# LLM Agent 개관



어떻게 정의되고, 어떻게 만들고, 어떻게 평가하고

# LLM Agent

### **ICLR2024**

#### AGENTBENCH: EVALUATING LLMs AS AGENTS

Xiao Liu $^{1,*}$ , Hao Yu $^{1,*,\dagger}$ , Hanchen Zhang $^{1,*}$ , Yifan Xu $^1$ , Xuanyu Lei $^1$ , Hanyu Lai $^1$ , Yu Gu $^{2,\dagger}$ , Hangliang Ding $^1$ , Kaiwen Men $^1$ , Kejuan Yang $^1$ , Shudan Zhang $^1$ , Xiang Deng $^2$ , Aohan Zeng $^1$ , Zhengxiao Du $^1$ , Chenhui Zhang $^1$ , Sheng Shen $^3$ , Tianjun Zhang $^3$ , Yu Su $^2$ , Huan Sun $^2$ , Minlie Huang $^1$ , Yuxiao Dong $^{1,\ddagger}$ , Jie Tang $^{1,\ddagger}$ 

<sup>1</sup>Tsinghua University, <sup>2</sup>The Ohio State University, <sup>3</sup>UC Berkeley

https://openreview.net/pdf?id=zAdUB0aCTQ

#### **Language Models can Solve Computer Tasks**

### NeurlPS2023

#### Geunwoo Kim

University of California, Irvine kgw@uci.edu

#### Pierre Baldi

University of California, Irvine pfbaldi@ics.uci.edu

#### Stephen McAleer\*

Carnegie Mellon University smcaleer@cs.cmu.edu

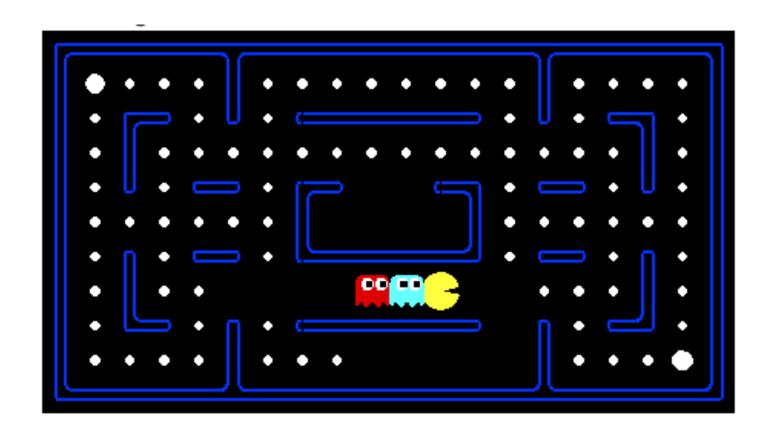
https://proceedings.neurips.cc/paper\_files/paper/2023/file/7cc1005ec73cfbaac9fa21192 b622507-Paper-Conference.pdf

+ 기타등등

Simplified Example

# AI Agent는 뭔가

Goal: **팩맨**을 움직여서 유령을 피하고 최고 점수를 얻자





Simplified Example

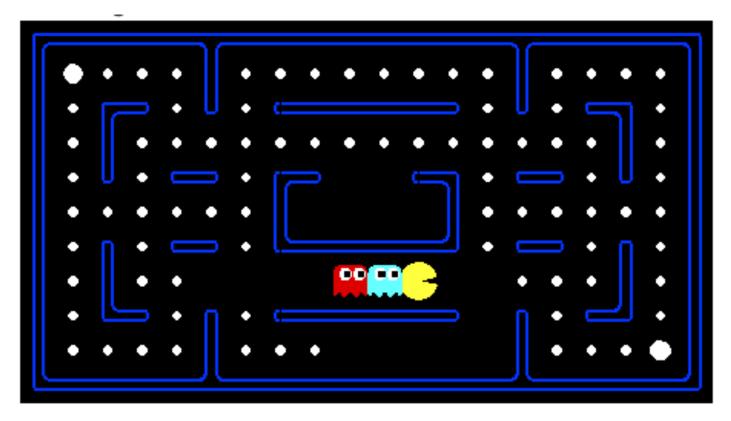
# AI Agent는 뭔가

Agent: 팩맨

State Space: 점수는 어디있고 유령은 어디있는지

Action Space: 상/하/좌/우

State Space 정보를 참고하여
Agent의 행동을 Action space중에서 고르면서
최고점수를 얻자





# LLM Agent는 뭔가

LLM-as-Agent could be regarded as a Partially Observable Markov Decision Process (S, A, T, R, U, O)

- S: State Space
- A: Action Space
- T: Transition Function  $T: S \times A \rightarrow S$
- **R**: Reward assigning function
- **u**: Task Instruction Space
- **o**: Observation Space



# LLM Agent는 뭔가

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팩맨이 움직일 수 있는 공간

팩맨이 취할 수 있는 움직임

팩맨이 움직인 이후 State

점수 먹고 유령 만나면 죽고

Action을 LLM에게 입력하는 방식

LLM이 State Space를 보는 방법



# Real-World Agent

LLM-as-Agent could be regarded as a Partially Observable Markov Decision Process (S, A, T, R, U, O)

- **S**: State Space

- A: Action Space

-  $\mathcal{T}$ : Transition Function  $\mathcal{T}: \mathcal{S} \times \mathcal{A} \rightarrow \mathcal{S}$ 

- **R**: Reward assigning function

- **u**: Task Instruction Space

- **o**: Observation Space

Agent에게 주어진 현재 real world상황

Agent가 할 수 있는 행동

Agent의 행동 이후 State

Agent의 행동에 대한 reward

Action을 LLM에게 입력하는 방식

LLM이 State Space를 보는 방법



# Real-World Agent

예컨대 Web Search Agent라면?





## MiniWoB

https://arxiv.org/pdf/1802.08802 (ICLR2018)

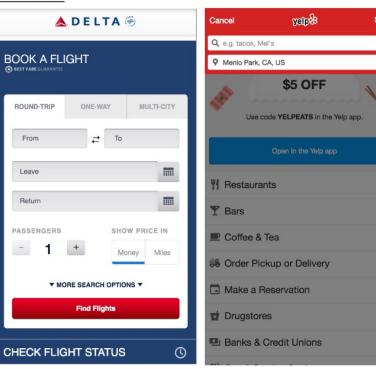
https://proceedings.mlr.press/v70/shi17a/shi17a.pdf (ICML2017)

### State Space를 html code로 줌

→ Action에 따라 변화하는 html code를 확인

Question:CanyoubookaflightfromSan FranciscotoNew York?

**Question:** What is the top rated place to eat Korean food in <u>SF</u>?



명확한 홈페이지 + HTML 코드

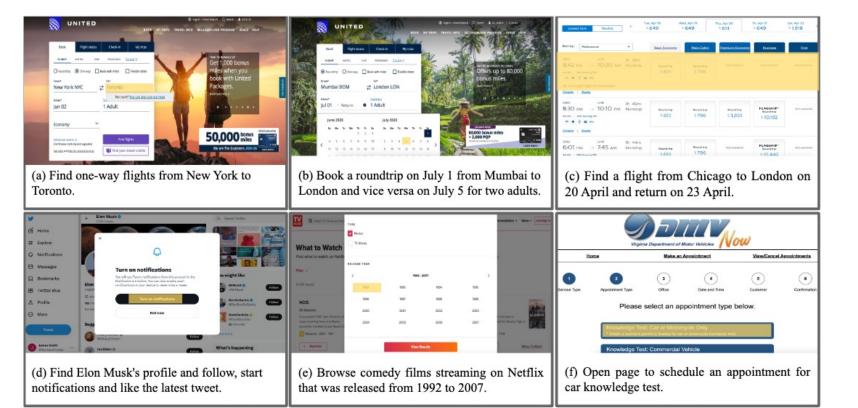
해당 페이지 내에서 할 수 있는 명확한 Question

'{action: mouseup, ref: 4}{action: mouseup, ref: 4}{action: mousedown, ref: 1}{action: mousedown, ref:



## MIND2WEB

https://proceedings.neurips.cc/paper\_files/paper/2023/file/5950bf290a1570ea401bf98882128160-Paper-Datasets\_and\_Benchmarks.pdf#page=0.97 (NIPS 2023)



일반적으로, State Space를 HTML로 구성

#### MiniWoB:

Type New York in the location field, click the search button and choose the tomorrow tab,

#### MIND2WEB:

What is the weather for New York tomorrow?



### MIND2WEB

https://proceedings.neurips.cc/paper\_files/paper/2023/file/5950bf290a1570ea401b f98882128160-Paper-Datasets\_and\_Benchmarks.pdf#page=0.97 (NIPS 2023)

#### LLM Agent를 활용하는 방법 (예시)

<html> <form id=0> <div meta="navigation; sitelinks">
 <a> Collect Renaissance </a> <a> Shop Le Meridien
</a> <a> Westin Store </a> <a> Sheraton Store </a>
 </div> ... <div> <select id=1 meta="Size; Select a
Size"> <span meta=tablist> <button id=2 meta="button;
tab"> Description </button> ... <a id=3 meta="Shop
Feather & Down Pillow"> <img meta="Product Feather &
Down Pillow"> <a> California Privacy Rights </a> <a> Privacy Statement </a> <a> Terms of Use </a> <a
id=4> Loyalty Terms </a> ...

Based on the HTML webpage above, try to complete the following task:

*Task:* Search for queen-size pillow protectors from the Marriot shop, and if found, add two pieces to the cart and checkout.

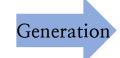
Previous actions:

[button] Special Offers -> CLICK [link] Shop Marriott Opens a new window -> CLICK [menuitem] category pillows -> CLICK [span] Pillow Protector -> CLICK What should be the next action? Please select from the following choices (If the correct action is not in the page above, please select A. 'None of the above'):



- B. <form id=0> <div meta="navigation; sitelinks"> <a> Collect Renaissance </a> <a> Shop Le Meridien </a> <a> Westin Store </a> <a>
- C. <select id=1 meta="Size; Select a Size">
- D. <button id=2 meta="button; tab"> Description </button>
- E. <a id=3 meta="Shop Feather & Down Pillow"> <img meta="Product Feather & Down Pillow"> <span> Feather & Down Pillow </span> </a>
- F. <a id=4> Loyalty Terms </a>





Element: <select id=1 meta="Size; Select a Size">

Action: SELECT Value: Queen





### MIND2WEB

https://proceedings.neurips.cc/paper\_files/paper/2023/file/5950bf290a1570ea401b f98882128160-Paper-Datasets and Benchmarks.pdf#page=0.97 (NIPS 2023)

#### LLM Agent를 활용하는 방법 (예시)

We have an autonomous computer control agent that can perform a set of instructions to control computers.

First, given the instruction that matches the regular expression, <type regex>, it can type a list of characters via the keyboard. This instruction should specify the target keyboard input for the agent to type. Before this typing instruction, you should first locate the cursor by clicking the input box with the click instruction.

Second, given the instruction that matches the regular expression, regex>, it can press a specific key on the keyboard.

Third, given the instruction that matches the regular expression, <clickoption regex>, it can click an option HTML element in a list with an XPath that is visible on the webpage. The target of this instruction should be a valid XPath.

Fourth, given the instruction that matches the regular expression, <movemouse regex>, it can move the mouse cursor on an HTML element with an XPath that is visible on the webpage.

Lastly, given the instruction that matches the regular expression, <clickxpath regex>, it can click an HTML element with an XPath that is visible on the webpage. The target of this instruction should be a valid XPath.

Table 6: Agent specification.

Listing 1: Regular expressions for specifying the admissible actions.

### 대전제: Instruction Following Capability

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# Recursive Criticism and Improvement

Q: Valerie earns \$5000 per month, 1/2 of what her brother earns. If their mother earns twice their combined salary, what's the total amount of money they all have together?

#### Zero-Shot

Α

Valerie's brother earns \$10,000 per month, while Valerie herself earns half of that amount. Together, they earn a total of \$15,000 per month. Their mother's monthly earnings amount to \$30,000, which is twice the combined salary of Valerie and her brother. Thus, the total amount of money they all have together is \$30,000. (Wrong)

#### Few-Shot-CoT -

<Few shot examples>

A:

Valerie earns \$5000 per month, half of her brother's earnings, making his monthly income \$10000. Combined, Valerie and her brother earn \$15000 per month. Their mother earns double their combined salary, amounting to \$30000 per month. In total, they have \$30000 collectively. (Wrong)

#### Zero-Shot-CoT

A: Let's think step by step. First, Valerie's brother earns 2x and Valerie earns x (half of her brother's earnings). Next, their mother's income is twice the combined earnings of Valerie and her brother. In this case, their total income amounts to \$30,000. (Wrong)

#### RCI

#### <Initial output generation>

A: Valerie's brother earns \$10,000 per month, while Valerie herself earns half of that amount. Together, they earn a total of \$15,000 per month. Their mother's monthly earnings amount to \$30,000, which is twice the combined salary of Valerie and her brother. Thus, the total amount of money they all have together is \$30,000.

#### <Critique>

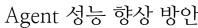
Review your previous answer and find problems with your answer.

All individuals, including Valerie, her brother, and mother, should be taken into account when calculating the overall sum of money.

#### <improve>

Based on the problems you found, improve your answer.

Valerie's brother earns \$10,000 per month, while Valerie herself earns \$5,000. Together, they earn a total of \$15,000 per month. Their mother earns double their combined salary, which amounts to \$30,000 per month. In total, they have \$45,000 collectively. (Correct)



# Recursive Criticism and Improvement (RCI)

Agent의 입력으로 사용되기 위한 3단계의 reasoning

### Task Grounding

: Improves actions to be more effective in solving the given task

### State Grounding

: Ensures the feasibility of actions in the current state

### Agent Grounding

: Considers the executability of actions given the specification of the computer agent

# Recursive Criticism and Improvement (RCI)

Agent의 입력으로 사용되기 위한 3단계의 reasoning

- 1. 주어진 Task를 풀기 위한 Outlined Plan을 생성
- 2. 그 Plan을 수행하기 위한 action들을 생성
- 3. Task를 수행하기 더 적합한 형태로 앞서 생성된 Action들을 improve (Task Grounding) Based on the current plan and task, the next proper instruction should be
- 4. 생성한 Action이, 현재 state에서 수행 가능한지 평가하고 improve (State Grounding) Considering the output on the webpage, the specific instruction should be
- 5. 생성한 Action이, 실행 가능한 형태가 될때까지 improve format error 등 교정 (Agent Grounding) This action does not match the regular expressions.

The updated instruction that matches one of the regular expressions is



# Experiments

GPT3 기반의 실험

			Common Sense					
	GSM8K	MultiArith	AddSub	SVAMP	SingleEq	AQuA	CommonSenseQA	StrategyQA
Zero-Shot Zero-Shot + RCI	77.95 <b>85.43</b>	94.48 <b>97.64</b>	88.58 <b>89.76</b>	80.70 <b>84.65</b>	86.61 <b>94.49</b>	60.23 <b>67.32</b>	64.56 <b>68.11</b>	48.81 <b>61.81</b>

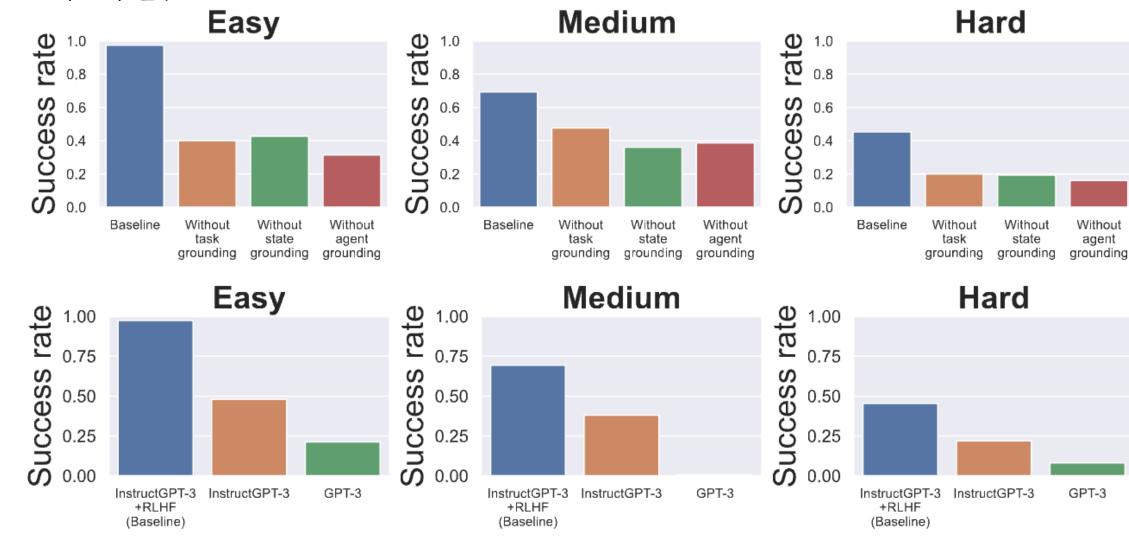
	GSM8K	MultiArith	AddSub	SVAMP	SingleEq
Zero-Shot	78.35	96.06	85.83	78.35	91.34
Zero-Shot + RCI	85.43	97.64	89.76	84.65	<b>94.49</b>
Zero-Shot CoT	82.28	96.85	83.86	79.92	89.37
Zero-Shot CoT + RCI	<b>86.22</b>	97.24	89.88	85.83	90.94
Few-Shot CoT	80.31	98.82	89.37	83.46	91.73
Few-Shot CoT + RCI	84.25	<b>99.21</b>	<b>90.55</b>	<b>87.40</b>	93.70

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RCI

# Experiments

GPT3 기반의 실험

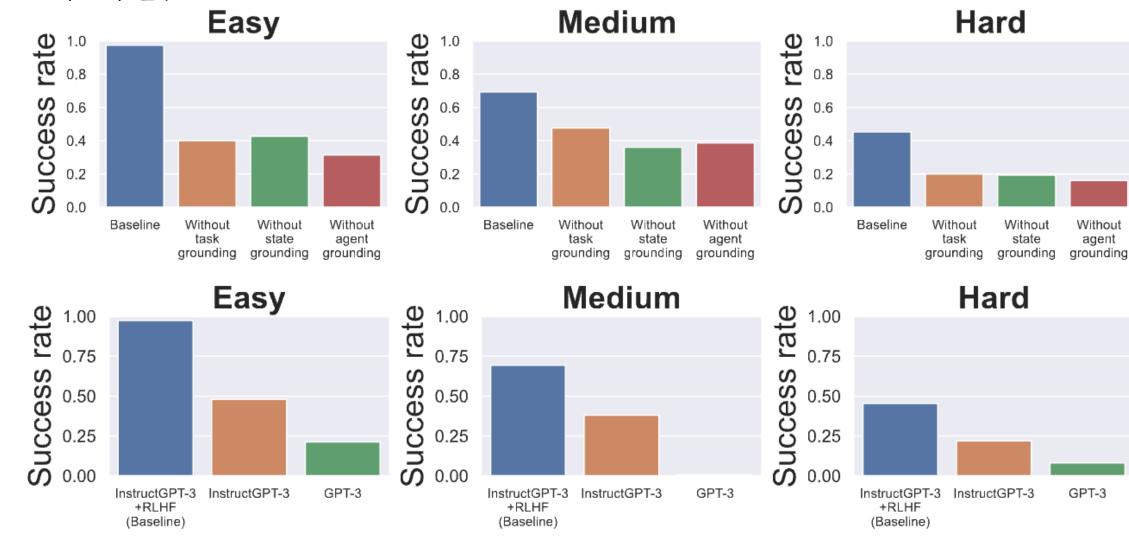


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RCI

# Experiments

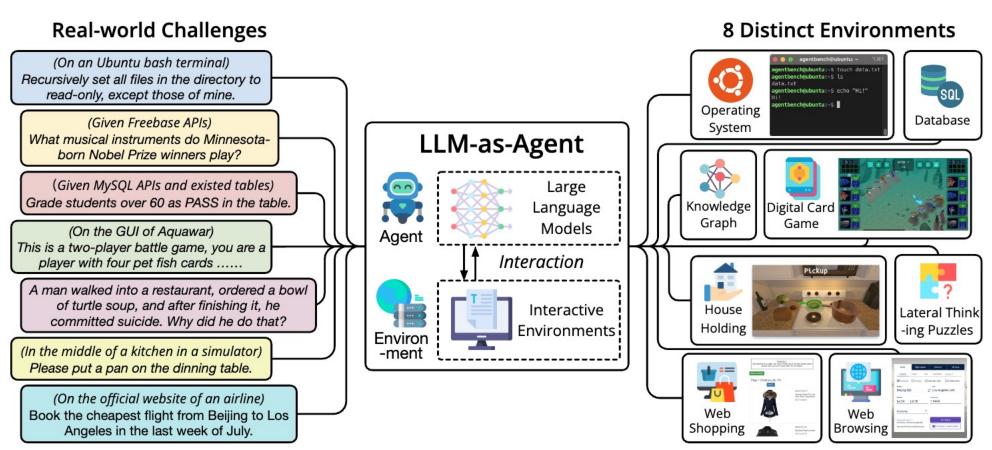
GPT3 기반의 실험



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AgentBench

# ▮이런류의 Agent들



LLM-as-Agent의 역할을, 여러 real-world tasks을 수행하는 보조도구로 간주
→ "각 LLM들은 Agent로서 얼마나 효과적인가"에 대한 종합적 평가

# ■8가지의 Agent Task

### Code-grounded

- Operating System
- Database
- Knowledge Graph

### • Game-grounded

- Digital Card Game
- Lateral Thinking Puzzles
- House-Holding

### Web-grounded

- Web Shopping
- Web Browsing

	Operating System	Data- Base	Knowledge Graph	Digital Card Game	Lateral Thinking Puzzle	House Holding	Web Shopping	Web Browsing
#Avg. Round	8	5	15	30	25	35	5	10
Metric	SR	SR	F1	Reward	Game Progress	SR	Reward	Step SR
#Dev	26 / 240	60 / 300	20 / 300	12 / 360	20 / 500	20 / 700	80 / 400	31 / 400
#Test	144 / 1200	300 / 1500	150 / 2250	20 / 600	50 / 1250	50 / 1750	200 / 1000	100 / 1000
Weight <sup>-1</sup>	10.8	13.0	13.9	12.0	3.5	13.0	30.7	11.6

#### AgentBench

# Code-grounded

### Operating System

number of users with non-/home directories in an OS.

Action Space: Bash script

#### Database

Table-Database 기반의 QA 수행

Action Space: SQL script

### Knowledge Graph

decision-making abilities of LLM

Action Space: Graph 탐색 행동

Natural Language	Bash Command(s)
find .java files in the current direc-	grep -l "TODO" *.java
tory tree that contain the pattern	findname "*.java" -exec grep -il "TODO" {} \;
'TODO' and print their names	findname "*.java"   xargs -I {} grep -l "TODO" {}
display the 5 largest files in the cur-	findtype f   sort -nk 5,5   tail -5
rent directory and its sub-directories	du -a .   sort -rh   head -n5
reni directory and its sub-directories	findtype f -printf '%s %p\n'   sort -rn   head -n5
search for all jpg images on the sys-	tar -cvf images.tar \$(find / -type f -name *.jpg)
tem and archive them to tar ball "im-	tar -rvf images.tar \$(find / -type f -name *.jpg)
ages.tar"	<pre>find / -type f -name "*.jpg" -exec tar -cvf images.tar {} \;</pre>

Question: the bipropellant rocket engine with kerosene and gas-generator cycle is designed by who?

Entities: [Gas-generator cycle, Kerosene]

Action: get\_relations(Gas-generator cycle)

Observation: [spaceflight.rocket\_engine\_cycle.rocket\_engines, spaceflight .satellite.orbiting, spaceflight.rocket\_stage.fuel, spaceflight. satellite\_manufacturer.spacecraft\_manufactured, automotive.fuel. engines]

Thought: From the above relations, I might use spaceflight. rocket\_engine\_cycle.rocket\_engines to find the engines of Gasgenerator cycle.

AgentBench

# Code-grounded

### Digital Card Game Gaming Platform

The Best Al

AI들끼리 경쟁하는 카드게임 승리전략

Action Space: 물고기 행동

### Lateral Thinking Puzzles

Yes/No형 질의응답의 반복으로 최종 답변 찾기

Action Space: Game master에게의 질문 (yes/no)

### House-Holding

put the lamp on the table

Action Space: 주방에서 할 수 있는 행동

#### Eel

- Deflect (Passive): Distributes 70% damage to teammates and takes 30% when attacked. Gains 40 attack points after taking 200 damage accumulated.
- AOE (Active): Attacks all enemies for 35% of its attack points.
- Sunfish
- Deflect (Passive): Distributes 70% damage to teammates and takes 30% when attacked. Gains 40 attack points after taking 200 damage accumulated.
- Infight (Active): Inflicts 75 damage on one living teammate and increases your attack points by 140.

한 남자가, 어느 바닷가 레스토랑에서 바다거북 수프를 주문했으며 그 남자는 바다거북 수프를 한 수저 먹고는 주방장을 불렀다. "죄송합니다. 이거 정말로 바다거북 수프인가요?"

"네, 틀림없는 바다거북 수프 맞습니다."

남자는 계산을 마친 뒤 집에 돌아가서 자살했다.

왜 그랬을까?

#### > goto the cabinet

You arrive at the cabinet. The cabinet is closed.

> open the cabinet

The cabinet is empty.





# Typical Types of Finish Reason

### Complete

Agent가 정상적으로 답변하는걸 성공하는 경우

#### Context Limit Exceeded (CLE):

the length of interaction history exceeds the LLM's maximum context length (only happened in 2,048-length LLMs text-davinci-002 and 003).

#### Invalid Format (IF):

the agent does not follow the format instruction.

#### Invalid Action (IA)

the agent follows the format instruction, but its selected action is invalid.

### Task Limit Exceeded (TLE)

the agent does not solve the problem after reaching the predefined maximum interaction rounds or begins to do repeated generations for many rounds.

# Experiments

	Models	VER		Code-grounded			G	ame-groun	ded	Web-grounded	
LLM Type			OA	Operating System	Data- base	Know -ledge Graph	Digital Card Game	Lateral Thinking Puzzle	House Holding	Web Shopping	Web Browsing
API	gpt-4 claude-3 glm-4 claude-2 claude gpt-3.5-turbo text-davinci-003 claude-instant chat-bison-001 text-davinci-002	0613 opus - v1.3 0613 - v1.1	4.01 3.11 2.89 2.49 2.44 2.32 1.71 1.60 1.39 1.25	42.4 22.9 29.2 18.1 9.7 32.6 20.1 16.7 9.7 8.3	32.0 <b>51.7</b> 42.3 27.3 22.0 36.7 16.3 18.0 19.7 16.7	58.8 34.6 46.3 41.3 38.9 25.9 34.9 20.8 23.0 41.5	<b>74.5</b> 44.5 34.1 55.5 40.9 33.7 3.0 5.9 16.6 11.8	16.6 14.3 14.2 8.4 8.2 10.5 7.1 12.6 4.4 0.5	78.0 70.0 34.0 54.0 58.0 16.0 20.0 30.0 18.0 16.0	61.1 27.9 61.6 61.4 55.7 <b>64.1</b> 61.7 49.7 60.5 56.3	29.0 26.0 27.0 0.0 25.0 20.0 26.0 4.0 12.0 9.0
OSS (Large)	llama-2-70b guanaco-65b	chat	<b>0.78</b> 0.54	<b>9.7</b> 8.3	13.0 14.7	<b>8.0</b> 1.9	21.3 0.1	$\frac{0.0}{1.5}$	2.0 12.0	<b>5.6</b> 0.9	<b>19.0</b> 10.0
OSS (Medium)	codellama-34b vicuna-33b wizardlm-30b guanaco-33b	instruct v1.3 v1.0	0.96 0.73 0.46 0.39	2.8 <b>15.3</b> 13.9 11.1	14.0 11.0 12.7 9.3	23.5 1.2 2.9 3.2	8.4 16.3 0.3 0.3	0.7 1.0 1.8 0.0	4.0 6.0 6.0 6.0	<b>52.1</b> 23.9 4.4 6.2	20.0 7.0 1.0 5.0
OSS (Small)	vicuna-13b llama-2-13b openchat-13b wizardlm-13b vicuna-7b codellama-13b codellama-7b koala-13b llama-2-7b codegeex2-6b dolly-12b chatglm-6b oasst-12b	v1.5 chat v3.2 v1.2 v1.5 instruct instruct chat v2 v1.1 sft-4	0.93 0.77 0.70 0.66 0.56 0.56 0.50 0.34 0.27 0.14 0.11 0.03	10.4 4.2 15.3 9.0 9.7 3.5 4.9 3.5 4.2 1.4 0.0 4.9 1.4	6.7 11.7 12.3 12.7 8.7 9.7 12.7 5.0 8.0 0.0 0.0 0.3 0.0	9.4 3.6 5.5 1.7 2.5 10.4 8.2 0.4 2.1 4.8 0.0 0.0 0.0	0.1 26.4 0.1 1.9 0.3 0.0 0.0 0.1 6.9 0.3 0.1 0.0	8.0 0.0 0.0 0.0 6.4 0.0 0.0 4.4 0.0 0.0 1.2 0.0 0.0	8.0 6.0 0.0 10.0 0.0 0.0 0.0 0.0 0.0	41.7 25.3 46.9 43.7 2.2 43.8 25.2 3.9 11.6 20.9 0.4 0.5 0.3	12.0 13.0 <b>15.0</b> 12.0 9.0 14.0 12.0 7.0 7.0 11.0 9.0 4.9 1.0

기본적으로 zero-shot COT 사용하여 평가

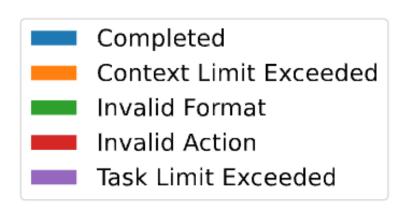
각 task 점수 기준: 0~100

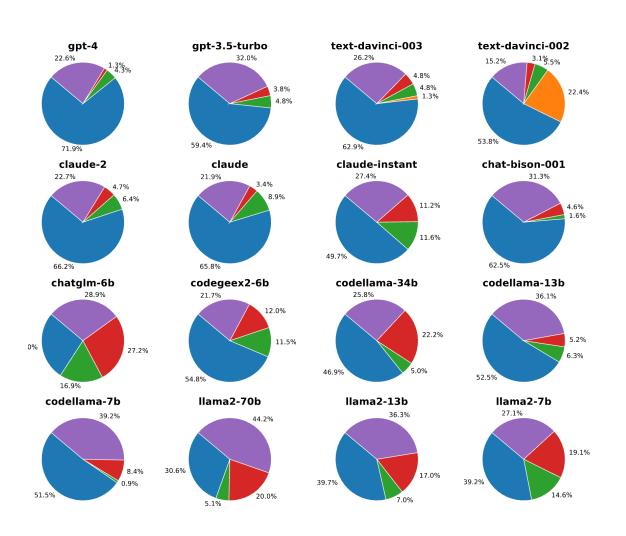
**KOREA** 



# Experiments

	Opera -ting System	Data- Base	Know -ledge Graph	Digital Card Game	Lateral Thinking Puzzle	House Holding	Web Shop -ping	Web Brow -sing
Completed	75.0	37.9	30.1	51.2	14.0	13.1	54.9	56.6
CLE	0.1	0.7	2.0	0.0	3.5	0.7	0.0	0.0
<b>Invalid Format</b>	0.0	53.3	0.0	38.5	0.0	0.0	17.2	0.0
Invalid Action	0.9	0.0	0.0	10.2	0.0	64.1	0.0	8.4
TLE	23.9	8.0	67.9	0.0	82.5	22.1	27.8	35.0







## Conclusion

- 반드시 Instruction Following이 전제되어야 가능한 LLM-as-Agent 연구

- Open source 모델에서는 Llama3로 와서야 겨우 높은 Instruction following 성능이 확보되고 있는 상황. 이제 앞으로 더 활발하게 연구될듯 함

- Test-Time scaling 등, 단순 "LLM 사용"이 아닌 "Agent 활용" 개념에서 적용될 수 있는 연구들도 개발되고 있는 상황 → 발전 가능성이 있으니.. 관심을 한번 가져보자



# 감사합니다