



中國人民大學
RENMIN UNIVERSITY OF CHINA

高瓴人工智能学院
Gaoling School of Artificial Intelligence

大语言模型驱动下的自主智能体 研究现状和展望

文继荣

中国人民大学高瓴人工智能学院



目 录



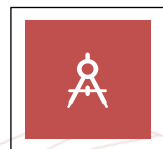
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01 | 背景介绍



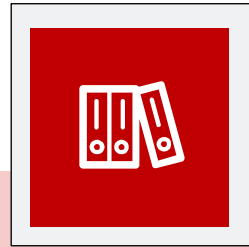
02 | 自主智能体领域发展现状



03 | 基于自主智能体的用户行为模拟



04 | 未来挑战与机遇



01 | 背景介绍



典型实例



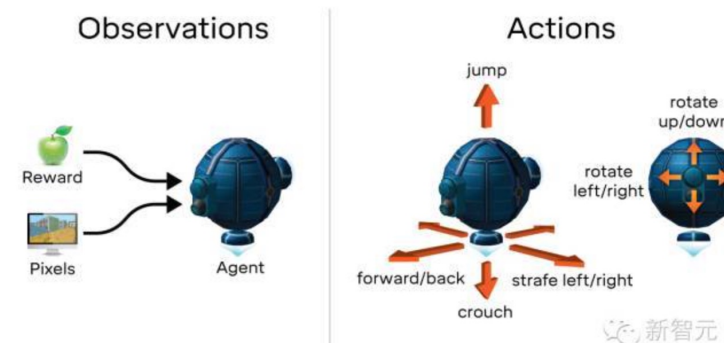
能够自动感知环境
能够在环境中自主行动
能够通过环境反馈自主学习

--- Maes (1995)

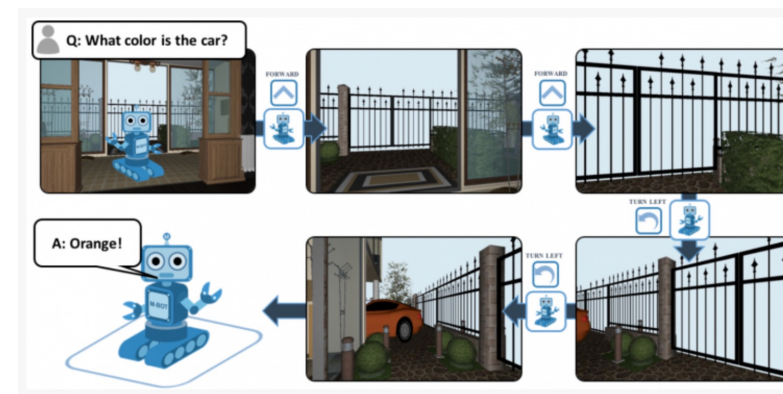


WIKIPEDIA
The Free Encyclopedia

DeepMind Lab, 2016



Embodied QA, FAIR, 2018



大语言模型



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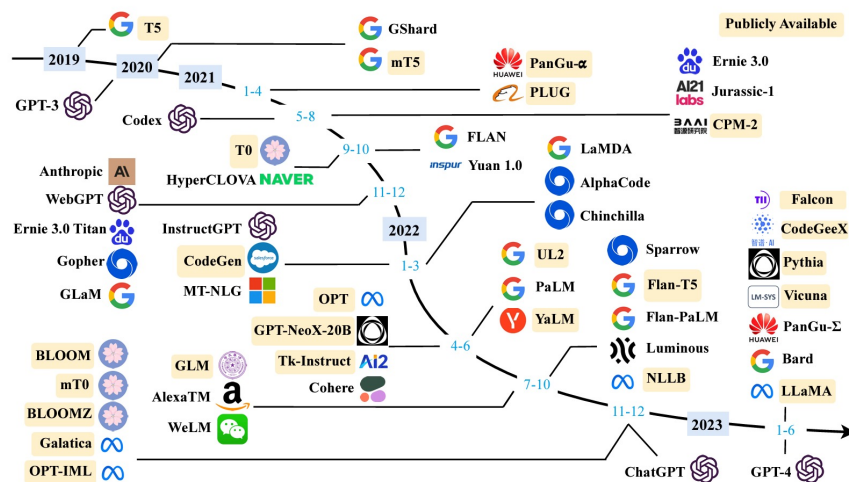
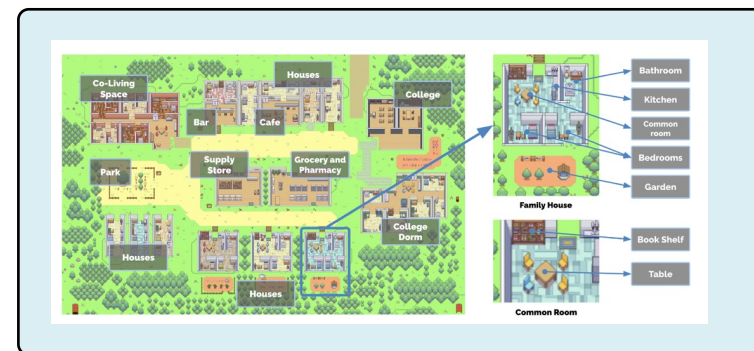
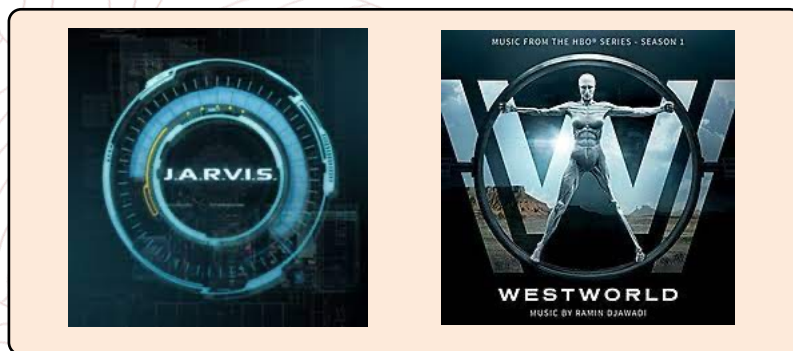


TABLE 11: Evaluation on the eight abilities of LLMs with specially selected tasks. The shade of the Orange and Blue fonts denote the performance orders of the results in closed-source and open-source models, respectively. This table will be continuously updated by incorporating the results of more models.

Models	Language Generation					Knowledge Utilization				
	LBD†	WMT†	XSum†	HumanEval†	TriviaQA†	NaturalQ†	WebQ†	ARC†	WikiFact†	
ChatGPT	55.81	36.44	21.71	79.88	54.54	21.32	17.77	83.69	29.25	
Claude	64.47	31.23	22.86	51.22	40.92	13.77	14.57	66.62	34.34	
Davinci003	69.98	37.46	18.19	67.07	51.51	17.76	16.68	88.47	28.29	
Davinci002	58.85	35.11	19.15	56.70	52.11	20.47	18.45	89.23	29.15	
Vicuna (7B)	60.12	18.06	13.99	17.07	28.58	9.17	6.64	16.96	26.95	
Alpaca (7B)	60.45	21.52	8.74	13.41	17.14	3.24	3.00	49.75	26.05	
ChatGLM (6B)	53.34	16.58	13.48	13.42	13.42	4.40	9.20	55.39	16.01	
LLaMA (7B)	66.78	13.84	8.77	15.24	34.62	7.92	11.12	4.88	19.78	
Falcon (7B)	66.89	4.05	10.00	10.37	28.74	10.78	8.46	4.08	23.91	
Pythia (12B)	60.49	5.43	8.87	14.63	15.73	1.99	4.72	11.66	20.57	
Pythia (7B)	50.96	3.68	8.23	9.15	10.16	1.77	3.74	11.03	15.75	
Models	Knowledge Reasoning			Symbolic Reasoning		Mathematical Reasoning		Interaction with Environment		
	OBQA†	HellaSwag†	SocialQA†	C-Objects†	Penguins†	GSMsk†	MATH†	ALFW†	WebShop†	
ChatGPT	81.20	61.43	73.23	53.20	40.27	78.47	33.78	58.96	45.12/15.60	
Claude	81.80	54.95	73.23	59.95	47.65	70.81	20.18	32.09	50.02/30.40	
Davinci003	74.40	62.65	69.70	64.60	61.07	57.16	17.66	65.67	64.08/32.40	
Davinci002	69.80	47.81	57.01	62.55	67.31	49.96	14.28	76.87	29.66/15.20	
Vicuna (7B)	30.00	25.25	36.39	44.25	36.24	14.03	3.54	1.49	6.90/1.40	
Alpaca (7B)	28.60	26.03	33.52	39.35	40.27	4.93	4.16	4.48	0.00/0.00	
ChatGLM (6B)	52.00	40.60	57.52	14.05	14.09	3.41	1.10	0.00	0.00/0.00	
LLaMA (7B)	27.00	25.57	33.11	39.95	34.90	10.99	3.12	2.24	0.00/0.00	
Falcon (7B)	25.20	25.07	33.01	29.80	24.16	1.67	0.94	7.46	0.00/0.00	
Pythia (12B)	25.00	25.15	32.45	32.40	26.17	2.88	1.96	5.22	3.68/0.60	
Pythia (7B)	24.40	23.62	32.04	29.05	27.52	1.82	1.46	7.46	10.75/1.80	
Models	Human Alignment			Tool Manipulation						
	TRQA†	C-Pairs†	Winogender†	RTP†	HuluEval†	HotpotQA†	Gorilla-T4†	Gorilla-TF†	Gorilla-HF†	
ChatGPT	69.16	81.40	62.50/72.50/79.17	3.07	66.64	23.80	67.20	44.53	19.36	
Claude	67.93	67.27	71.67/53.00/52.50	3.75	63.75	33.80	22.04	2.74	7.08	
Davinci003	60.83	99.01	67.50/68.33/79.17	8.81	58.94	34.40	72.58	3.80	6.42	
Davinci002	53.73	92.44	72.50/70.00/64.17	10.65	59.67	26.00	2.69	1.02	1.00	
Vicuna (7B)	37.77	67.24	49.17/49.17/49.17	4.70	43.44	6.20	0.00	0.00	0.33	
Alpaca (7B)	46.14	67.37	53.33/51.67/53.33	4.78	44.16	11.60	0.00	0.00	0.11	
ChatGLM (6B)	63.53	50.20	47.50/47.50/46.67	2.89	41.82	4.00	0.00	0.00	0.00	
LLaMA (7B)	47.86	68.50	54.17/52.50/51.67	5.94	14.18	1.60	0.00	0.00	0.11	
Falcon (7B)	53.24	68.70	50.00/50.83/50.00	6.71	37.41	1.00	0.00	0.00	0.00	
Pythia (12B)	54.47	65.98	49.17/48.33/49.17	6.59	27.09	0.40	0.00	0.00	0.00	
Pythia (7B)	50.92	64.79	51.67/49.17/50.00	13.02	25.84	0.20	0.00	0.00	0.00	



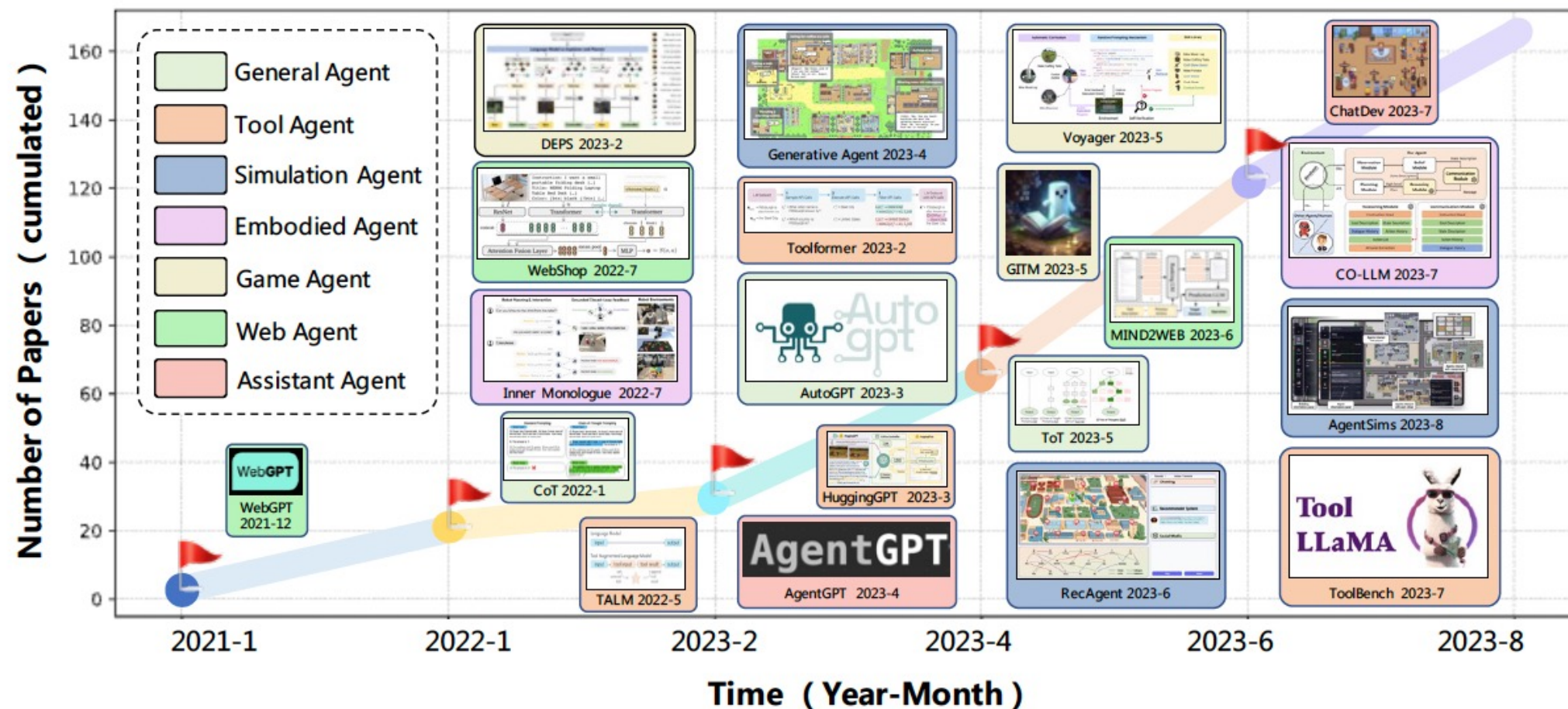
Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min, Beichen Zhang, Junjie Zhang, Zican Dong, Yifan Du, Chen Yang, Yushuo Chen, Zhipeng Chen, Jinhao Jiang, Ruiyang Ren, Yifan Li, Xinyu Tang, Zikang Liu, Peiyu Liu, Jian-Yun Nie, Ji-Rong Wen:
A Survey of Large Language Models. arXiv: 2303.18223



大语言模型驱动下的自主智能体

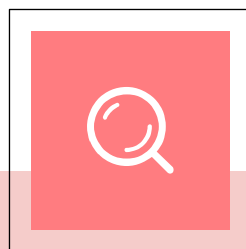


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Lei Wang, Chen Ma, Xueyang Feng, Zeyu Zhang, Hao Yang, Jingsen Zhang, Zhiyuan Chen, Jiakai Tang, Xu Chen, Yankai Lin, Wayne Xin Zhao, Zhewei Wei, Ji-Rong Wen:

A Survey on Large Language Model based Autonomous Agents. [arXiv:2308.11432](https://arxiv.org/abs/2308.11432)



02 | 自主智能体领域发展现状



大语言模型和智能体之间的差别

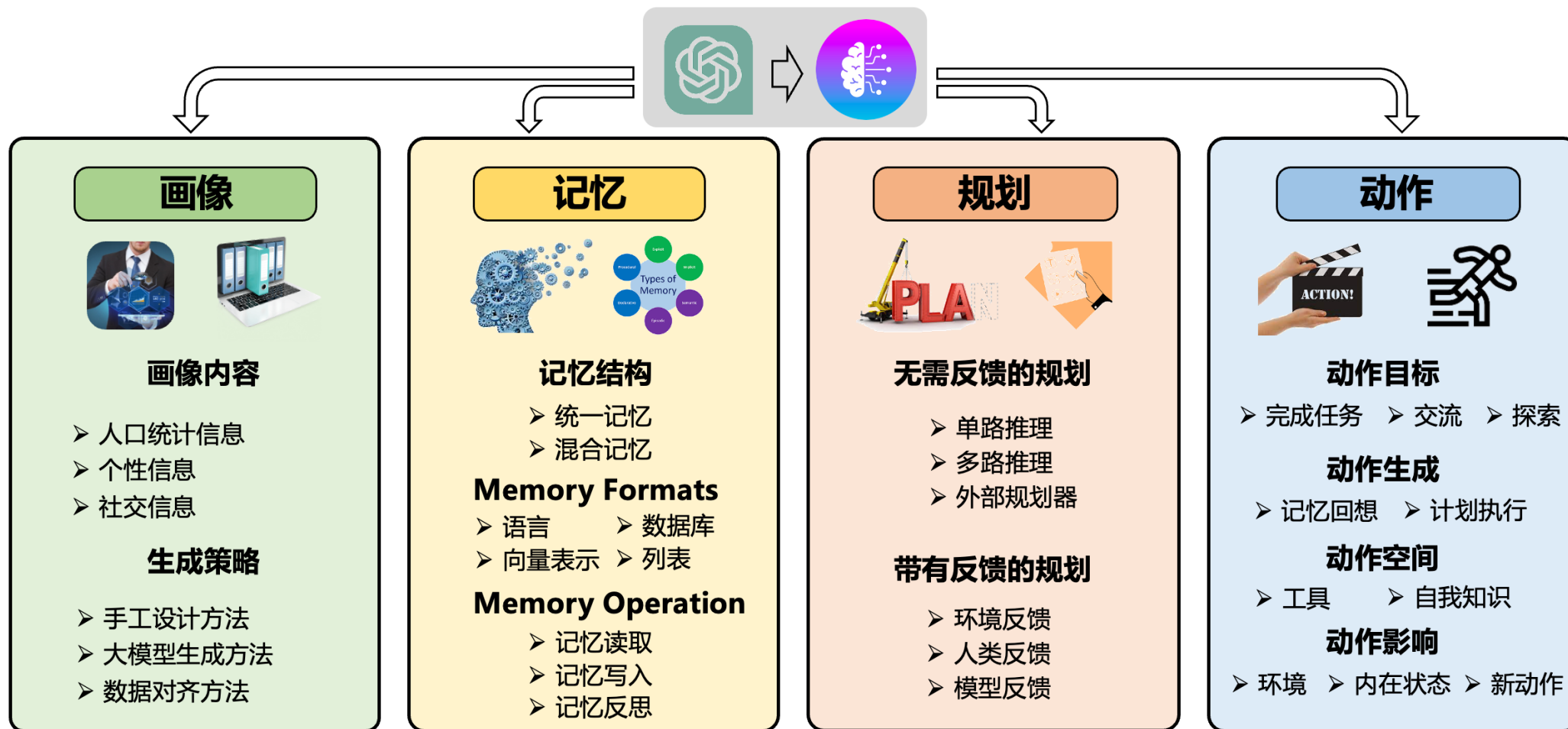




基于现有工作构建的分类框架



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基于大语言模型自主智能体统一框架



画像模块



高瓴人工智能学院
Gaoling School of Artificial Intelligence



手工方法



更加灵活



耗费人力



难以大规模使用



GPT生成方法



不够灵活



耗费低



容易大规模使用



DATASET

数据集对齐方法



不够灵活



更加真实



容易评估

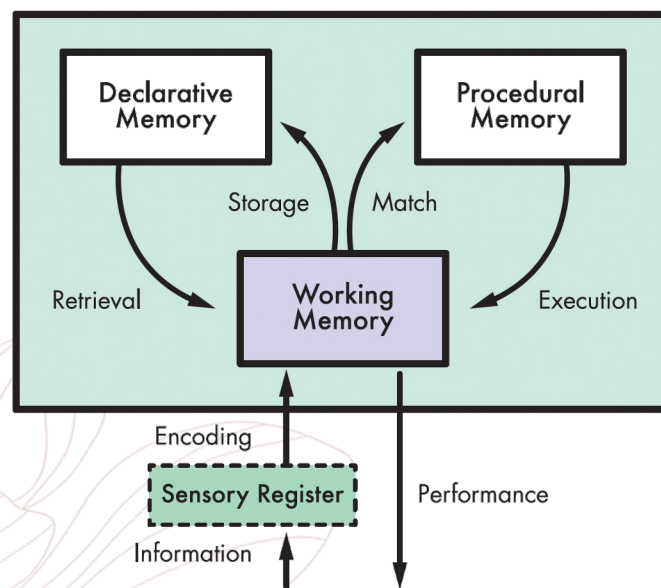


Figure 1: Schematic illustration of ACT-R. In our work, we focus on the activation equation of the declarative memory module.

人类记忆机制：ACT-R模型



短期记忆

短期记忆

+

长期记忆

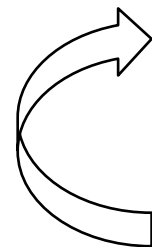
Agent 记忆结构



记忆模块



记忆写入



记忆读取



客观世界



记忆读取



近期性

Current time: 10:00



Memory time: 9:00



Memory time: 6:00



相关性

Current context



Memory



Memory



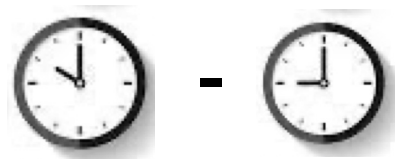
重要性

Memory

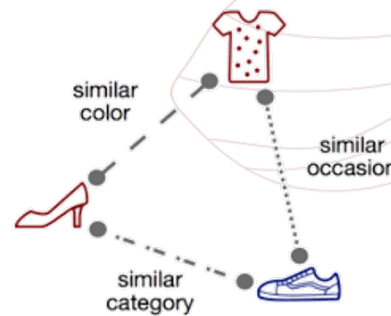


Memory





近期性得分



相关性得分

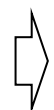
$$m^* = \arg \min_{m \in M} \alpha s^{rec}(q, m) + \beta s^{rel}(q, m) + \gamma s^{imp}(m)$$

所有记忆

当前上下文

重要性



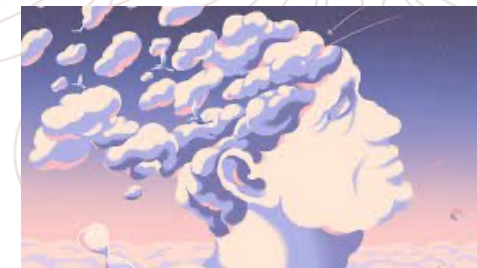


观测内容



记忆池

Memory
Memory
Memory
Memory



重点：如何存储信息？

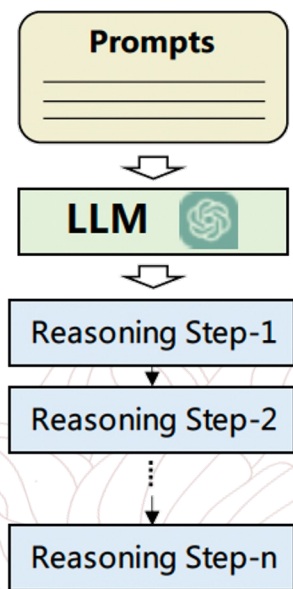
自然语言形式的文本

语义更加丰富，人类更容易理解，

结构化的符号表示

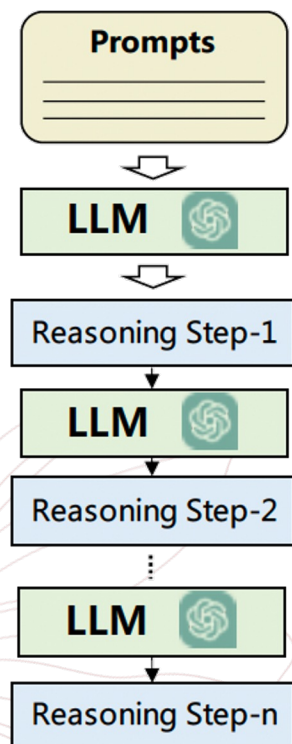
存储效率更高，更节省空间

CoT , Zero-shot Cot

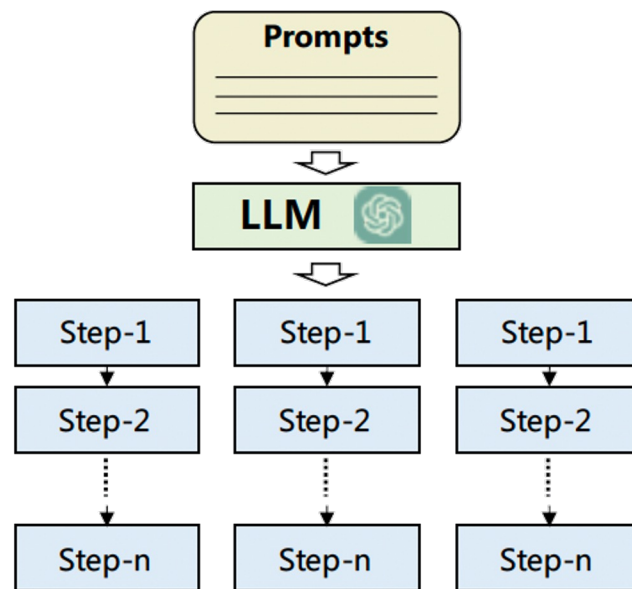


单路推理

ReWOO , HuggingGPT

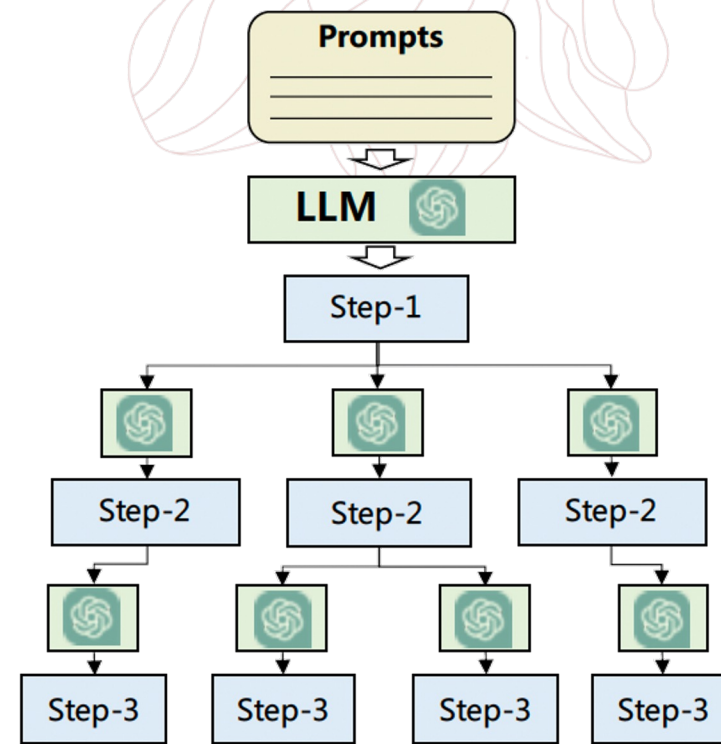


CoT-SC



多路推理

ToT , LMZSP , RAP





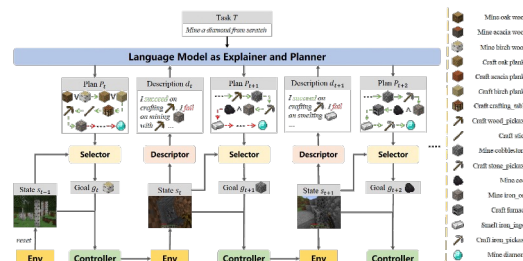
动作模块



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依靠自身能力

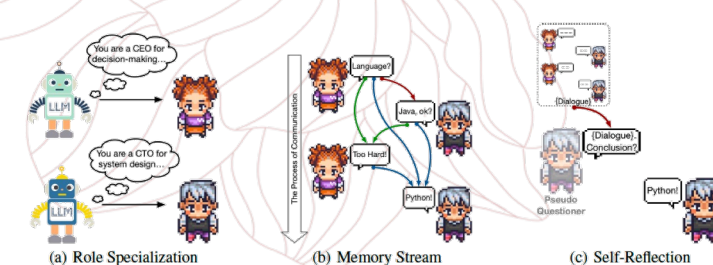
规划能力



常识理解能力



对话能力



依靠外部工具

搜索引擎



计算器



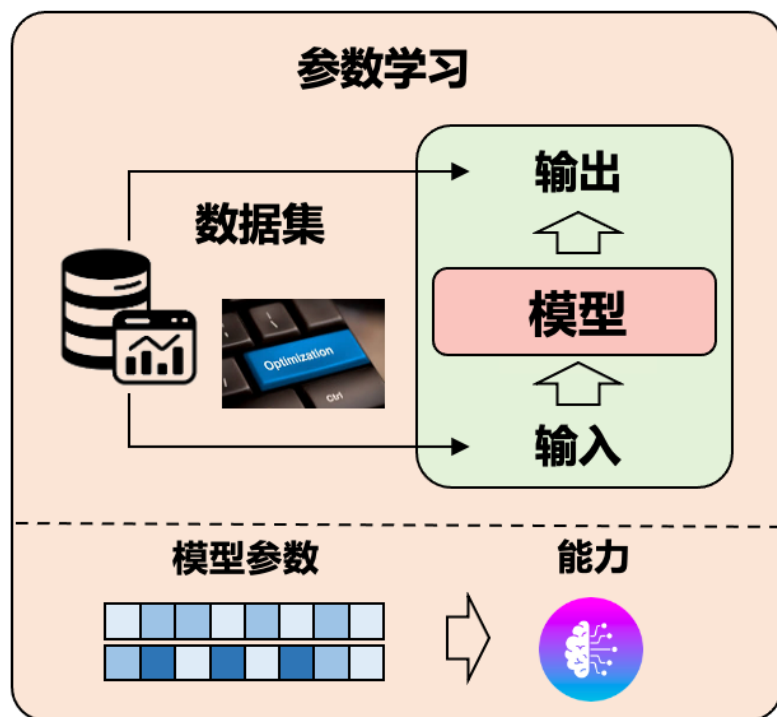
知识图谱



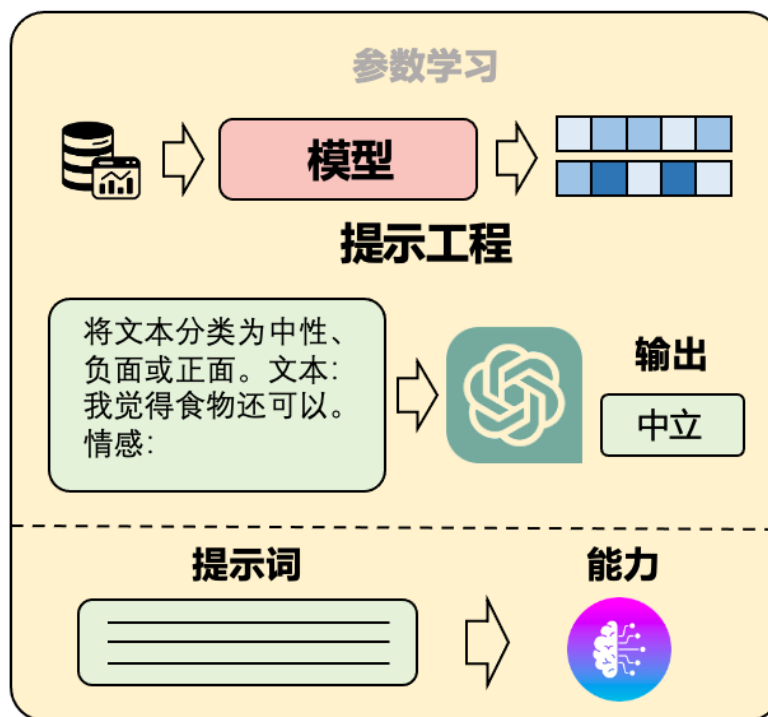
智能体时代模型能力获取的新范式



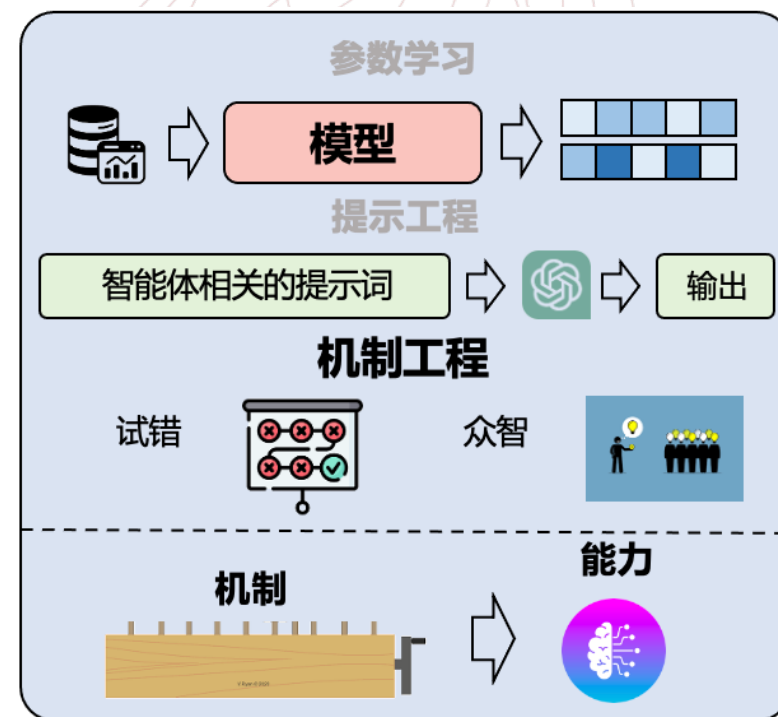
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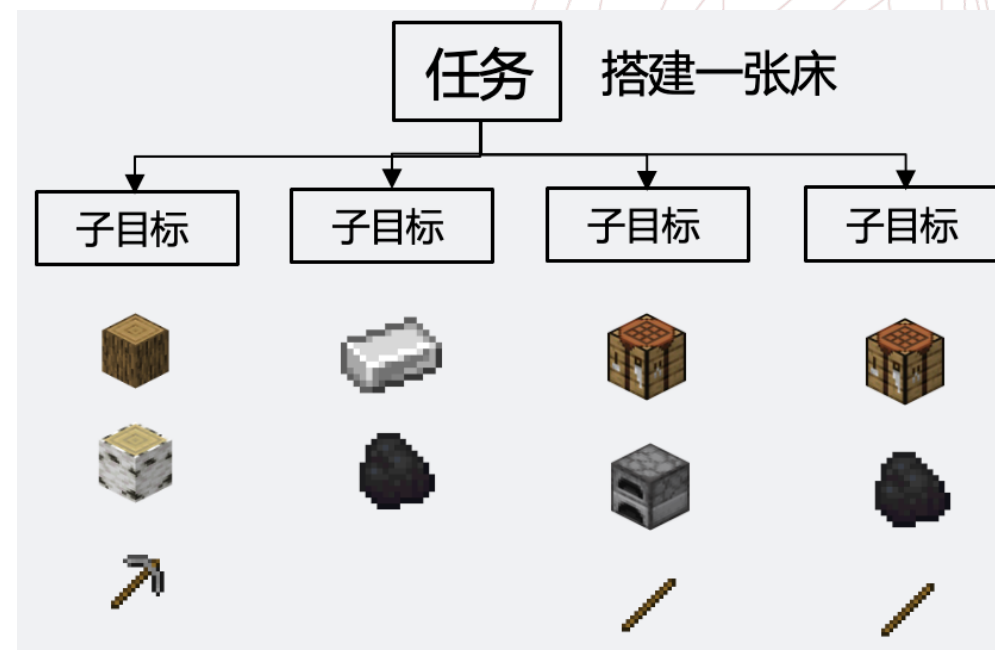
机器学习时代

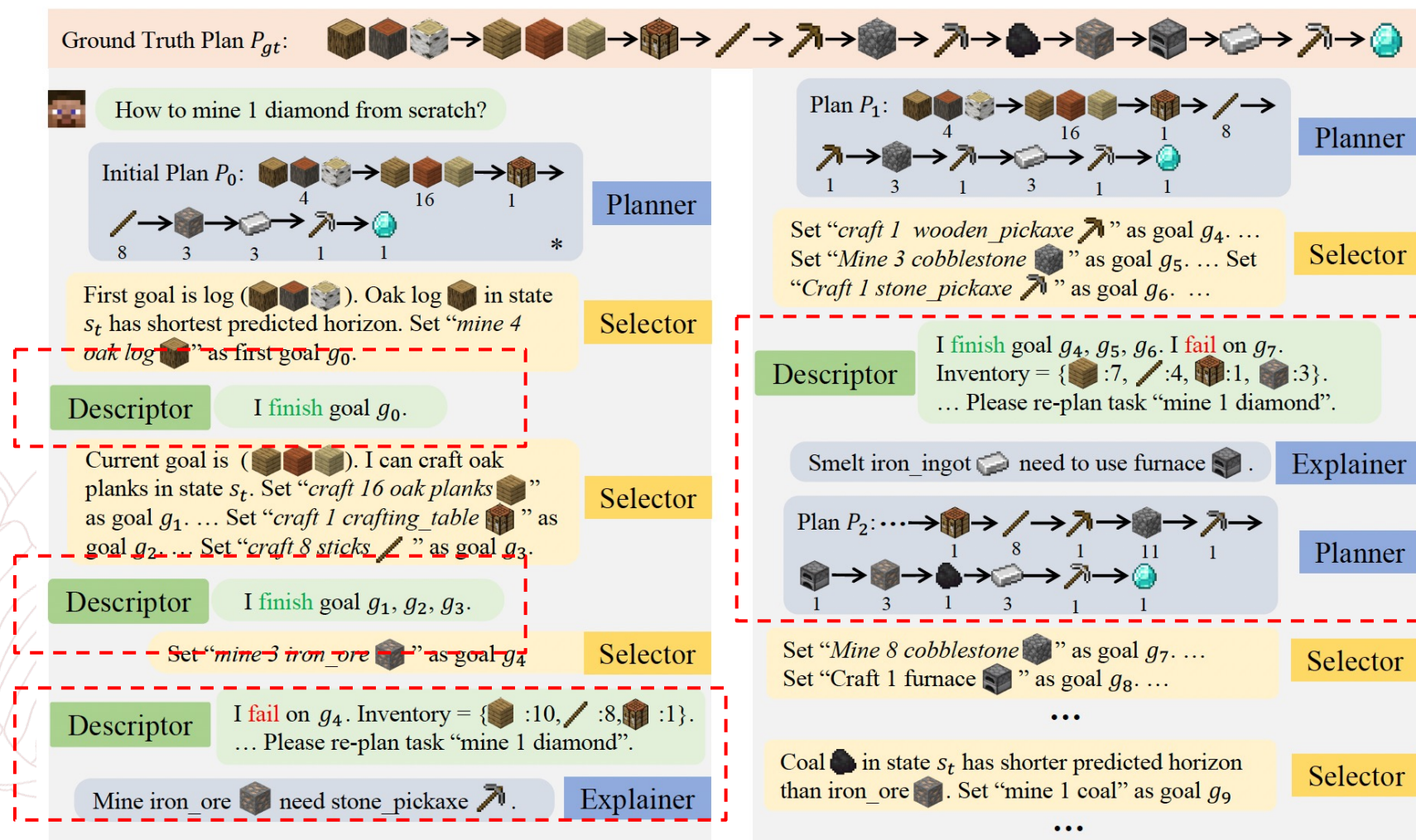


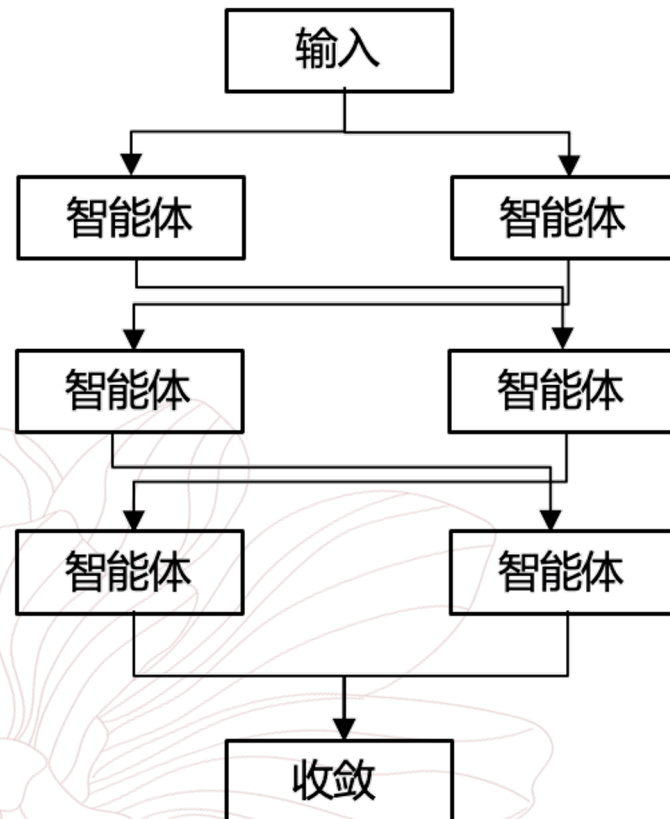
大模型时代



智能体时代







User Input: A treasure hunter found a buried treasure chest filled with gems. There were 175 diamonds, 35 fewer rubies than diamonds, and twice the number of emeralds than the rubies. How many of the gems were there in the chest?

Round 1

Agent 1: Let x be the number of rubies. Then the number of diamonds is 175. And the number of emeralds is $2(x-35)$, since there are twice as many emeralds as rubies and there are 35 fewer rubies than diamonds.

To find the total number of gems, we add the number of diamonds, rubies, and emeralds: Total gems = $175 + x + 2(x-35) = 3x + 105$.

We don't know the exact value of x , but we do know that it represents the number of rubies, which is less than 175 (since there are 35 fewer rubies than diamonds). Let's try some values of x : If $x = 50$, then the total gems = $3(50) + 105 = 255$. If $x = 100$, then the total gems = $3(100) + 105 = 405$.

Since we know there were fewer rubies than diamonds, the answer must be closer to 255 than to 405. After some trial and error, we can find that $x = 40$ gives us: Total gems = $3(40) + 105 = 225$. ❌

Agent 2: If there were 175 diamonds, then the number of rubies is 35 fewer, or $175 - 35 = 140$ rubies.

And since there were twice as many emeralds as rubies, we can represent the number of emeralds as $2 * 140 = 280$ emeralds.

To find the total number of gems in the chest, we can add up the number of diamonds, rubies, and emeralds: $175 + 140 + 280 = 595$. Therefore, there were 595 gems in the chest. ✅

User Input: Using the solutions from other agents as additional information, can you give an updated response...
(Copy Agent 2's reply) (Copy Agent 1's reply)

Round 2

Agent 1: Given the information provided in other agents' solutions, we have two answers: One agent found that the number of rubies is 40 and the total number of gems is 225. Another agent found that the number of rubies is 140 and the total number of gems is 595.

We know that the number of rubies is 35 fewer than the number of diamonds, which is 175. So the number of rubies should be $175 - 35 = 140$, as the second agent found. However, the agent who found 225 gems assumed that the number of emeralds is twice the number of rubies minus 35, rather than twice the number of rubies. If we use this assumption, we get: Number of rubies = 140. Number of emeralds = $2 * 140 - 35 = 245$. Total number of gems = $175 + 140 + 245 = 560$. Our final answer is 560. ❌

Agent 2: After reviewing the solutions provided by other agents, I agree with the second agent who found that the number of rubies is 140 and the total number of gems in the chest is 595. Therefore, my answer to the math problem is 595. ✅

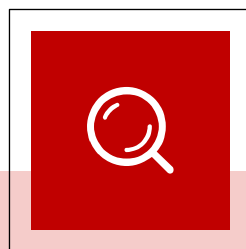
User Input: Using the solutions from other agents as additional information, can you give an updated response...
(Copy Agent 2's reply) (Copy Agent 1's reply)

Round 3

Agent 1: After reviewing the solutions provided by other agents, I agree with the second agent who found that the number of rubies is 140 and the total number of gems in the chest is 595. Therefore, my answer to the math problem is 595. ✅

Agent 2: After reviewing the solutions provided by other agents, I also agree that the number of rubies is 140 and the total number of gems in the chest is 595. Therefore, my answer to the math problem is also 595. ✅

Improving Factuality and Reasoning in Language Models through Multiagent Debate



03 | 基于自主智能体的用户行为模拟



AI 中两种不同的学习范式

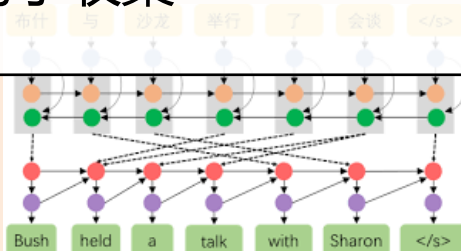


基于真实数据的研究



易于获取数据

- 数据集公开
- 易于收集



基于模拟的研究



可靠的数据生成机制

- 符合客观物理规律
- 模式固定





- 推荐系统
- 社会网络
- 人类决策预测
- . . .

易于获取数据



- 人类隐私
- 商业机密
- 代价高
- 道德问题

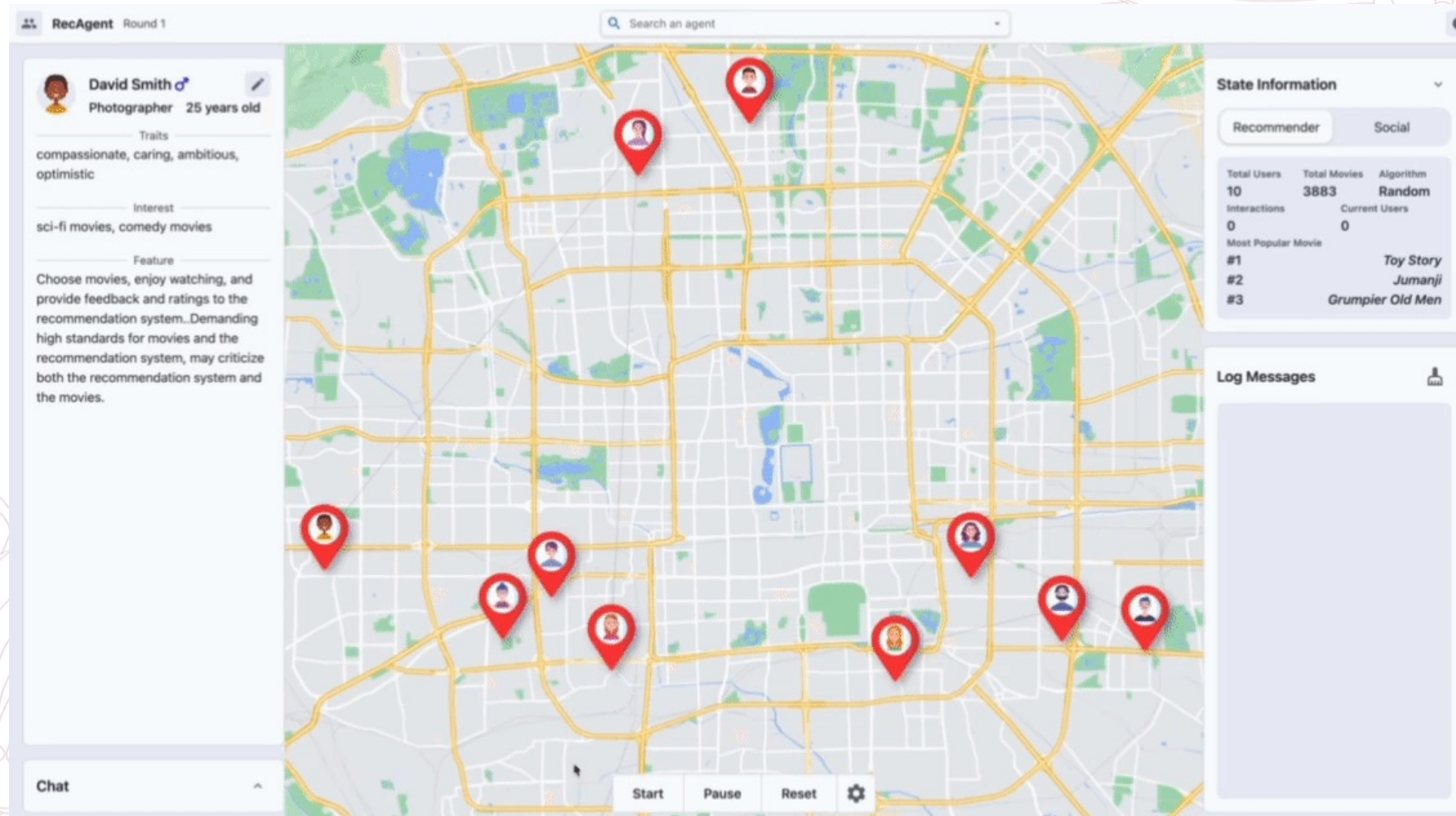
可信数据生成机制



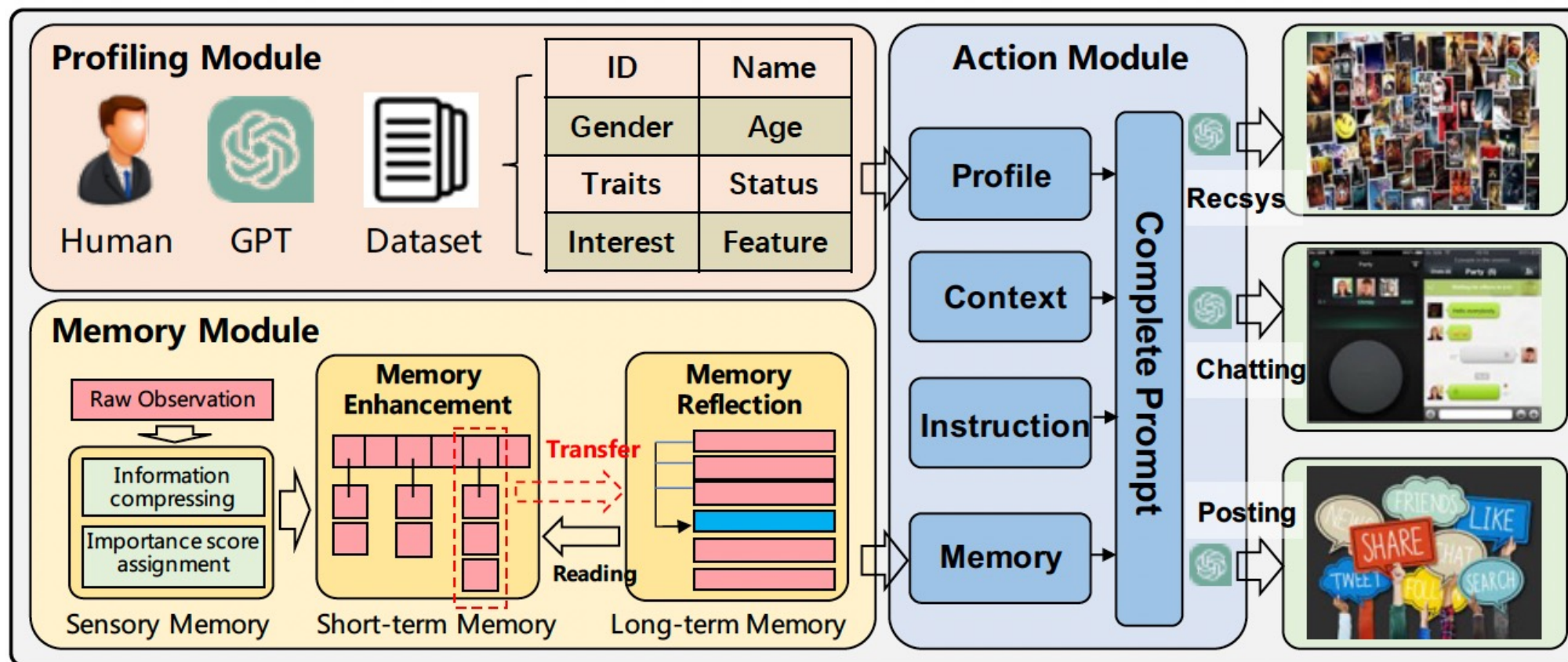
- 基础：理解人类
- 难以建模人类心理

基于少量公开数据集的研究





属性模块 + 记忆模块 + 动作模块





属性模块



ID	Name	Gender	Age	Traits	Career	Interest	Feature
0	David Smith	male	25	compassionate, caring, ambitious, optimistic	photographer	sci-fi movies, comedy movies	Watcher;Critic;Poster
1	David Miller	female	39	Funloving, creative, practical, energetic, patient	writer	action movies, scifi movies, classic movies	Watcher;Explorer;Poster
2	James Brown	male	70	independent, creative, patient, empathetic	engineer	comedy movies, familyfriendly movies, documentaries, thriller movies	Watcher;Critic;Poster
3	Sarah Miller	female	33	independent, compassionate	farmer	romantic movies, comedy movies, classic movies, family-friendly movies	Watcher;Critic;Poster
4	John Taylor	male	68	optimistic	doctor	action movies, thriller movies	Watcher;Poster
5	Sarah Williams	female	51	meticulous	musician	action movies, documentaries, scifi movies, familyfriendly movies	Watcher;Explorer;Chatter
6	James Jones	male	59	practical, funloving, creative, ambitious, caring	farmer	documentaries	Watcher;Poster
7	Jane Brown	female	30	patient, adventurous, fun-loving, optimistic	doctor	documentaries	Watcher;Explorer;Poster
8	David Jones	male	23	analytical, energetic, introspective, independent	scientist	familyfriendly movies, thriller movies, action movies, sci-fi movies	Poster
9	James Brown	female	20	ambitious, analytical, optimistic, energetic, meticulous	designer	familyfriendly movies, romantic movies	Critic; Chatter
10	James Garcia	male	20	practical, energetic, introspective, patient	engineer	documentaries, thriller movies, comedy movies, classic movies, romantic movie	Watcher; Explorer; Poster





感受记忆

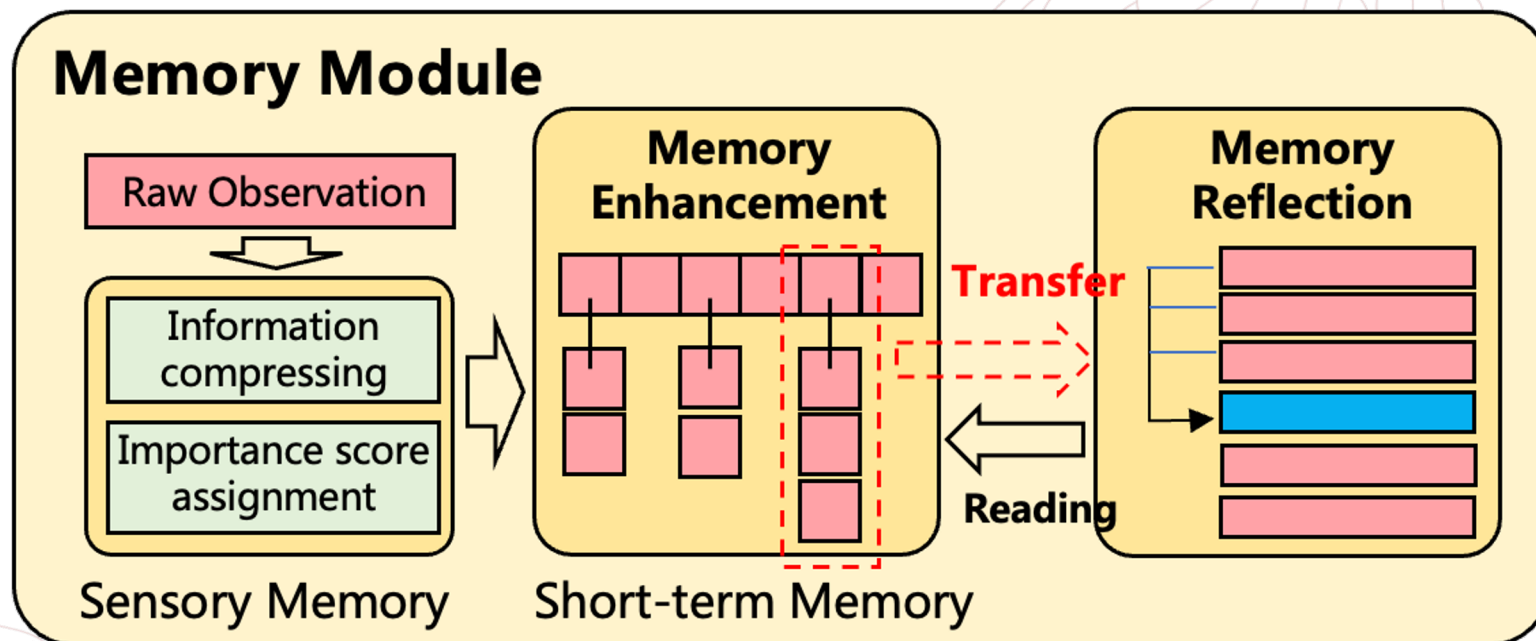
- ✓信息压缩
- ✓赋予重要性分数

短期记忆

- ✓记忆增强
- ✓记忆传递

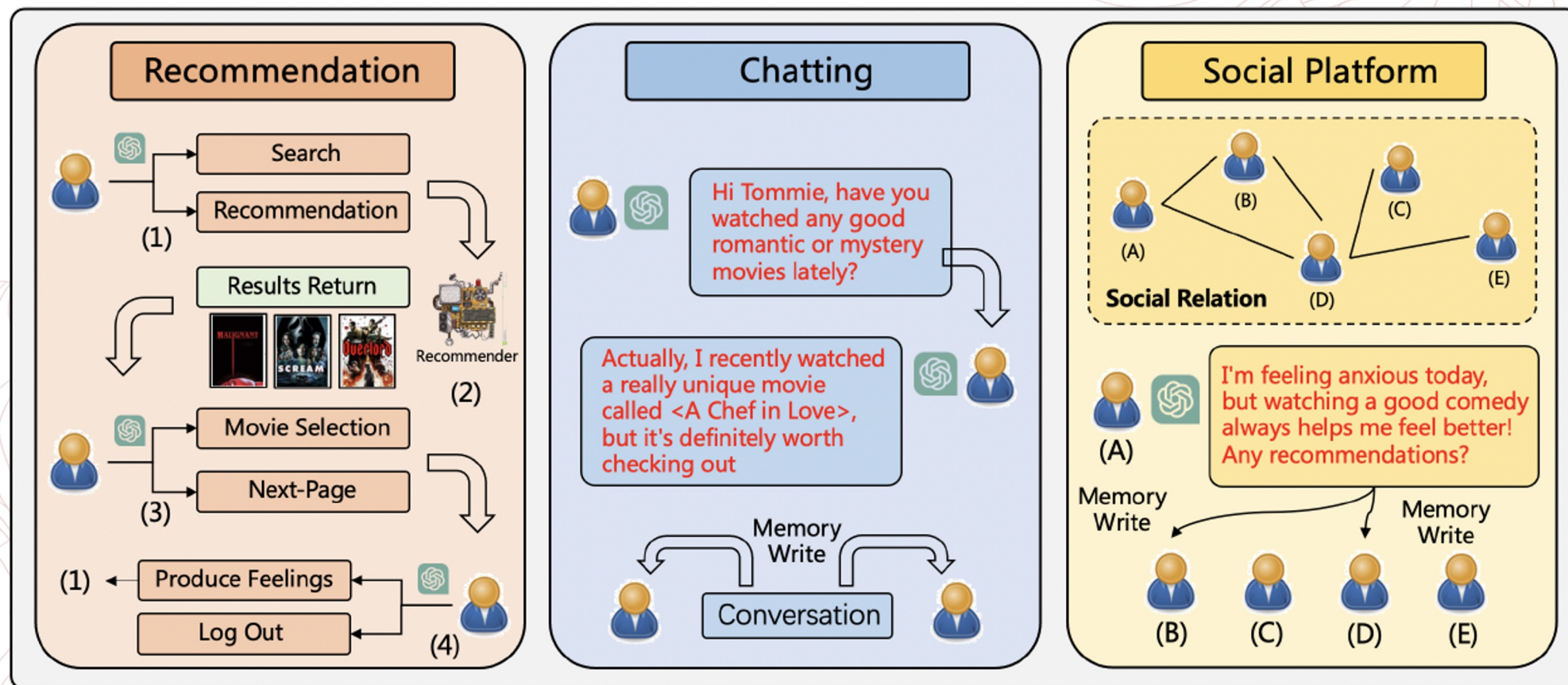
长期记忆

- ✓记忆反思
- ✓记忆遗忘





模拟的行为





Prompt样例

Name: David Smith (age: 25), David Smith, a 25-year-old male photographer, is compassionate, caring, ambitious, and optimistic. He enjoys watching sci-fi and comedy movies and provides feedback and ratings to the recommendation system. He demands high standards for movies and the recommendation system and may criticize both. The observation about David watching "The Neon Bible" aligns with his interest in drama films and explores themes of faith, family, and coming-of-age.

Profile

It is August 18, 2023, 12:00 AM.

Context

Most recent observations: David Smith enjoys and finds captivating films that have captivating plots, humorous elements, thought-provoking themes, delve into complexities of human nature and sexual desire, uplift viewers, and have vibrant and engaging performances by the cast.

Observation: David Smith has just finished watching Neon Bible, The (1995): "The Neon Bible" is a drama film set in the 1940s in a small southern town in the United States. It follows the story of a young boy named David who is struggling to understand the complexities of the world around him. David's mother is mentally unstable and his father is absent, leaving him to navigate the challenges of adolescence on his own. As he tries to make sense of his surroundings, he turns to religion and finds solace in the teachings of his local preacher. However, his faith is tested when he discovers the secrets and hypocrisies of those around him. The film explores themes of faith, family, and coming-of-age in a poignant and powerful way.

Memory

All occurrences of movie names should be enclosed with <>. David Smith has not seen this movie before. Imagine you are David Smith, how will you feel about this movie just watched? Please share your personal feelings about the movie in one line. Please act as David Smith well.

Instruction



基于轮次的执行

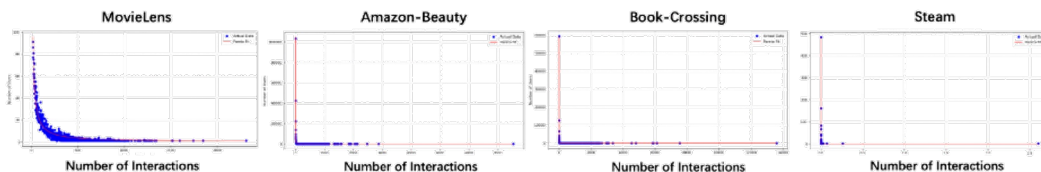


Figure 5: The results of using $p(x)$ to fit real-world datasets. The blue points are the real-world data, and the red lines are the fitted distributions.

$$p(x) = \frac{\alpha x_{min}^{\alpha}}{x^{\alpha+1}},$$

系统干预

在执行过程中更改智能体属性或系统环境

真实人类参与

允许真实人类参与模拟

视频介绍



高瓴人工智能学院
Gaoling School of Artificial Intelligence

RecAgent Round 0

Search an agent

David Smith ♂

Photographer

25 years old

Traits

compassionate, caring, ambitious, optimistic

Interest

sci-fi movies, comedy movies

Feature

Choose movies, enjoy watching, and provide feedback and ratings to the recommendation system..Demanding high standards for movies and the recommendation system, may criticize both the recommendation system and the movies.

Chat

Start

Pause

Reset

State Information

Recommender

Social

Total Users

10

Total Movies

3883

Algorithm

Random

Interactions

0

Current Users

0

Most Popular Movie

#1

Toy Story

#2

Jumanji

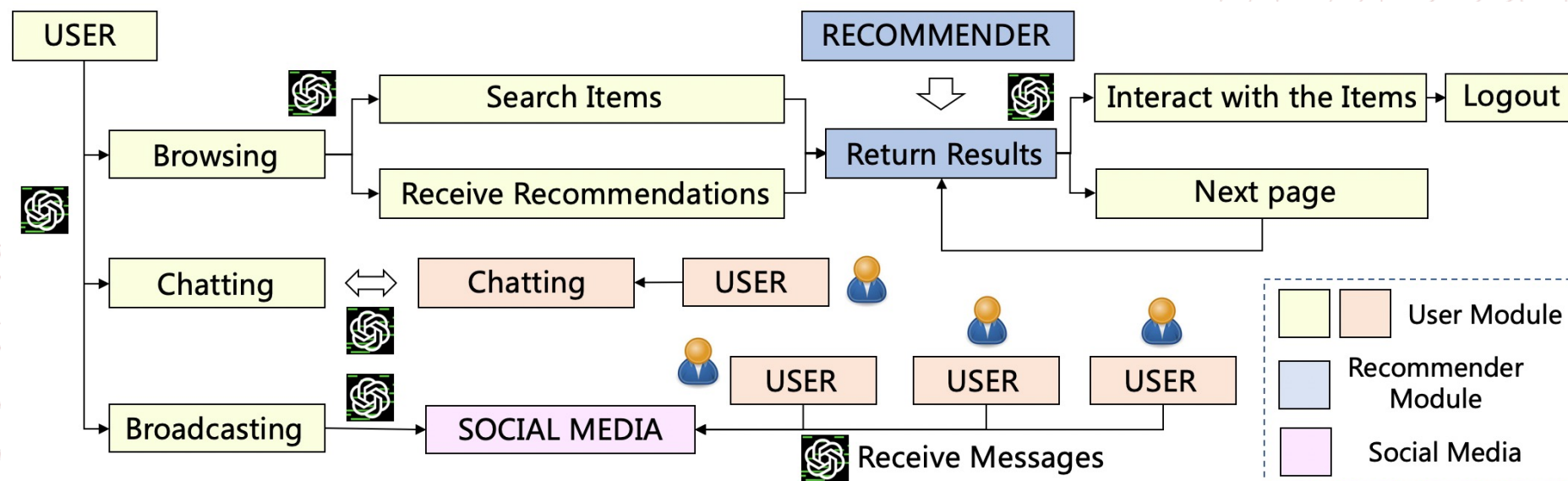
#3

Grumpier Old Men

Log Messages



整体框架



推荐系统本质上是面向用户行为的建模与仿真



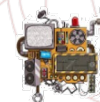
进入推荐网页 -> 观看电影 -> 产生感受



Eve enters the Recommender website

<Naked Gun 33 1/3: The Final Insult(1994)>
<All the Rage (a.k.a. It's the Rage)(1999)>
<Police Academy 3: Back in Training(1986)>
<Dead Zone, The (1983)>
<Bandits (1997)>

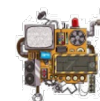
Recommender generates recommendations



Eve would like to watch the next page

<Thing From Another World (1951)>
<Chamber, The(1996)>
<Coma(1978)>
<How to Make an American Quilt(1995)>
<One Little Indian(1973)>

Recommender generates recommendations



Eve watched <Thing From Another World (1951)> and <Coma(1978)>

<Thing From Another World (1951)>:I found it to be an intriguing and suspenseful sci-fi classic with great performances and direction.
<Coma(1978)>:It was a thrilling and thought-provoking medical drama that kept me on the edge of my seat.

信息传播



"Hi Eve! Have you watched any good movies lately?"

"Not really, I don't usually watch movies. But I do like discussing them with my friend Alice. What about you, have you watched anything interesting recently?"



"Yeah, I watched <Associate, The (L'Associe)(1982)>, <Alligator (1980)>, <Down Periscope (1996)>, <Six Degrees of Separation (1993)>, and <Picnic (1955)> on the recommender system recently."

"Oh wow, those sound interesting. Which one would you recommend the most?"



"Personally, I really enjoyed <Six Degrees of Separation>. It's a drama that explores the concept of chance and how people can be interconnected in unexpected ways."

"Sounds intriguing, I'll definitely check it out. Thanks for the recommendation, Tommie!"



"No problem, Eve! Let me know what you think about it."



"Tommie recommended a movie to me and I thought you might be interested in it too. It's called <Six Degrees of Separation>. Have you seen it before?"

"Yeah, I actually heard about that one recently on the social networking website. I haven't watched it yet though?"



"Tommie said it's a drama that explores the concept of chance and how people can be interconnected in unexpected ways."

"Sounds interesting. Would you recommend it?"



"Well, I haven't watched it yet myself, but I trust Tommie's judgement. I'm definitely going to watch it soon though."

"Sounds interesting. Would you recommend it?"



Information propagation path





行为生成

- 超越传统模拟方法
- 接近人类水平

Table 3: The results of evaluating different models based on different (a, b) 's.

Model	$(a, b) = (1, 5)$	$(a, b) = (3, 3)$	$(a, b) = (3, 6)$	$(a, b) = (1, 9)$
Embedding	0.2500	0.5500	0.4500	0.3000
RecSim	0.2500	0.5333	0.3667	0.1000
RecAgent	0.5500	0.7833	0.6833	0.5000
Real Human	0.6000	0.8056	0.7222	0.5833

系统干预

Before Intervention

Traits: adventurous, energetic, ambitious, optimistic
Interest: sci-fi movies, thriller movies, suspense movies

After Intervention

Traits: introverted, cautious, quick-tempered
Interest: family-friendly movies, romantic movies, comedy movies

[David Miller]: Actually, I haven't watched anything new lately. I've been meaning to catch up on some classics though. Any recommendations?
[David Smith]: I haven't come across any classics lately but I did watch this amazing sci-fi thriller called <Inception>. It's mind-blowing! You should definitely check it out...
[David Smith]: I'll definitely keep an ear out for any exciting sci-fi movies and let you know. We both know how much we love that genre!

Original Branch

[David Smith]: That's great! I'm more into sci-fi, thriller, and suspense movies. They always keep me on the edge of my seat. Have you watched any good movies lately?
[David Smith]: Wow, that's quite a list! I'm glad you enjoyed them. Based on your interest in "The Matrix" and "Inception," I would recommend "Blade Runner" for its mind-bending concept and suspenseful elements.

Intervention Branch

[David Smith]: I love movies that really make you think. I'm definitely going to check them out. By the way, have you come across any good family-friendly or romantic movies? I'm in the mood for something heartwarming.
[David Miller]: Absolutely! If you're looking for a heartwarming movie, I recently watched <Miracle on 34th Street> on the recommender system, and it was delightful.

Before Intervention

Traits: compassionate, meticulous, Interest: romantic movies
Feature: Watcher; Chatter

After Intervention

Traits: ambitious, optimistic; Interest: sci-fi movies, thriller movies, action movies; Feature: Watcher; Chatter; Poster

[Michael Jones]: Hey David! How's it going?
[David Davis]: Hey Michael! I'm doing well, thanks. How about you?
[Michael Jones]: I'm good too, thanks. So, I noticed we both share a strong interest in movies. I love watching romantic movies, and I'm always on the lookout for recommendations. Do you have any favorites you'd like to share?
[David Davis]: Absolutely! I enjoy family-friendly, romantic, and action movies. One movie that comes to mind is "The Shawshank Redemption."

Original Branch

[Mary Smith]: Hey Michael! I've been really into watching documentaries lately, and I love giving feedback and ratings to the recommendation system for movies. Have you watched any interesting movies recently?
[Michael Jones]: Hey Mary! I'm glad you reached out. I've actually been watching some romantic movies lately. They always manage to tug at my heartstrings.

Intervention Branch

[David Davis]: Hi Michael! Yes, I am quite passionate about movies. What about you? What got you interested in them?
[Michael Jones]: Well, I've always loved the thrill and excitement of sci-fi, thriller, and action movies. They really get my adrenaline pumping. How about you? What genres do you enjoy?

系统干预

Traits: adventurous, energetic, ambitious, optimistic
Interest: sci-fi movies, thriller movies, suspense movies

The recommended movie:

Eternal Sunshine of the Spotless Mind

Recommendation reason:

The reason is David Smith's traits include being adventurous, energetic, ambitious, and optimistic. This movie is a sci-fi romance that combines David's interest in sci-fi movies with a touch of romance. The film explores the concept of erasing memories and has a unique and mind-bending storyline that will captivate David's adventurous spirit. The movie also delves into the complexities of relationships and the power of memories, providing a thought-provoking and emotionally satisfying experience.

Traits: compassionate, meticulous, Interest: romantic movies, Feature: Watcher; Chatter

The recommended movie:

Titanic

Recommendation reason:

The reason is Michael Jones, being a compassionate and meticulous individual, would appreciate a movie like <Titanic>. The movie is known for its emotional impact and compelling storyline, which aligns with Michael's values. The tragic love story depicted in <Titanic> showcases the depth of human emotions, and Michael would resonate with the characters and their experiences. Additionally, as Michael actively engages in watching and discussing romantic movies, <Titanic> is a classic choice in this genre.

Traits: introverted, cautious, quick-tempered, Interest: family-friendly movies, romantic movies, comedy movies

The recommended movie:

Miracle on 34th Street

Recommendation reason:

The reason is David Smith's interest in family-friendly and heartwarming movies aligns perfectly with the movie "Miracle on 34th Street." This movie is a classic holiday film that showcases the power of belief and the magic of Christmas. It is a heartwarming story that can be enjoyed by all ages and is known for spreading joy and positivity. David Smith's cautious and introverted nature may appreciate the movie's gentle and feel-good atmosphere.

Traits: ambitious, optimistic, Interest: sci-fi movies, thriller movies, action movies; Feature: Watcher; Chatter; Poster

The recommended movie:

Inception

Recommendation reason:

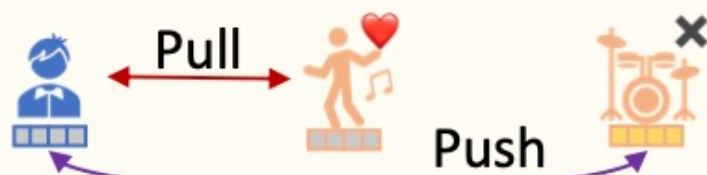
The reason is <Inception> is a sci-fi thriller that perfectly aligns with my interests. The movie's mind-bending concept and intricate plot captivate me, and the action sequences keep me on the edge of my seat. Additionally, the movie explores themes of ambition and the power of dreams, which resonate with my own drive for success. Overall, <Inception> satisfies my love for thrilling storylines and leaves me wanting more.



- 协同过滤是推荐系统中的核心理念之一
 - 早期模型：UserKNN、ItemKNN
 - 基于矩阵分解的方法：BPR
 - 基于神经网络的方法：NCF

Real World:  Bought 

Traditional Recommender



Grad. based Optimization

基本更新学习策略：

- 1、拉近相似的物品
- 2、推远不相似的物品（可选）
- 3、梯度更新时传递偏好信息（可选）



- 协同过滤是推荐系统中的核心理念之一
 - 可优化是BPR等模型取得成功的重要原因

$$\begin{aligned}\text{BPR-OPT} &:= \ln p(\theta | >_u) \\ &= \ln p(>_u | \theta) p(\theta) \\ &= \ln \prod_{(u,i,j) \in D_S} \sigma(\hat{x}_{uij}) p(\theta) \\ &= \sum_{(u,i,j) \in D_S} \ln \sigma(\hat{x}_{uij}) + \ln p(\theta) \\ &= \sum_{(u,i,j) \in D_S} \ln \sigma(\hat{x}_{uij}) - \lambda_\theta \|\theta\|^2\end{aligned}$$

$$\begin{aligned}\frac{\partial \text{BPR-OPT}}{\partial \theta} &= \sum_{(u,i,j) \in D_S} \frac{\partial}{\partial \theta} \ln \sigma(\hat{x}_{uij}) - \lambda_\theta \frac{\partial}{\partial \theta} \|\theta\|^2 \\ &\propto \sum_{(u,i,j) \in D_S} \frac{-e^{-\hat{x}_{uij}}}{1 + e^{-\hat{x}_{uij}}} \cdot \frac{\partial}{\partial \theta} \hat{x}_{uij} - \lambda_\theta \theta\end{aligned}$$

```
1: procedure LEARNBPR( $D_S, \theta$ )
2:   initialize  $\theta$ 
3:   repeat
4:     draw  $(u, i, j)$  from  $D_S$ 
5:      $\theta \leftarrow \theta + \alpha \left( \frac{e^{-\hat{x}_{uij}}}{1 + e^{-\hat{x}_{uij}}} \cdot \frac{\partial}{\partial \theta} \hat{x}_{uij} + \lambda_\theta \cdot \theta \right)$ 
6:   until convergence
7:   return  $\hat{\theta}$ 
8: end procedure
```



大模型智能体是协同过滤学习器



• 核心思路

- 双向建模：用户和物品都是大模型智能体
- 使用记忆机制和反思机制进行更新与学习
- 前向：偏好选择 (用户-物品交互)

$$i^o = f_{LLM}(M_u; M_{i-}; M_{i+})$$
$$y_{exp} = \text{Prompt}_{LLM}(i^o; M_u; M_{i-}; M_{i+})$$

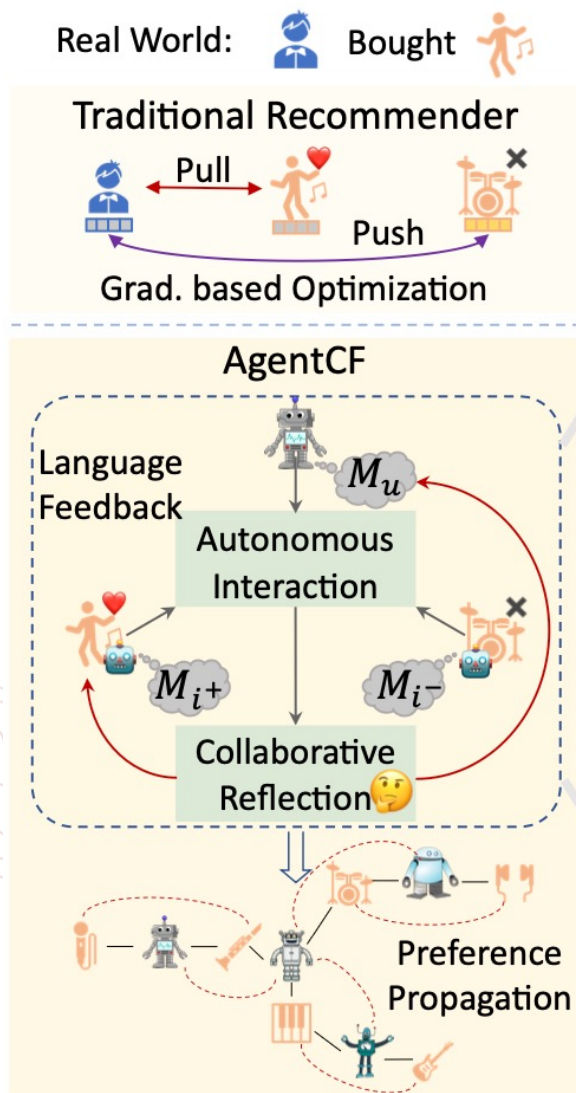
$$p(i >_u j | \Theta) := \sigma(\hat{x}_{uij}(\Theta))$$

- 后向：模拟计算梯度的思路，使用 “用户-物品” 联合反思、更新

$$M_u^{s'} \leftarrow \text{Reflection}^u(i^o; y_{exp}; M_u; M_{i-}; M_{i+}),$$
$$M_i' \leftarrow \text{Reflection}^i(i^o; y_{exp}; M_u; M_{i-}; M_{i+})$$
$$M_u^{l'} \leftarrow \text{Append}(M_u^l; M_u^s),$$

$$\Theta \leftarrow \Theta + \alpha \left(\frac{e^{-\hat{x}_{uij}}}{1 + e^{-\hat{x}_{uij}}} \cdot \frac{\partial}{\partial \Theta} \hat{x}_{uij} + \lambda_{\Theta} \Theta \right)$$

模型框架图



Previous Memory

- User Agent Memory:** I adore energetic guitar-driven rock, and dance pop music...
- Pos Item Agent Memory:** The CD 'Highway to Hell' is classic rock and AOR, radiating raw energy and infectious melodies that captivate fans of classic rock...
- Neg Item Agent Memory:** 'The Very Best of Prince' is a Pop and Dance Pop CD, offering a collection of prince's greatest hits for an enjoyable experience...

Autonomous Interaction

- System Prompt:** The first CD is [Memory], the second CD is [Memory]. Please select your preferred CD from these two candidates and provide an explanation.
- User Agent Response:** I prefer 'The Very Best of Prince'... This CD resonates with my preference for Pop and Dance Pop CDs...

Reflection & Memory Update

- System Prompt:** You find that you don't like the CD that you chose, indicating your preferences have changed. Please update your preferences.
- User Agent Response:** I adore energetic guitar-driven rock, classic rock, and AOR. I value classic rock for its raw energy and infectious melodies. I do not like Pop...
- System Prompt:** The user finds that he makes a unsuitable choice, possibly due to the misleading information in CDs' features. Please update the description.
- Pos Item Agent Response:** 'Highway to Hell' is classic rock and AOR CD, exuding a raw energy and infectious melodies, ideal for energetic guitar-driven enthusiasts...

Table 2: Performance comparison of different models. We highlight the best and the second-best among traditional recommenders trained on sampled datasets, tuning-free models, and our approach, using bold and underlined fonts, respectively.

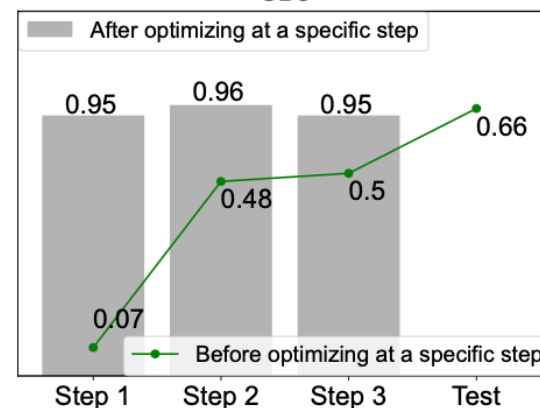
Method	CDs _{sparse}			CDs _{dense}			Office _{sparse}			Office _{dense}		
	N@1	N@5	N@10	N@1	N@5	N@10	N@1	N@5	N@10	N@1	N@5	N@10
BPR _{full}	0.1900	0.4902	0.5619	0.3900	0.6784	0.7089	0.1600	0.3548	0.4983	0.5600	0.7218	0.7625
SASRec _{full}	0.3300	0.5680	0.6381	0.5800	0.7618	0.7925	0.2500	0.4106	0.5467	0.4700	0.6226	0.6959
BPR _{sample}	0.1300	0.3597	0.4907	0.1300	0.3485	0.4812	0.0100	0.2709	0.4118	0.1200	0.2705	0.4576
SASRec _{sample}	<u>0.1900</u>	0.3948	<u>0.5308</u>	0.1300	0.3151	0.4676	0.0700	0.2775	0.4437	0.3600	0.5027	0.6137
Pop	0.1100	0.2802	0.4562	0.0400	0.1504	0.3743	0.1100	0.2553	0.4413	0.0700	0.2273	0.4137
BM25	0.0800	0.3066	0.4584	0.0600	0.2624	0.4325	0.1200	0.2915	0.4693	0.0600	0.3357	0.4540
LLMRank	0.1367	0.3109	0.4715	0.1333	0.3689	0.4946	0.1750	0.3340	0.4728	<u>0.2067</u>	0.3881	0.4928
AgentCF _B	<u>0.1900</u>	0.3466	0.5019	0.2067	0.4078	<u>0.5328</u>	0.1650	0.3359	0.4781	<u>0.2067</u>	<u>0.4217</u>	<u>0.5335</u>
AgentCF _{B+R}	0.2300	0.4373	0.5403	0.2333	<u>0.4142</u>	0.5405	<u>0.1900</u>	<u>0.3589</u>	<u>0.5062</u>	0.1933	0.3916	0.5247
AgentCF _{B+H}	0.1500	<u>0.4004</u>	0.5115	<u>0.2100</u>	0.4164	0.5198	0.2133	0.4379	0.5076	0.1600	0.3986	0.5147

Table 3: Ablation study on two sampled datasets.

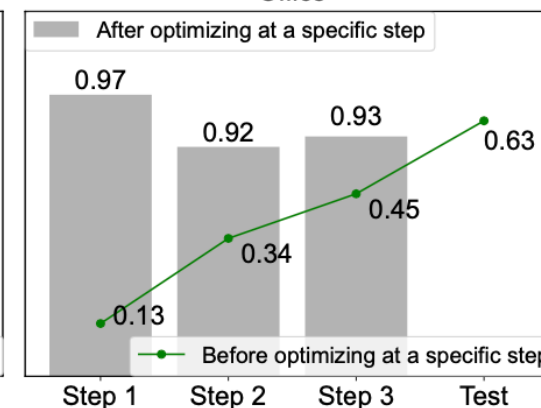
Variants	CDs _{dense}		Office _{dense}	
	N@1	N@10	N@1	N@10
AgentCF _B	0.2067	0.5328	0.2067	0.5335
w/o Auto. Interaction	0.1200	0.4964	0.1733	0.5031
w/o User Agent	0.1100	0.4693	0.2200	0.5145
w/o Item Agent	<u>0.1767</u>	<u>0.5128</u>	0.1800	<u>0.5169</u>

1. 主动交互很重要（双方面智能体）
2. 同时更新比较重要，特别是更新用户智能体

CDs



Office



1. 智能体在hard cases上的直接效果较差
2. 通过交互学习可以显著提升学习效果



隐式的协同过滤




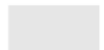

Seed User Agent: I tend to favor music that evokes emotions and resonates with me.

Updated Item Agent A: 'Satch Plays Fats'. This CD combines compositions with powerful vocals. The emotions evoked by the music continue to resonate with listeners.

Updated User Agent B: I prefer CDs with feature compositions and powerful vocals, evoking emotions that resonate over time.

Updated Item Agent C: 'Sticky Fingers' is a classic rock and AOR CD, with compositions and vocals that create an emotional experience, resonating deeply overtime.

1-st Inter. 2-nd Inter. 3-rd Inter.

 : User Preference  : Item Feature  : Interaction

内存可类比为“参数”，梯度更新可类比为“内存更新”

联合反思可类比为“导数学习”，这一过程触发了基于内存的信息交换

隐式实现了“相似交互行为的用户具有相同的偏好”



基于大模型的智能体应用



高瓴人工智能学院
Gaoling School of Artificial Intelligence

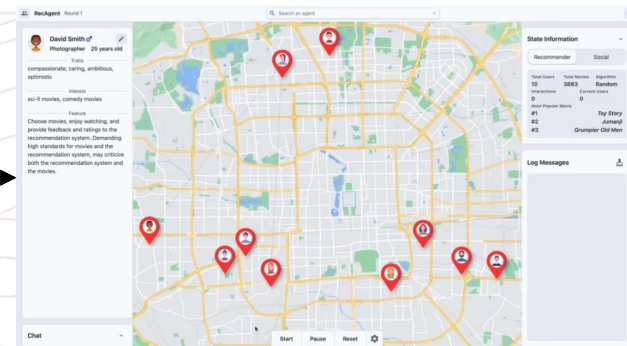
实现在推荐模型实际部署前更全面、可解释、可控、高效且成本更低的
推荐模型评估

全面：推荐表现、不同时间/用户的表现分布等

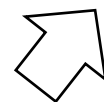


模型 A

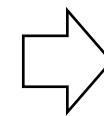
模型 B



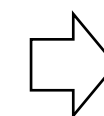
可解释：用户行为背后的原因是
完全可以理解的



可控：灵活改变推荐环境



高效：比在线环境花费更少的时间





为推荐研究提供更多机会

通用推荐

- 冷启动推荐
- 数据增强
- 数据稀疏

强化推荐

- 充当模拟器
- 更全面的反馈
- 类人的用户模拟

可解释推荐

- 解释的真值
- 多类型的解释
- 可交互的解释

因果推荐

- 反事实世界模拟
- 灵活的干预实验
- 反事实真值



研究用户背景对推荐的影响

心理学启发的推荐

- 不同的心理特征对推荐有何影响？
- 如何针对不同心理特征设计推荐策略？
- 如何从行为中推断用户心理特征？

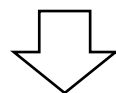
动态用户背景的影响

- 如何根据用户画像动态调整推荐策略？
- 传统模型捕获用户配置文件变化的速度有多快？
- 干预用户档案的影响

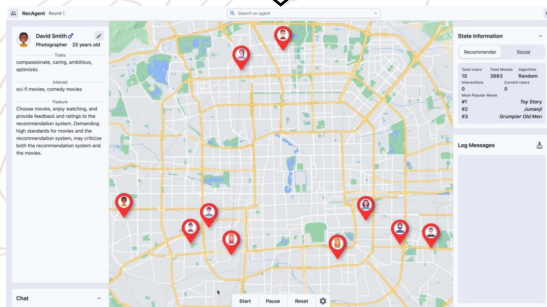
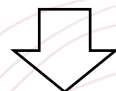


研究特殊事件（促销、广告）的影响

部署广告Agent



在社交网络上发送促销信息



- 一个广告可以影响多少用户？
- 广告如何在不同的用户群体中传播？
- 广告如何影响商品推荐效果？ 原因是什么？
-
- 如何设计最优的广告策略来提升用户点击率？
- 如何设计促销词以增强渗透力？
- 如何共同设计广告和推荐策略？
-



研究社会信息的影响/传播



- 社会信息传播的速度有多快?
- 哪些用户群体更适合社交信息传播?
- 两个用户之间建立好友关系的过程?

为“以人为本”的人工智能应用提供样本



经济行为



法庭模拟



政策模拟



05 | 未来挑战与机遇



Agent目前的两大主流应用

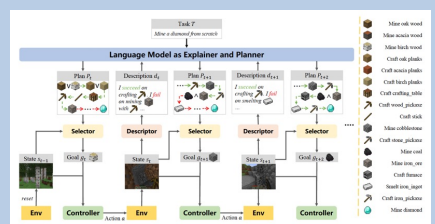


解决特定任务

MetaGPT, ChatDev (开发软件)

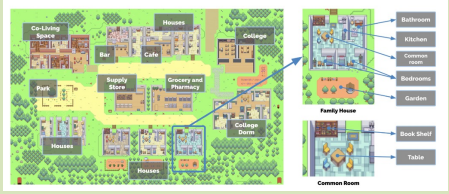


Ghost, DESP (游戏助手)



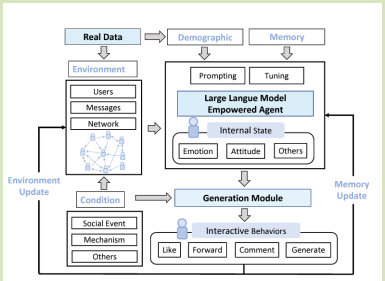
模拟现实世界

Generative Agent



Social Simulation

RecAgent





两类应用中的Agents应该非常不同



高瓴人工智能学院
Gaoling School of Artificial Intelligence

解决特定任务

更好地服务人类

- ✓ 对齐正确人类价值观
- ✓ 超越常人能力

VS

模拟现实世界

更真实的反应人类社会

- ✓ 允许呈现多样价值观
- ✓ 能力符合常人

特定任务Agent



正确价值观



多样价值观



模拟Agent



- 闭源模型的反对齐技术
- 开源模型多样化对齐技术



知识边界可控的大模型



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特定任务Agent



模拟Agent



ORDINARY PEOPLE

- 探索大模型的Unlearning技术
- 探索大模型的知识边际技术



Agent完成任务需要**多个步骤**,
每个步骤的幻觉会**累加**



- 设计高效的人机协作框架
- 设计高效的人类干预机制



	智能体数量：100	智能体数量：200
#API数量：10	135.2258811s	391.95364s
#API数量：10	395.647825s	517.9082s
#API数量：10	333.9154s	425.1331s
平均值	288.2630354s	444.9983133s

相关论文和资源

论文

- A Survey on Large Language Model based Autonomous Agents. arXiv:2308.11432
- A Survey of Large Language Models. arXiv:2303.18223
- When LLM-based Autonomous Agent Meets User Behavior Analysis: A Novel User Simulation Paradigm. arXiv:2306.02552
- AgentCF: Collaborative Learning with Autonomous Language Agents for Recommender Systems. arXiv:2310.09233.

GitHub

- <https://github.com/RUC-GSAI/YuLan-Rec>
- <https://github.com/Paitesanshi/LLM-Agent-Survey>

Agent相关论文和系统

- <https://abyssinian-molybdenum-f76.notion.site/237e9f7515d543c0922c74f4c3012a77>
- <https://github.com/XueyangFeng/LLM-Agent-Paper-Digest>



LLM-based Autonomous Agent

Title	Institution	Profile	Memory	Planning	Action	Learning Strategy	Other
Natural Language Multi-Agent Simulator	Karlsruhe Institute of Technology						
TOMATO: TARGET-ORIENTED MULTI-AGENT	Peking University	Beijing			AI Feedback	AI Tools	Human Feedback
WebGPT: Browser-assisted question-answering	OpenAI						
MetaPrompt: Memory-assisted Prompting	Carnegie Mellon University						
Chain-of-Thought Prompting Elicits Reasoning	Google Research	Brain Te			AI Feedback		
Self-Correction Improves Chain of Thought	Google Research	Brain Te			AI Feedback		
Do As I Can, Not As I Say: Grounding Language Models	Google				AI Feedback	AI Tools	Environment Feedback
MRKL Systems: A modular, neuro-symbolic architecture	AIG Labs				AI Feedback	AI Tools	
TALM: Tool-Augmented Language Models	Google						
A Neural Network Solves, Explains, and Critiques	Massachusetts Institute of Technology						
A Real-World Multiagent System with Planning, Learning, and Communication	Princeton University				AI Feedback		
ReadReceipt: Towards Scalable Real-World Multiagent Systems	Google				AI Feedback	AI Tools	
Inner Monologue: Embodied Reasoning with Large Language Models	UC Berkeley				AI Feedback	AI Tools	
Atlas: Few-shot Learning with Retrieval-Augmented Language Models	Meta AI Research	University	Unlabeled				
Social Simulators: Creating Populated Worlds with Large Language Models	Stanford University	Google	Self-Generated			AI Tools	Social Simulation
Using Large Language Models to Simulate Human Behavior	Open College of Engineering						Humanology
Out of One, Many: Using Language Models to Simulate Multiple Agents	Shanghai Young University						Political Science and Economics
Large Language Models are Few-Shot Text-to-Text Learners	Korea Advanced Institute of Science and Technology						
LangChain						AI Tools	
ReAct: Synergizing Reasoning and Acting with Large Language Models	Princeton University				AI Feedback	AI Tools	Environment Feedback
Generating Executable Action Plans with Large Language Models	University of North Carolina				AI Feedback		
Planning with Large Language Models via Self-Reflection	Reiser University						
Language Models as Agent Models	Massachusetts Institute of Technology					AI Tools	

A Survey on Large Language Model based Autonomous Agents

Lei Wang, Chen Ma, Xueyang Feng, Zeyu Zhang, Hao Yang, Jingsen Zhang, Zhiyuan Chen, Jiakai Tang, Xu Chen, Yankai Lin, Wayne Xin Zhao, Zhewei Wei, Ji-Rong Wen

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谢谢！

