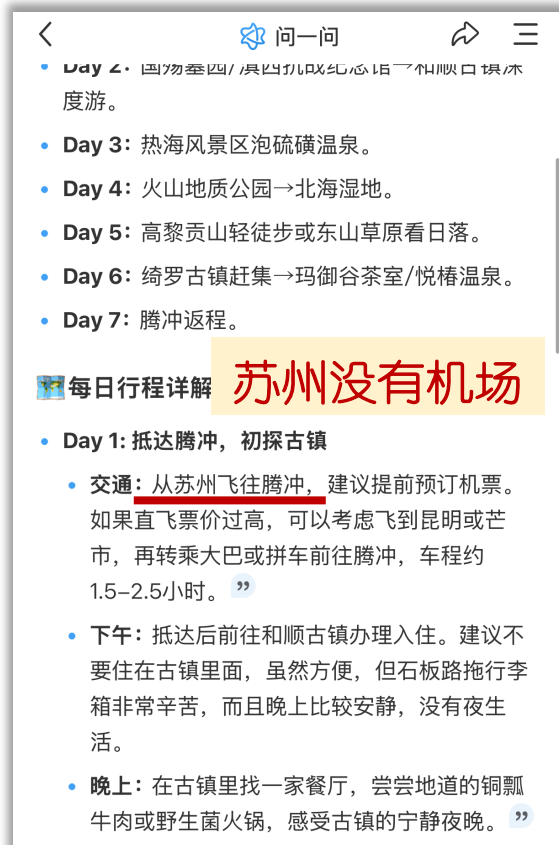


Failure Case

用户：帮我规划一个苏州到云南腾冲、芒市5日游的规划

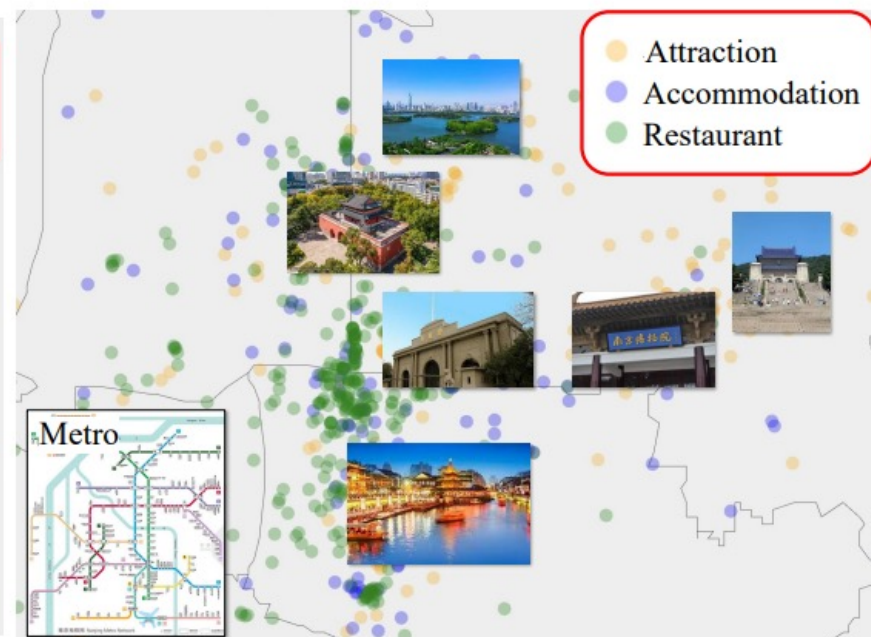
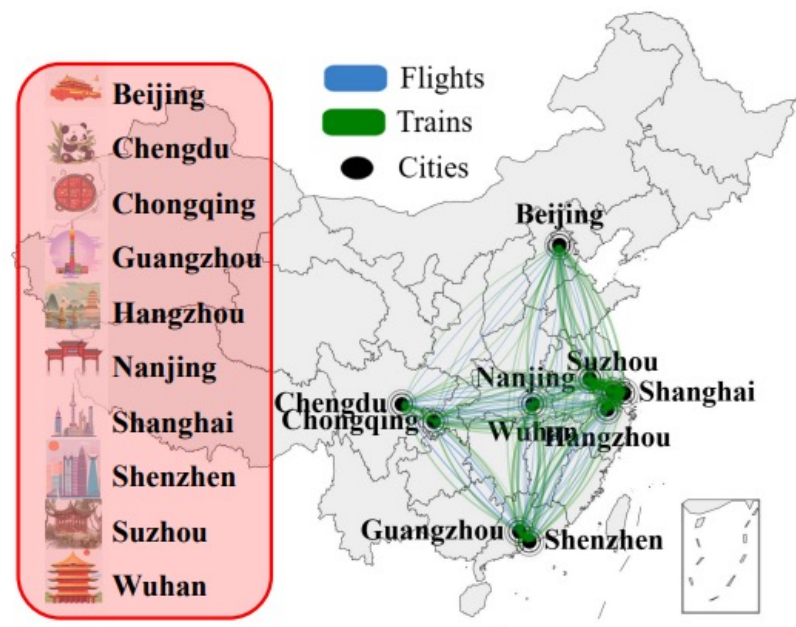
信息错误、仅能粗粒度规划

规划方案不可行、不合理



ChinaTravel: An Open-Ended Travel Planning Benchmark

- **GDP前10城市**: 上海、北京、深圳、重庆、广州、苏州、成都、杭州、武汉、南京
- **6.5K+ 跨城交通**: 720架次飞机、5770班次火车.....
- **3K+ 景点**: 人文景观、自然景观、美术馆、博物馆、纪念馆、公园、游乐园.....
- **4K+ 宾馆**: 洗衣服务、充电桩、停车场、宠物友好、会议厅、泳池、健身房.....



Real Travel Requirements

- 需求收集：团队收集来自**300+人的真实自然语言需求**，构建了以**16个符号概念**为基础的约束需求
- 指标定义：包含**游、食、住、行**四个基础视角，构建了**23条可行性指标**，基本覆盖日常出游需要

信息类型	具体信息
基础信息	游玩天数、游玩人数、总开销
游	景点类型、景点名称
食	食物类型、餐馆名称、人均单次餐饮价格
住	酒店特征、酒店名称、房间个数、房间类型、酒店房间价格
行	市内交通方式、城际交通方式、火车类型

可行性指标	
基础信息	游玩天数、游玩人数、总开销
游	选择景点在目标城市存在、在景点的开放时间进行访问、在旅程中访问景点不重复、景点的门票信息正确……
食	选择餐馆在目标城市存在、在餐馆的开放时间进行访问、在旅程中访问餐馆不重复、餐馆的人均价格信息正确……
住	选择酒店在目标城市存在、房间信息满足人数需求……
行	选择交通方式是存在的、给出交通方案的价格正确、给出交通方案的时间正确、给出交通方案的距离正确……
时间	给出的规划方案中每个事件按时间顺序发生，无冲突
空间	在不同地点的事件安排都需要保证给出可行的交通方式

ChinaTravel: Domain-Specific Language (DSL)

LLM友好、可组合、可验证

- **类 Python 语法**: 可组合的原子概念 (空间、时间、成本、类型.....)
- **程序化验证**: 可行性 $\wedge$ 逻辑约束 $\wedge$ 优先级排序
- **可组合泛化**: 新约束可由少量基本概念组合而成
- **可扩展性强**: 数百种人类需求约束, 可通过约 20 个原子概念表达

判断餐饮预算是否超过1000

```
# Dining expenses <= 1000 CNY.
dining_cost = 0
for act_i in allactivities(plan):
    typ = activity_type(act_i)
    if typ=="breakfast" or typ=="lunch" or
       typ=="dinner": dining_cost =
        dining_cost + activity_cost(act_i)
return dining_cost <= 1000
```

判断参观的景点总数量

```
# Arriving in Shanghai should be before
  6 PM on the second day.
return_time = 0
for act_i in day_activities(plan, 2):
    typ = activity_type(act_i)
    dest = transport_destination(act_i)
    if (typ=="train" or typ=="airplane")
        and des=="Shanghai": return_time
        == activity_endtime(act_i)
return return_time < "18:00"
```

Baseline Neuro-Symbolic Method

Natural Language -> DSL

LLM Guided
Symbolic Search

DSL Verify
LLM Revise



Query

I am in **Shanghai** now and would like to go to **Beijing** for 2 days, visit some **museums**, and taste some **local cuisine**. My **budget is 5,000 yuan** and I hope to **visit as many attractions as possible**. Please give me a travel plan.

LLM
Extraction

Validated Plan

Reasoning

$x.type = museums,$
 $\exists x \in Attraction_visiting$

$x.cuisine = Beijing\ Cuisine,$
 $\exists x \in Restaurants_visiting$

$total_budget \leq 5000$

Plan Verification
Failed

Completed Plan

DFS

当前规划

[Day 1, Activity 1]

Train, G104, 06:27 → 13:12, 票价: 693

上海虹桥火车站 → 北京南火车站

[Day 1, Activity 2]

故宫博物院, 14:00 → 17:30

[Day 1, Activity 3] ?

Type(四季民福) = 北京菜
Type(新荣记) ≠ 北京菜

当前时间: 17:30

当前位置: 故宫博物院

1. 接下来该去景点、餐厅还是宾馆?

Rule-based choice

$17:30 > 17:00$

$17:30 < 20:00$

2. 接下来该去哪个地方?

逐步规划

LLM-based choice

现在是17:30, 我们可以找一个餐厅吃晚饭。



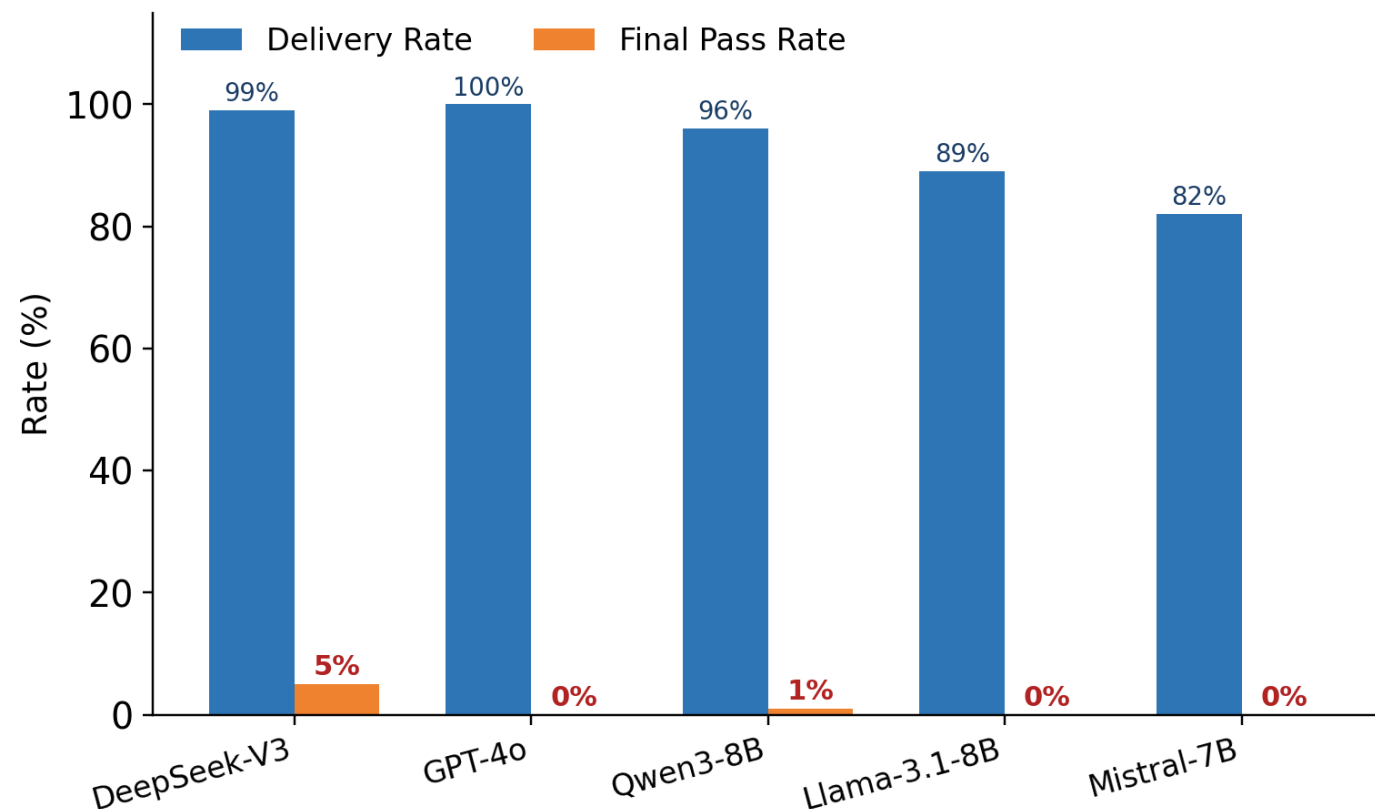
餐厅查询()

四季民福是知名餐厅,
有着很好吃的北京烤鸭。

Rule-based choice

LLM-based choice

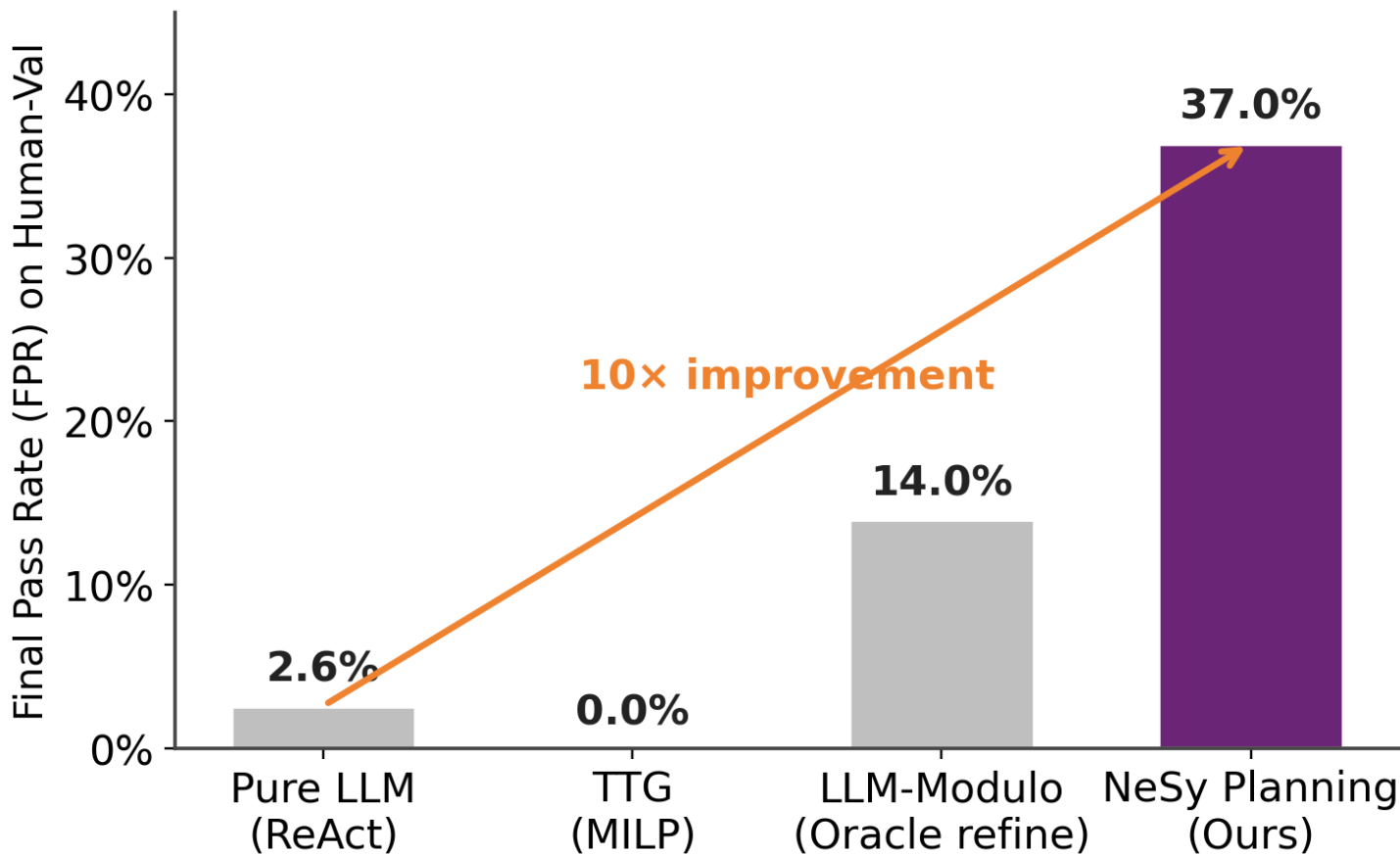
Results of LLM Agent



- Structured output $\neq$ valid plan: **High DR masks low FPR**
- GPT-4o: **0% FPR**
- DeepSeek-V3 (ReAct): 5% on Easy, **~0% on human splits**

LLM能生成看似合理的规划，但在长程、多约束的真实任务上，约束满足率几乎为0！

Results of Neuro-Symbolic Agent

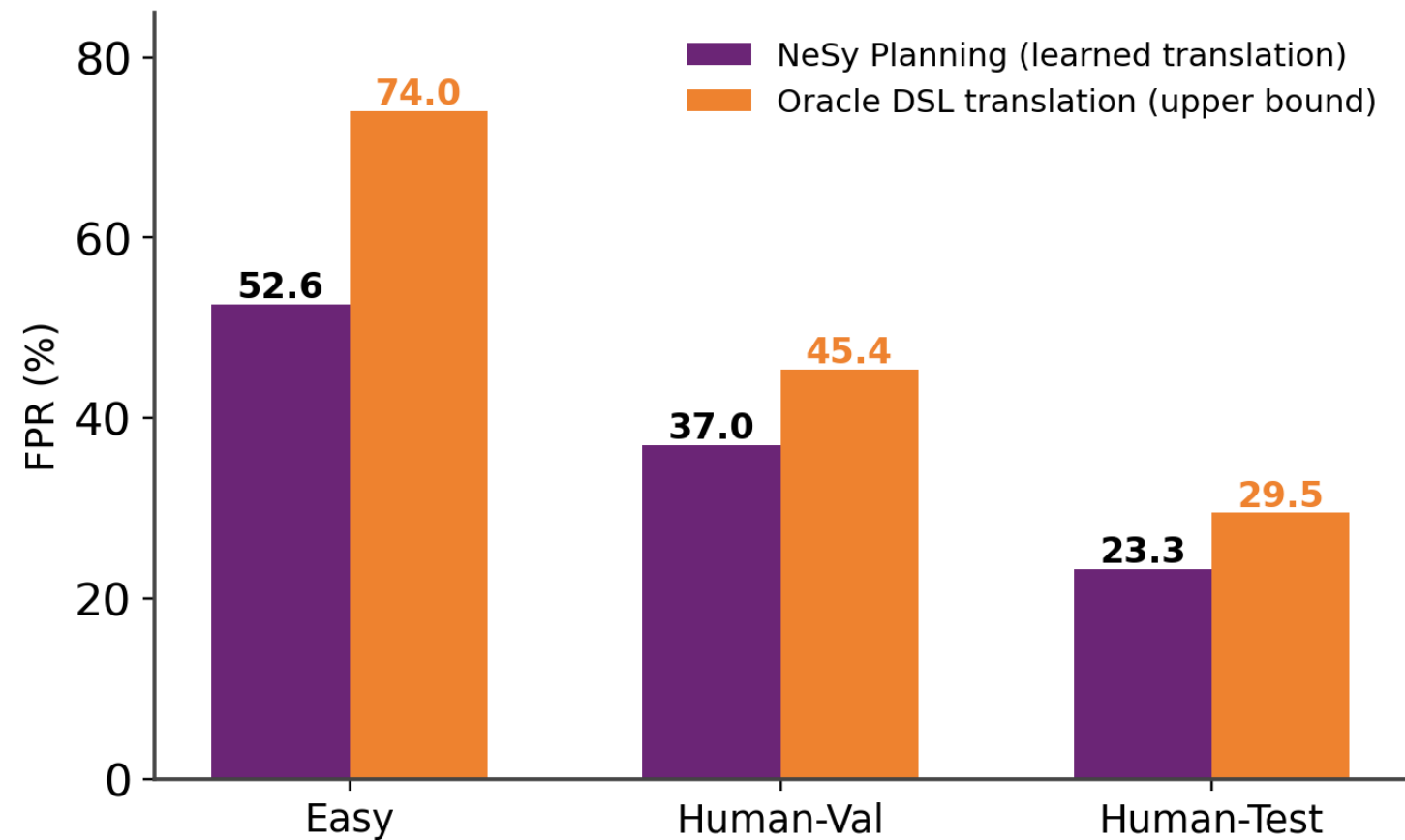


2.6% → 37.0%
Pure LLM → NeSy Planning
神经符号方法取得15倍性能提升

观点

让 LLM 做语言理解、让符号层处理长程搜索、让验证器闭环纠错，
三者各司其职，效果远好于把所有事情都丢给 LLM

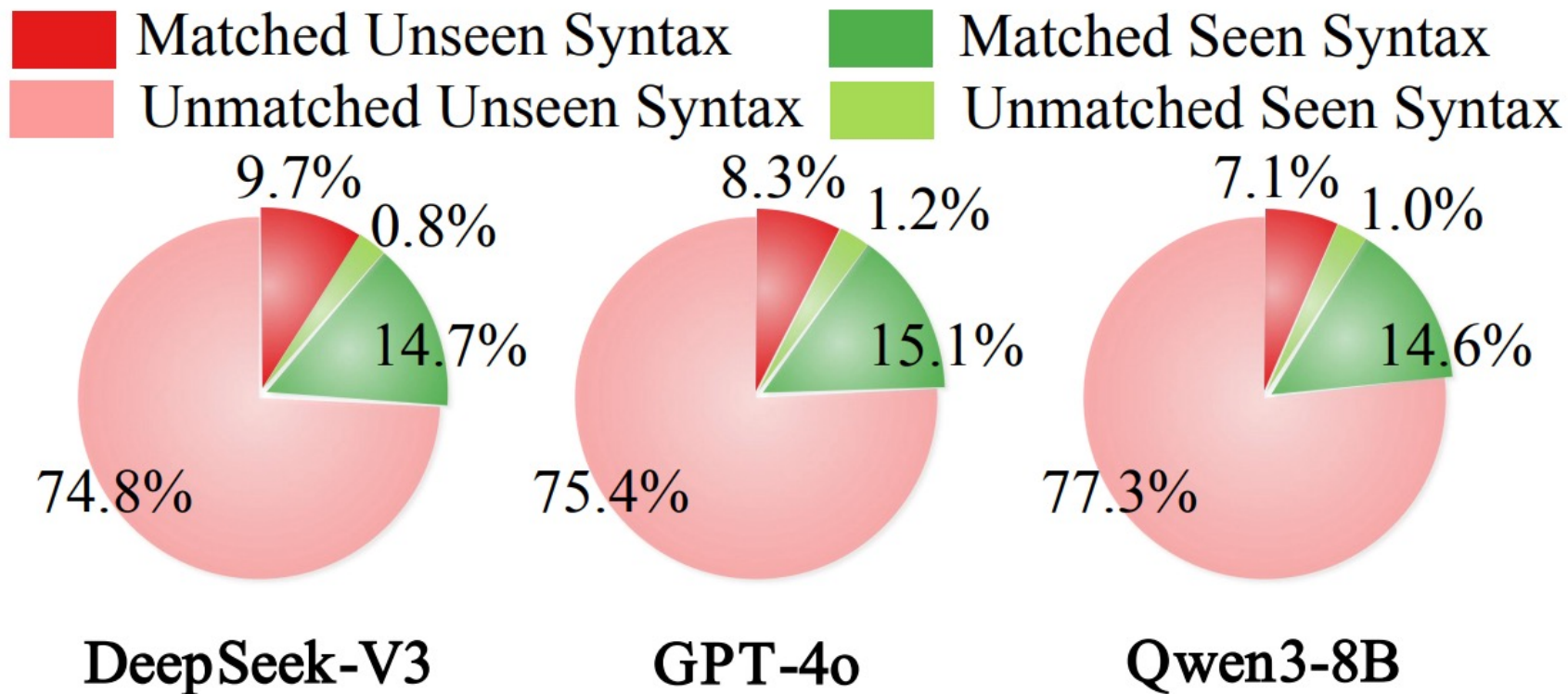
Challenge



- 给出正确的DSL语言，成功率可显著提升
- LLM在理解开放用户需求并将其翻译成符号语言上仍存在挑战
- 即便给定标准的DSL语言，符号求解器约束通过率也并非100%，搜索效率仍然是挑战

Compositional Generalization

在开放式旅行规划中，用户会把时间、预算、类型、偏好等基础概念组合为训练阶段未见过的新约束，LLM难以实现稳定的组合泛化



TPC Challenge @ IJCAI 2206

第二届智能旅行规划挑战赛 @ IJCAI 2026 正式开赛！



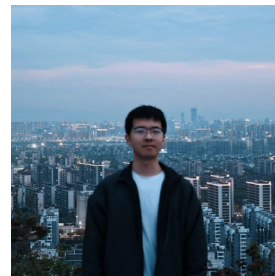
比赛官网

Timeline

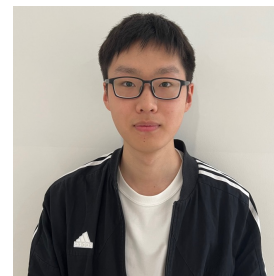
- 比赛正式启动：2026.06.01
- 第一阶段提交：2026.08.01
- 第二阶段评测：2026.08.01-07
- 技术报告提交：2026.08.07
- 最终结果公布：2026.08.10

<https://chinatravel-competition.github.io/IJCAI2026>

Summary



Jie-Jing Shao



Bo-Wen Zhang



Jin Ye

- LLM对于长程规划、约束满足问题仍面临显著挑战
- 让LLM做语言理解、符号层处理长程搜索、验证器闭环纠错，效果更好
- 如何实现自然语言 -> 符号语言转换、如何提升组合泛化能力仍是挑战

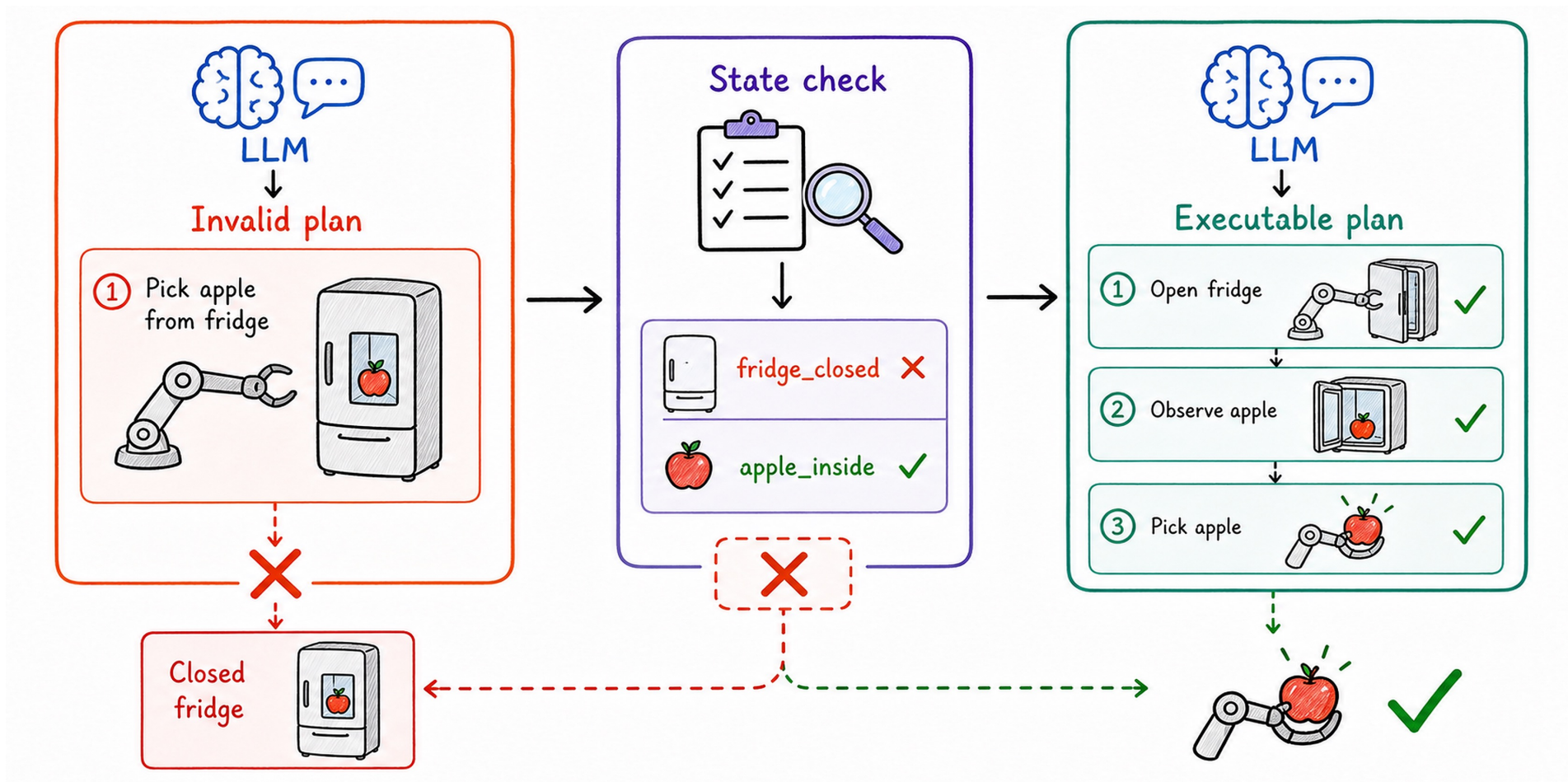
相关文献：

- Jie-Jing Shao, Bo-Wen Zhang, Xiao-Wen Yang, Bai-Zhi Chen, Si-Yu Han, Jing-Hao Pang, Wen-Da Wei, Guo-Hao Cai, Zhen-Hua Dong, Lan-Zhe Guo, Yu-Feng Li. **ChinaTravel: A Real-World Benchmark for Language Agent in Chinese Travel Planning. ICLR 2026.**
- Bo-Wen Zhang, Jin Ye, Jie-Jing Shao, Yu-Feng Li, Lan-Zhe Guo. **Mind the Gap to Trustworthy LLM Agents: A Systematic Evaluation on Constraint Satisfaction for Real-World Travel Planning. AAAI 2026 Trust Agent Workshop Best Student Paper Award.**
- Bo-Wen Zhang, Jin Ye, Jie-Jing Shao, Xiao-Wen Yang, Kun-Yang Yu, Zhi Zhou, Yu-Feng Li, Lan-Zhe Guo. **A Review of the IJCAI 2025 Travel Planning Challenge: Benchmarking LLM Agents with Compositional Constraints. Frontiers of Computer Science.**

Neuro-Symbolic Agent for Embodied Planning

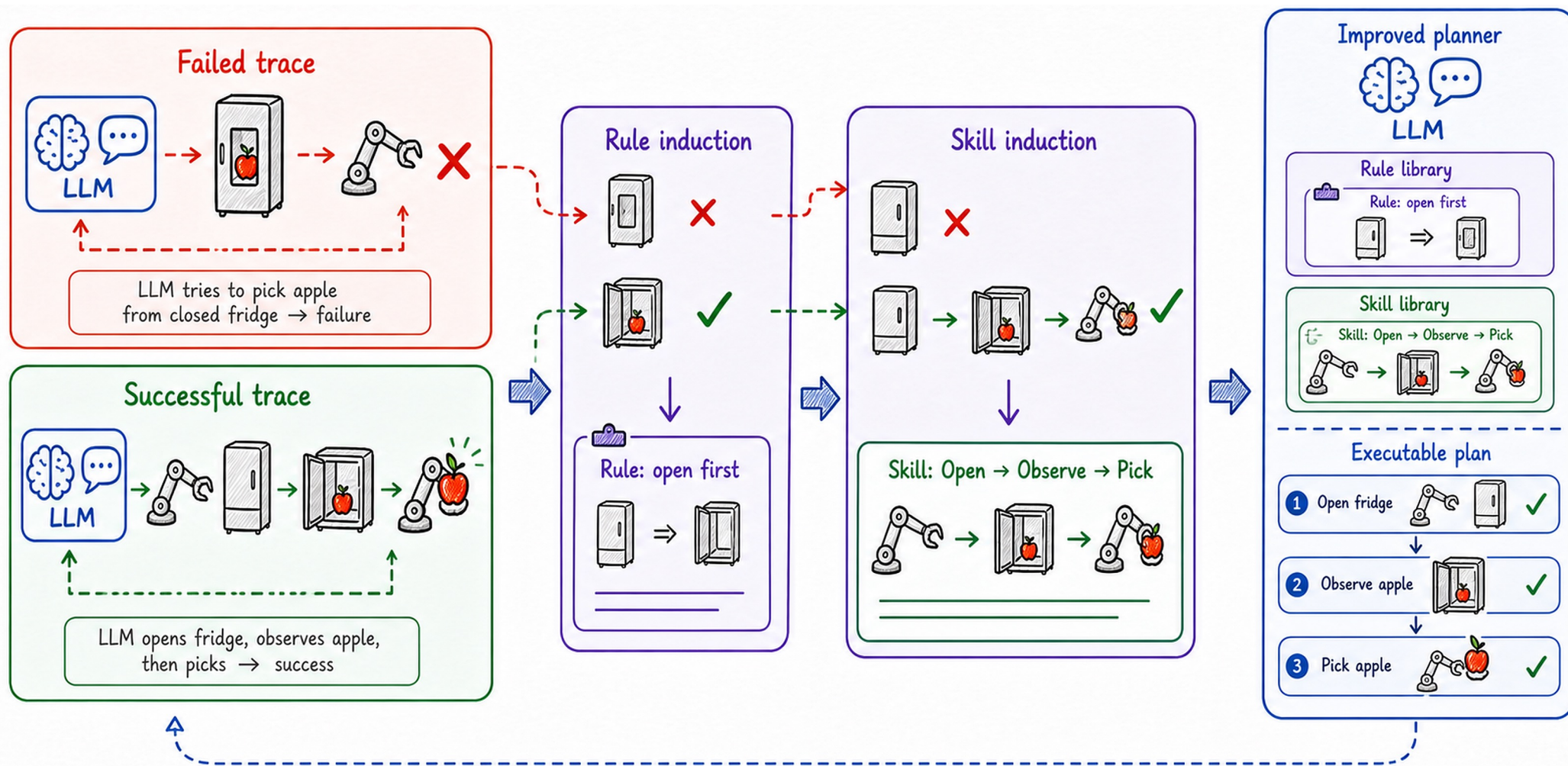
Challenges of Embodied Planning

Embodied Planning: 模型不仅需要生成合理的规划，还需要满足环境状态与物理约束，例如动作前提、可达性、**affordance**、安全约束等



Rule/Skill Induction

规则/技能学习：从成功与失败的交互轨迹中，归纳出可复用的规则与技能，进而约束LLM动作选择，指导生成可执行的规划

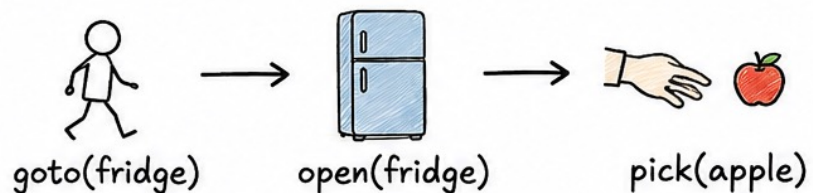


Embodied Agent Skill

既有Skill通常仅依赖大模型归纳，表示形式为参数化的动作脚本

已有方法通常把交互轨迹压缩成参数化动作脚本

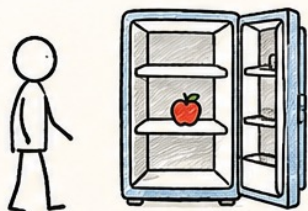
Script: `get_apple_from_fridge`



State-Blind Skill

- 缺少显式条件判断：不知道何时 `open` / `skip`
- 缺少动态变量绑定：目标对象依赖当前状态
- 环境偏移时容易失败，长程任务错误累积

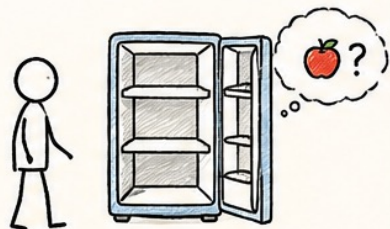
1. Fridge already open



Script tries to
`open(fridge)` again

✗ Fail
(unnecessary action)

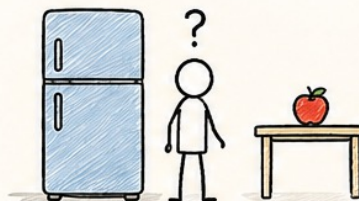
2. Apple not in fridge



Script tries to
`pick(apple)`

✗ Fail
(object not found)

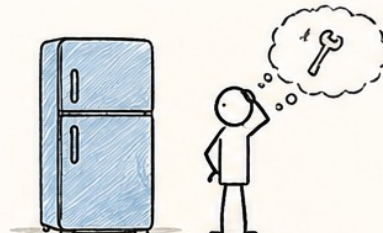
3. Apple in other place



Script still
`open(fridge)` / `pick(apple)`

✗ Fail
(wrong location)

4. Need other action first



Script cannot handle
missing preconditions

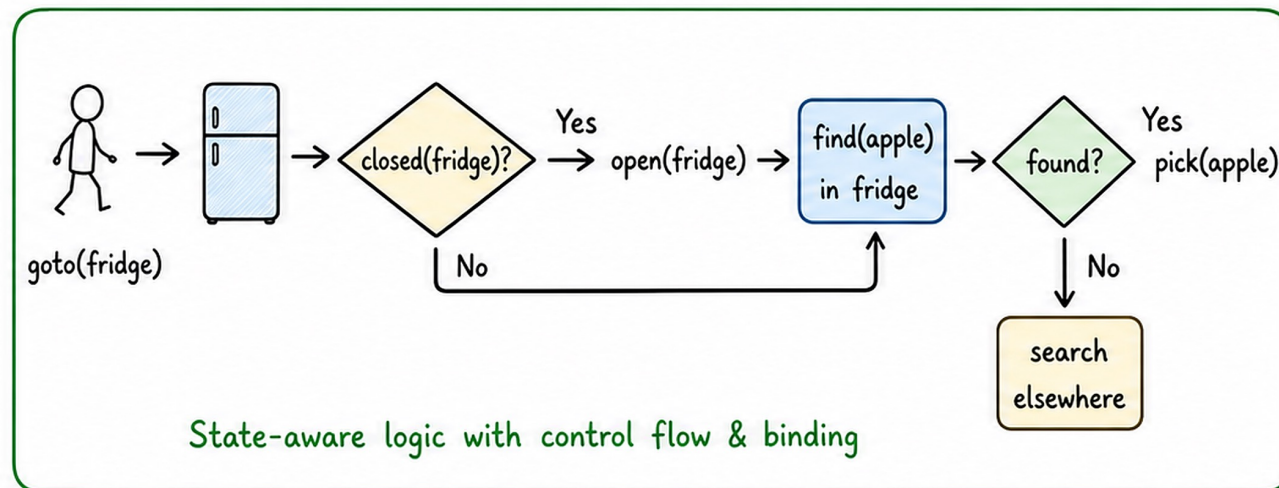
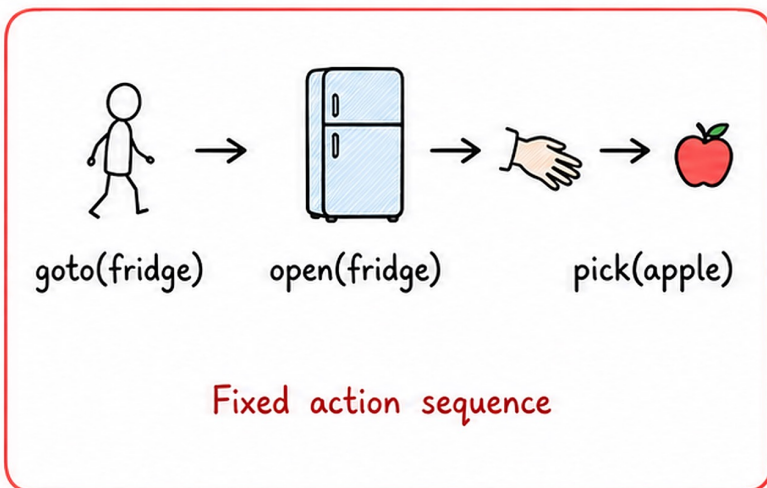
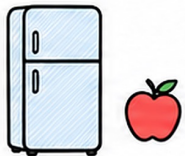
✗ Fail
(missing dependency)

Neuro-Symbolic Skill

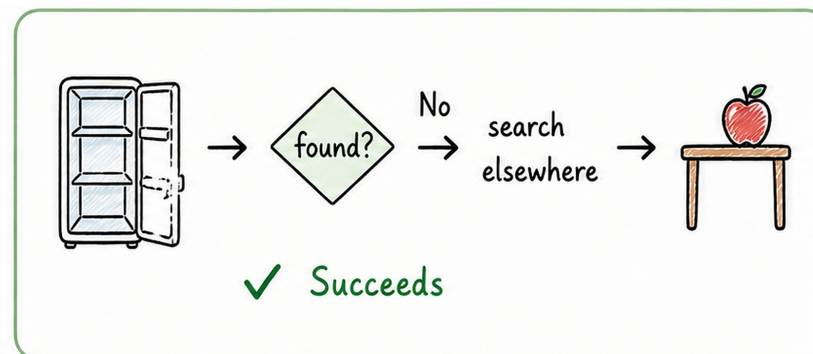
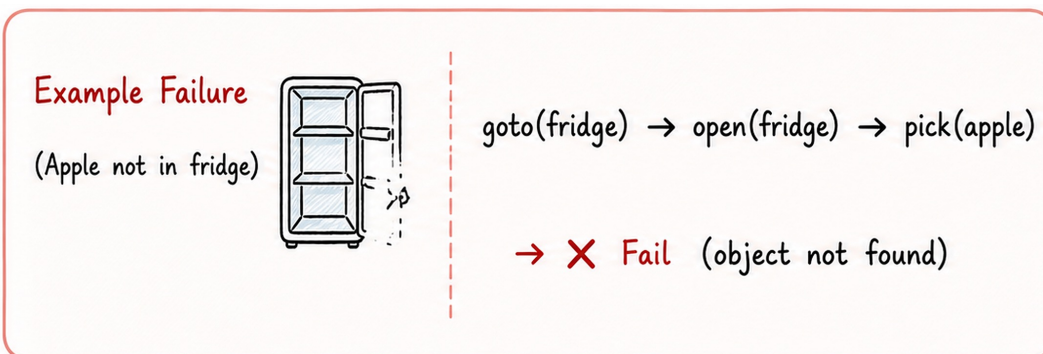
Neuro-Symbolic Skill: “状态谓词 + 控制流 + 动态变量绑定”的可执行图

Example Task:

Get apple
from fridge



Neuro-Symbolic Skill Learns **When, Why, and How** to act

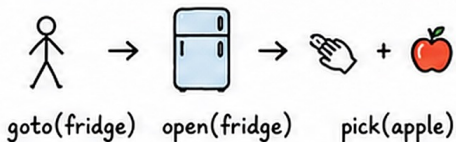


Offline Skill Induction from Successful Trajectories

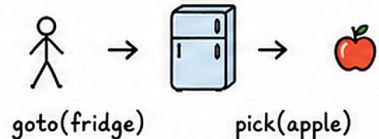
1. Collect Successful Trajectories

Task: Find and pick an apple

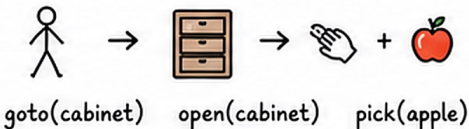
Trajectory 1



Trajectory 2



Trajectory 3



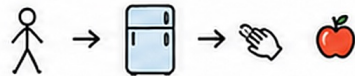
All trajectories are successful (task completed).

2. Segment into Sub-goal Trajectories

Extract same sub-goal

Sub-goal:
Get apple from receptacle

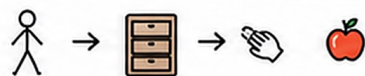
Sub-traj 1
(fridge closed)



Sub-traj 2
(fridge already open)



Sub-traj 3
(another receptacle)



3. Logic Discovery & Generalization

Find common patterns



Discover Conditions
Sometimes the receptacle is closed, sometimes open.

if closed(receptacle)



Discover Variable Binding
Apple instance varies.
Need to find it in the current state.

target = select_one(x,
is_type(x, apple) ^
contains(receptacle, x))

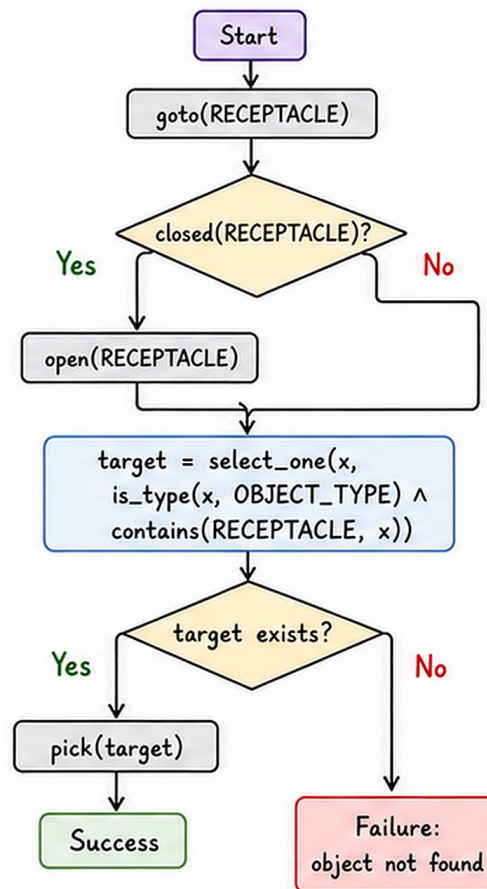


Discover Abstraction
Receptacle can be fridge,
cabinet, drawer, etc.

PARAM: RECEPTACLE
PARAM: OBJECT_TYPE

4. Build Skill Graph (Consolidated Program)

Assemble into a graph



5. Add to Skill Library

Reusable skill

Skill Library



get_object_from_receptacle

Parameters:

- OBJECT_TYPE
- RECEPTACLE

Description:

Find and pick an object of given type from the given receptacle.

Preconditions:

- RECEPTACLE is reachable
- OBJECT_TYPE is pickable

Postconditions:

- The object is picked by the agent.

Online Skill Evolution

1. Task & Planning

High-level task

Get an apple

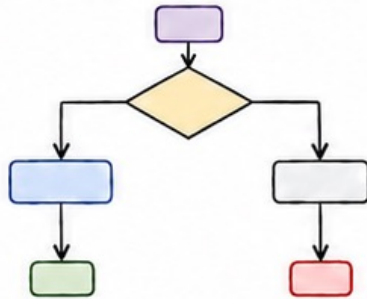
Planner selects skill and fills in parameters.

Call: `get_object_from_receptacle`
(`OBJECT_TYPE=apple`,
`RECEPTACLE=fridge`)



2. Execute Skill

Run skill graph



Interact with environment using neural grounding.

3. Failure Diagnosis

If skill fails

Failure:
object not found
(in fridge)



Return symbolic diagnosis with context.

4. Reflective Planning

Reason about alternatives



Maybe the apple is on the table?

- Analyze failure reason
- Consider alternative places
- Plan recovery steps

5. Recovery Execution

Execute recovery trajectory

`goto(table)`

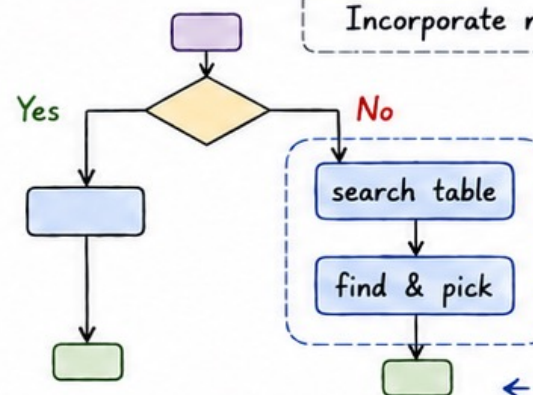
`find(apple)`

`pick(apple)`

✓ Recovery succeeds!

6. Skill Honing (Graph Update)

Incorporate new logic



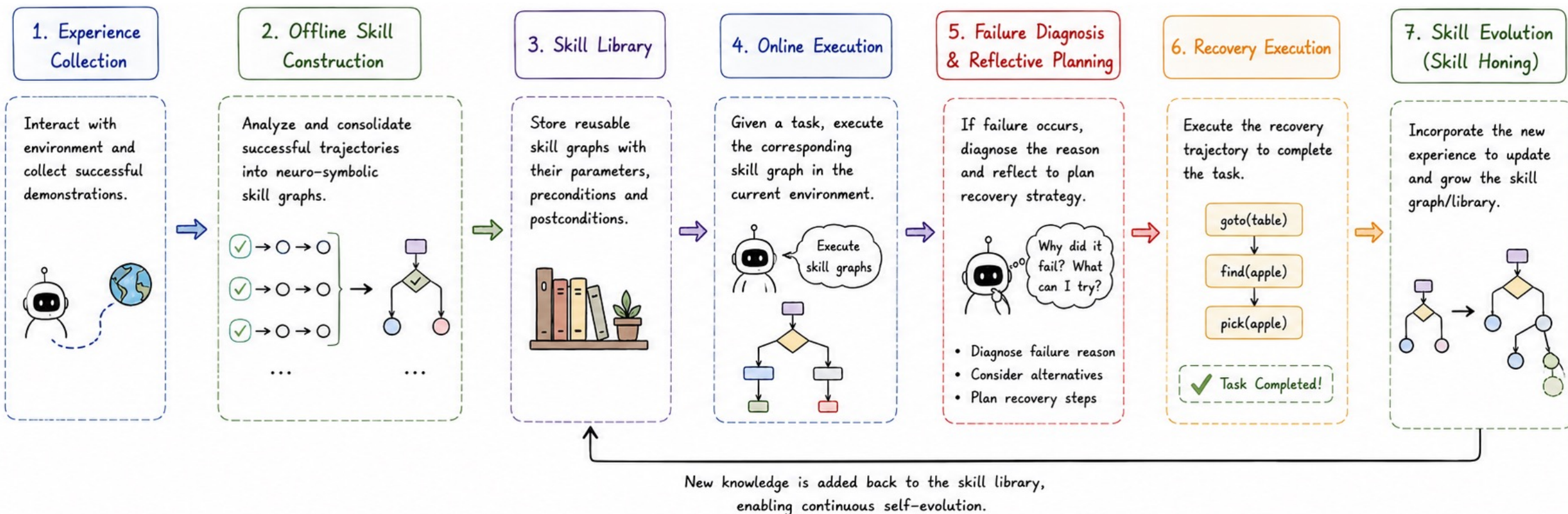
Newly added branch to handle the failure case.



The skill graph grows and becomes more robust over time.

Neuro-Symbolic Skill

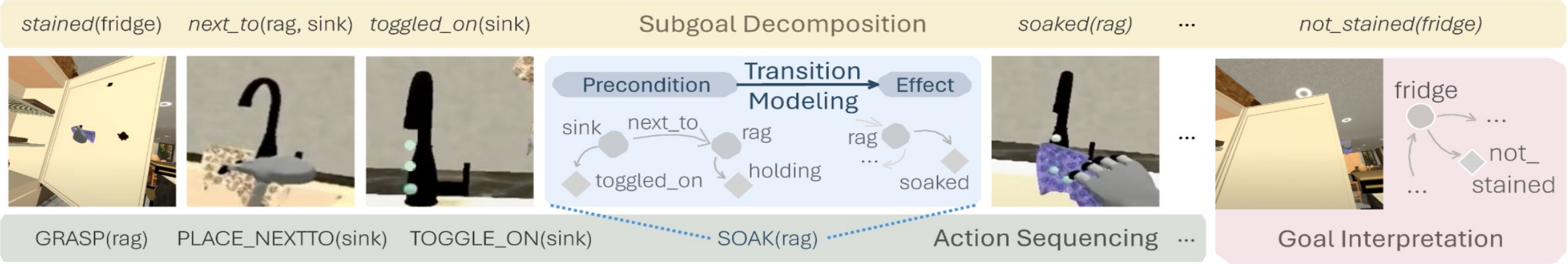
将智能体的成功交互轨迹从状态盲的动作脚本，提升为包含**神经感知Grounding**、**符号变量绑定**、**显式控制流**和**失败修复机制**的逻辑驱动技能图



Experimental Results

在Embodied Agent Interface Benchmark，包含Vitual Home与Behavior两个场景，
均验证了所提“失败-反思-规则提取-重规划”机制的性能

Task: use the rag to clean the refrigerator



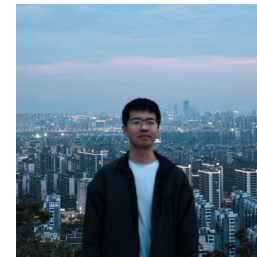
Model	Overall Perf.	Average Perf.		Goal Interpretation		Action Sequencing				Subgoal Decomposition				Transition Modeling			
		Module SR		F_1		Task SR		Execution SR		Task SR		Execution SR		F_1		Planner SR	
		V	B	V	B	V	B	V	B	V	B	V	B	V	B	V	B
GPT-4o	52.25	49.41	55.09	24.9	77.4	68.3	40.0	83.6	50.0	68.1	45.0	85.1	51.0	43.1	62.9	29.6	53.0
GPT-o3	64.43	61.75	67.10	35.3	79.1	68.9	64.6	83.2	70.8	74.3	52.0	87.1	57.3	44.6	52.4	92.4	93.0
GPT-5	68.32	68.09	68.55	36.3	79.2	72.3	71.0	84.9	74.0	73.2	54.0	87.2	60.0	36.4	43.0	86.3	97.0
Re ¹ Prompt	74.54	71.58	77.50	49.0	84.9	71.2	73.0	84.9	78.0	74.7	80.0	88.0	86.6	54.8	43.0	91.4	97.0
Re ² Agent	81.36	76.36	86.35	57.9	85.0	73.5	81.0	84.9	91.0	74.7	80.0	86.6	88.0	98.8	99.8	99.9	99.0

Experimental Results

在ALFWorld、WebShop、TextCraft中的实验验证所提方法的有效性，
Online Evolution可进一步显著提升性能

Method	ALFWorld	WebShop		TextCraft
	Success Rate (%)	Score(%)	Success Rate (%)	Success Rate (%)
ReAct (Yao et al., 2022b)	85.8	44.0	20.0	62.0
Reflexion (Shinn et al., 2023)	84.3	40.8	23.0	59.0
ADaPT (Prasad et al., 2024)	67.9	45.8	29.0	72.5
StateAct (Rozanov & Rei, 2025)	84.3	40.6	8.00	83.0
AWM _{offline} (Wang et al., 2025c)	88.6±1.1	51.8±1.7	32.2±1.3	66.3±2.0
AWM (Wang et al., 2025c)	91.3±0.8	49.2±1.9	30.0±2.0	92.5±3.6
ASI (Wang et al., 2025b)	70.6±1.9	7.7±1.7	7.50±3.0	77.8±1.8
NSI w.o. online honing	93.5±1.9	58.8±1.8	30.5±1.5	78.5±2.5
NSI (Ours)	98.0±1.2	76.5±1.2	44.5±1.5	95.2±0.8

Summary



Jie-Jing Shao



Yang Chen

- 具身规划的输出必须满足**环境状态与物理约束**，能在环境中被真实执行
- 符号可以作为 LLM 规划与环境执行间的**verification layer**，负责检查错误、诊断原因、指导修复

获斯坦福Fei-Fei Li教授主办的CVPR 2026 EmbodiedBench Challenge 冠军、NeurIPS 2025 Embodied Agent Challenge 最具创新算法奖



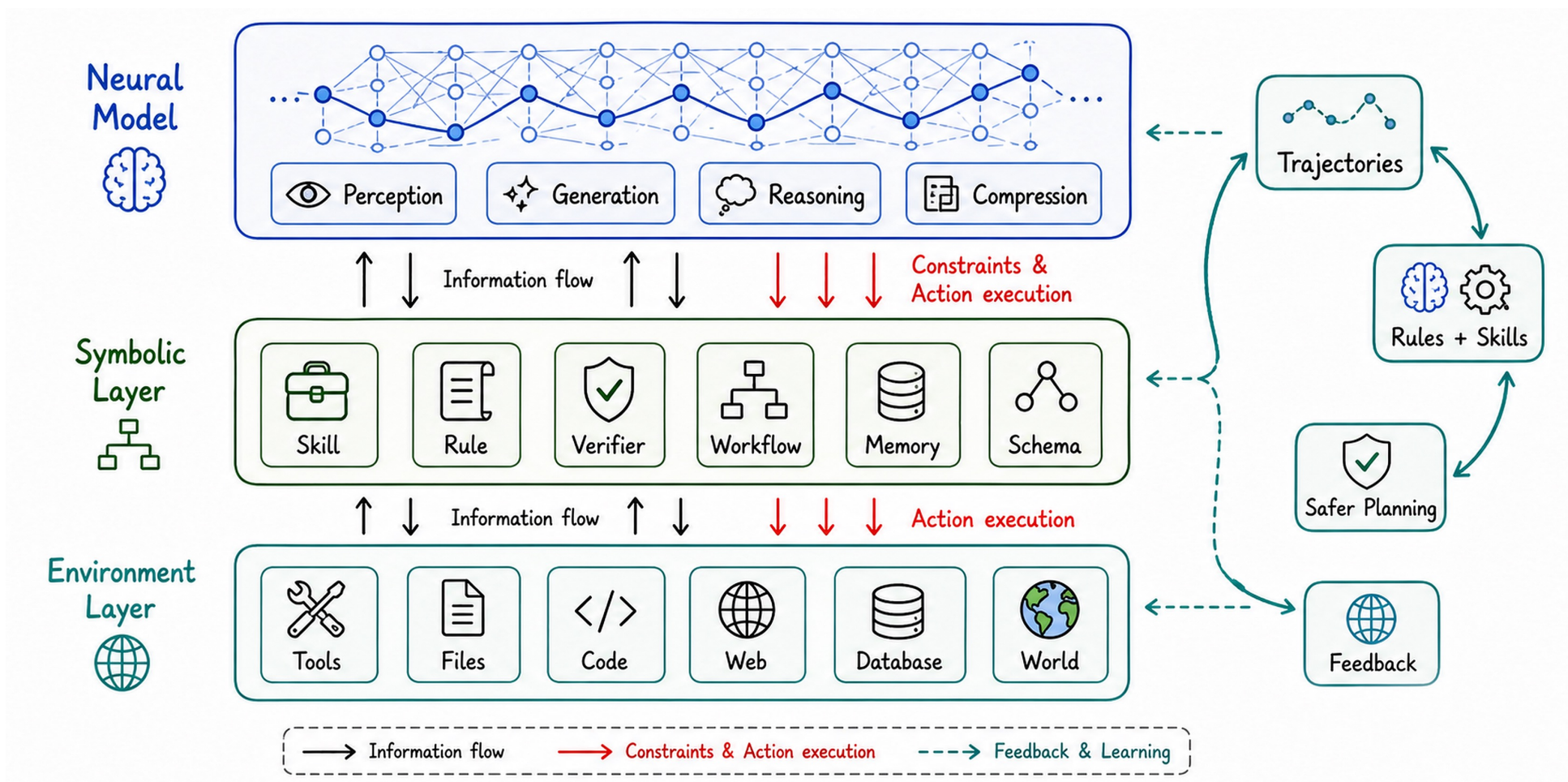
相关文献

- Jie-Jing Shao, Haiyan Yin, Yueming Lyu, Xingrui Yu, Lan-Zhe Guo, Ivor W. Tsang, James T. Kwok, Yu-Feng Li. **Lifting Traces to Logic: Programmatic Skill Induction with Neuro-Symbolic Learning for Long-Horizon Agentic Tasks. ICML 2026.**
- Yang Chen, Hong-Jie You, Jie-Jing Shao, Xiao-Wen Yang, Ming Yang, Yu-Feng Li, Lan-Zhe Guo. **Re2 Agent: Reflective Rule Induction and Rule-Guided Refinement for Embodied Planning. CVPR 2026 Foundation Model Meet Embodied Agents Workshop.**

Takeaway

神经网络把经验压缩进权重；符号学习把经验压缩进可操作结构

Agent 既需要大模型感知与推理能力，也需要维护可验证、可泛化的符号结构



Thank you!

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