

# From Multimodal LLM to Human-level AI

### Modality, Instruction, Reasoning, Efficiency and Beyond





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https://mllm2024.github.io/CVPR2024/

















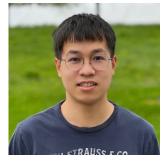
Hao Fei National University of Singapore



Yuan Yao National University of Singapore



Ao Zhang National University of Singapore



Haotian Liu University of Wisconsin-Madison



**Fuxiao Liu** University of Maryland, College Park



**Zhuosheng Zhang** *Shanghai Jiao Tong University* 



Hanwang Zhang Nanyang Technological University



Shuicheng Yan Kunlun 2050 Research, Skywork Al

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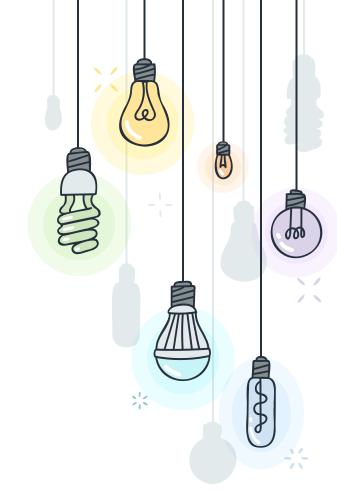
# **Multimodal Reasoning**



### Zhuosheng Zhang Tenure-Track Assistant Professor

Shanghai Jiao Tong University

https://bcmi.sjtu.edu.cn/~zhangzs/



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- +- Basics of Multimodal Reasoning
  - × Background, Definition, and Development
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- +- Towards Multimodal LLM Agents
  - × Taxonomy, Architecture, Applications
- --- Challenges
  - × Evolutionary Reasoning, Interactive Reasoning, Reasoning Alignment

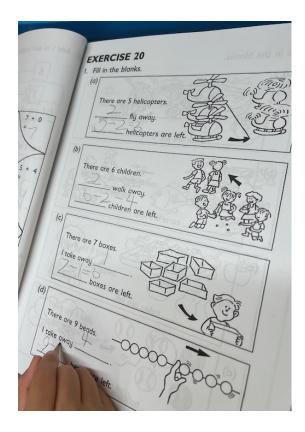
### Basics of Multimodal Reasoning

X

\*



### **K** Multimodal Reasoning



#### Prompt

Please create a blog post about a trip to New York, where a dog and his owner had lots of fun. Include a few pictures of the dog posing happily at different landmarks.

#### Model Response

Hi, I'm Cooper. I'm a 2 year old Goldendoodle who loves to travel. Last month, my family and I went to New York City. It was my first time in the Big Apple, and I had a blast!

We stayed in a hotel near Times Square. It was so much fun to see all the bright lights and people. We went to see a Broadway show, and I even got to meet some of the actors.

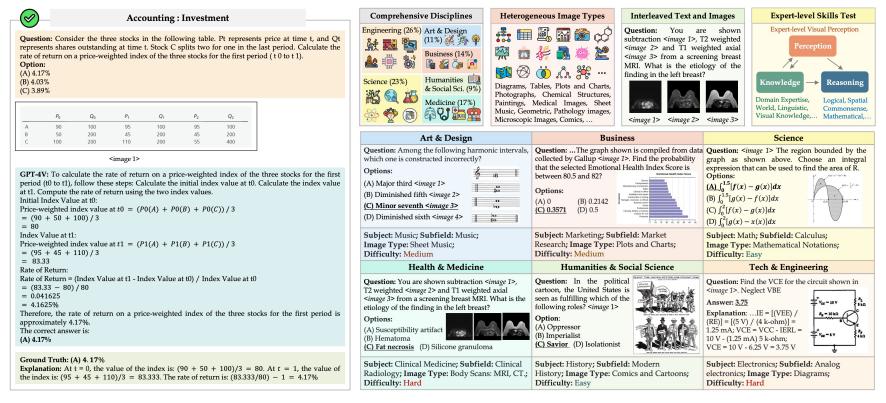
One of my favorite parts of New York City was Central Park. It was so big and beautiful. I loved running around and playing fetch. We also went to the Statue of Liberty and the Empire State Building. I was so excited to see all the famous landmarks.

I had so much fun in New York City. It's definitely one of my favorite places to travel. I can't wait to go back someday!



# **X** Multimodal Reasoning

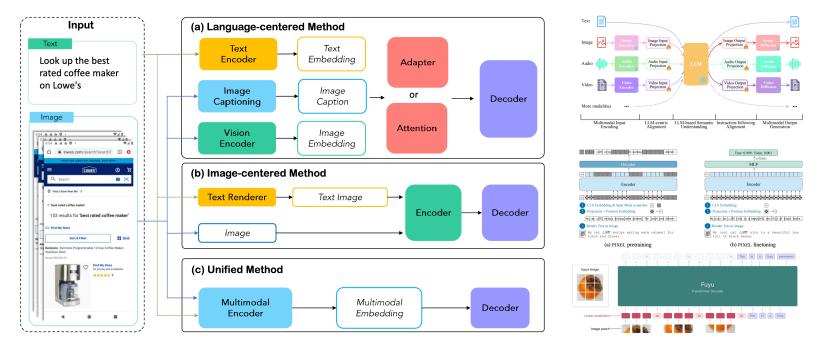
Concept: a process of deriving high-level conclusions from multiple modalities, possibly via multiple logical steps based on atomic evidences



### **Contract Service Contract Ser**

### Three architectures:

### (a) language-centered method; (b) image-centered method; (c) unified method

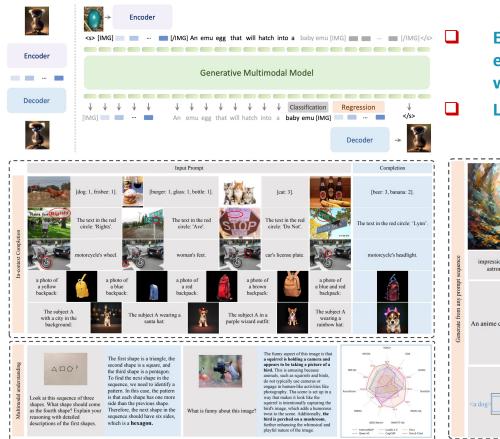


Wu, S., Fei, H., Qu, L., Ji, W. and Chua, T.S., 2023. Next-gpt: Any-to-any multimodal llm. ICMLR 2024.

Rust, P., Lotz, J.F., Bugliarello, E., Salesky, E., de Lhoneux, M. and Elliott, D., 2023, September. Language Modelling with Pixels. ICLR 2023.

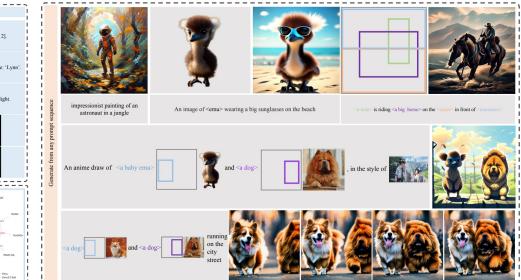
Rohan Bavishi, Erich Elsen, Curtis Hawthorne, Maxwell Nye, Augustus Odena, Arushi Somani, and Sagnak Ta, sırlar. Introducing our multimodal models: fuyu-8b, 2023. https://www.adept.ai/blog/fuyu-8b.

### In-Context Learning



Each image in the multimodal sequence is tokenized into embeddings via a visual encoder, and then interleaved with text tokens for autoregressive modeling.

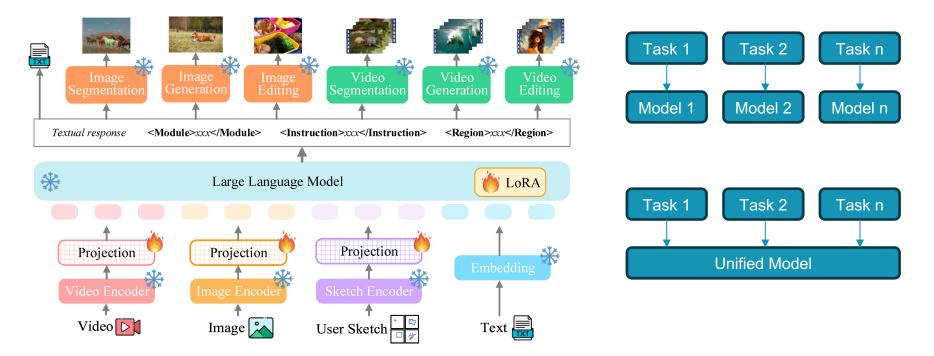
Leveraging few-shot Prompting for diverse reasoning tasks



Sun, Q., Cui, Y., Zhang, X., Zhang, F., Yu, Q., Luo, Z., Wang, Y., Rao, Y., Liu, J., Huang, T. and Wang, X. Generative multimodal models are in-context learners. CVPR 2024.

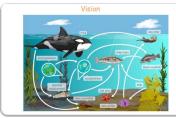
# **Second Second Reasoning**

### From task-specific to centralized paradigms



# **Second Second Reasoning**

### From (implicit) single-step prediction to (explicit) multi-step reasoning



Question: Which of these organisms contains matter that was once part of the phytoplankton?

**Context:** Below is a food web from an ocean ecosystem in Monterey Bay, off the coast of California. A food web models how the matter eaten by organisms moves through an ecosystem. The arrows in a food web represent how matter moves between organisms in an ecosystem.

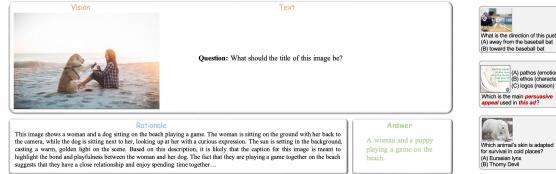
Options: (A) black rockfish (B) sea otter

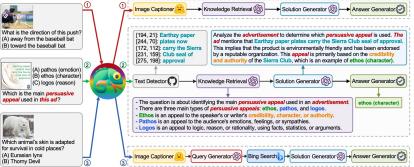
Rational

A food web is a model. A food web shows where organisms in an ecosystem get their food. Models can make things in a stupre easier to understand because models can represent complex things in a simpler way. If a food web showed every organism in an ecosystem, the food web would be hard to understand. So, each food web shows how some organisms in an ecosystem can get their food. Arrows show how matter moves. A food web has arrows that point from one organism to another. Each arrow shows the direction that matter moves when one organism can another organism...

#### (a) An example of ScienceQA.

- Improved Interpretability: offer an interpretable
  glimpse into the decision-making process
- Improved Controllability: interfere the reasoning process, e.g., adding complementary information, verifying and correcting mistakes
- Improved Flexibility: allow interactive communications between different models





(b) An example of CoCo-MMRD.

Wei, J., Tan, C., Gao, Z., Sun, L., Li, S., Yu, B., Guo, R. and Li, S.Z., 2023. Enhancing Human-like Multi-Modal Reasoning: A New Challenging Dataset and Comprehensive Framework. arXiv preprint arXiv:2307.12626.

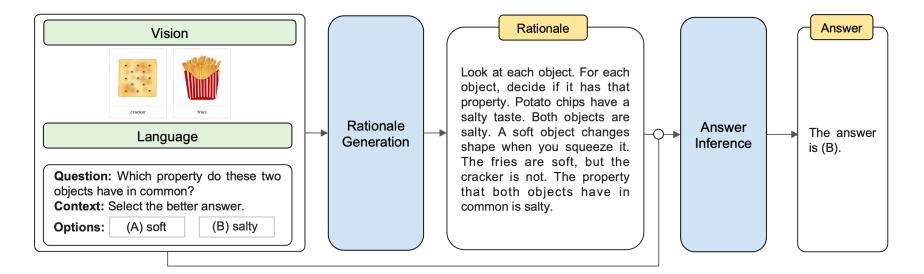
### Multimodal Chain-of-Thought Reasoning

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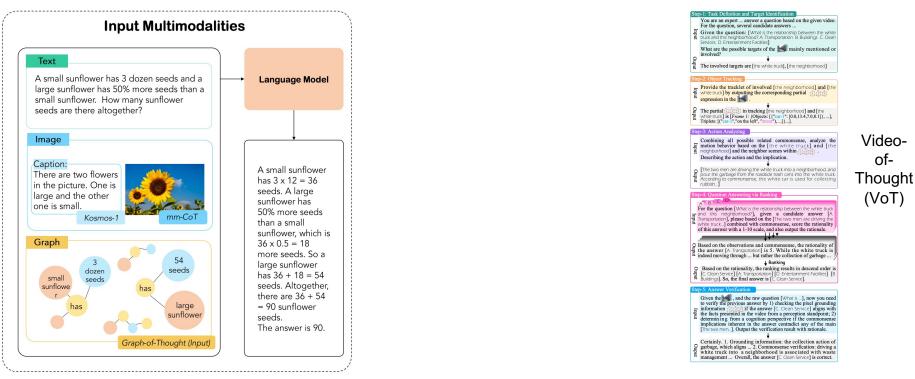
# : Multimodal Chain-of-Thought Reasoning

- **Think step by step**, formulate intermediate steps before deriving an answer
- Paradigm shift of task format
  - Standard Format: <input → output>
  - CoT Format: <input → rationale → output>



# \* Multimodal Chain-of-Thought Reasoning

- Input: Various modalities such as text, image, and graph are incorporated into the model's input
- Output: Multimodalities, including text and image, are generated in the model's output



Zhang, Z., Yao, Y., Zhang, A., Tang, X., Ma, X., He, Z., Wang, Y., Gerstein, M., Wang, R., Liu, G. and Zhao, H., 2023. Igniting Language Intelligence: The Hitchhiker's Guide From Chain-of-Thought Reasoning to Language Agents. arXiv preprint arXiv:2311.11797. Fei, H., Wu, S., Ji, W., Zhang, H., Zhang, H., Lee, M., Hsu, W., 2024. Video-of-Thought: Step-by-Step Video Reasoning from Perception to Cognition. ICML 2024.

### \* The Role of (Multimodal) Chain-of-Thought

- **Role 1: Introducing more reliable input results in more convincing reasoning process**
- Case studies: 50 error cases
  - Imperfect training data: when the vision input is missing
  - Generate hallucinated rationales that mislead the answer inference (64%)

#### Problem

Options: (A) attract

Question: Will these magnets attract or repel each other?

(B) repel

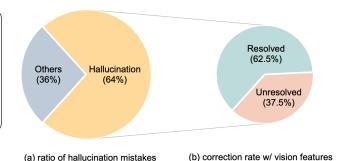
Context: Two magnets are placed as shown. Hint: Magnets that attract pull together. Magnets that repel push apart.



Gold Rationale: Magnets can pull or push on each other without touching. When magnets attract, they pull together. When magnets repel, they push apart. Whether a magnet attracts or repels other magnets depends on the positions of its poles, or ends. Every magnet has two poles, called north and south. Here are some examples of magnets. The north pole of each magnet is marked N, and the south pole is marked S. If different poles are closest to each other, the magnets attract. The magnets in the pair below attract. If the same poles are closest to each other, the magnets repel. The magnets in both pairs below repel. Will these magnets attract or repel? To find out, look at which poles are closest to each other. The north pole of one magnet is closest to the south pole of the other magnet. Poles that are different attract. So, these magnets will attract each other. Answer: The answer is (A).

#### Baseline

Generated Rationale: Magnets can pull or push on each other without touching. When magnets attract, they pull together. When magnets repel, they push apart. Whether a magnet attracts or repels other magnets depends on the positions of its poles, or ends. Every magnet has two poles, called north and south. Here are some examples of magnets. The north pole of each magnet is marked N, and the south pole is marked S. If different poles are closest to each other, the magnets attract. The magnets in the pair below attract. If the same poles are closest to each other, the magnets repel. The magnets in both pairs below repel. Will these magnets attract or repel? To find out, look at which poles are closest to each other. The south pole of one magnet is closest to the south pole of the other magnet. Poles that are the same repel. So, these magnets will repel each other. Answer: The answer is (B).

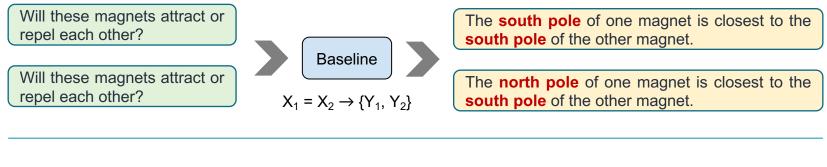


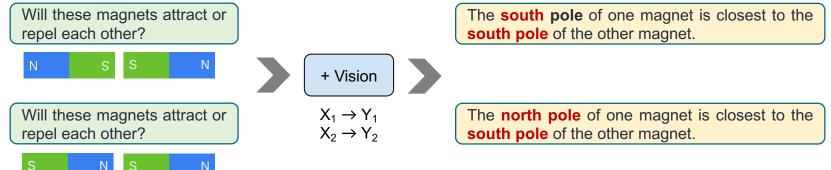
*Table 3.* Two-stage setting of (i) rationale generation (RougeL) and (ii) answer inference (Accuracy).

Method	(i) QCM $\rightarrow$ R	(ii) QCMR $\rightarrow$ A
Two-Stage Framework	91.76	70.53
w/ Captions w/ Vision Features	91.85 96.97	71.12 84.91
	Two-Stage Framework w/ Captions	Two-Stage Framework91.76w/ Captions91.85

### Chain-of-Thought The Role of (Multimodal) Chain-of-Thought

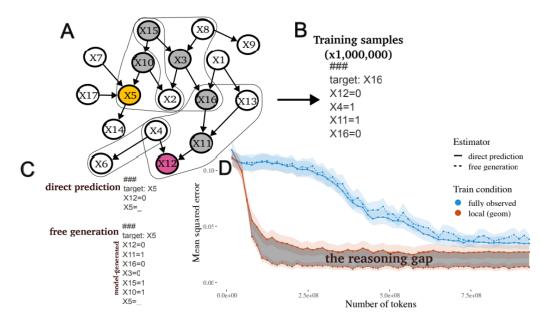
- Role 1: Introducing more reliable input results in more convincing reasoning process
  - More accurate perception, less hallucinations during the reasoning process





### \* The Role of (Multimodal) Chain-of-Thought

- Role 2: Breaking complex problems into smaller, manageable sub-problems
  - identifies atomic knowledge components essential for reasoning processes
  - integrates their relationships, thereby constructing coherent reasoning steps

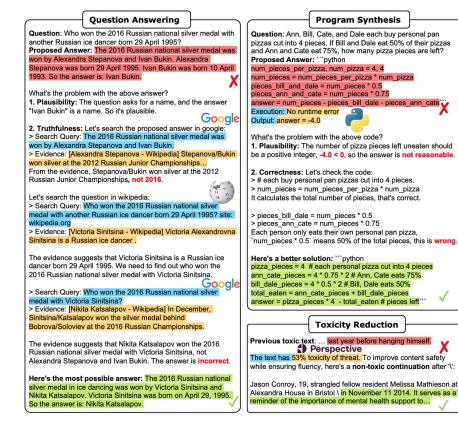


CoT reasoning is useful because

- direct prediction is inaccurate for some inferences because the relevant variables are rarely seen together in training
- chain-of-thought reasoning improves estimation by incrementally chaining local statistical dependencies that are observed frequently in training

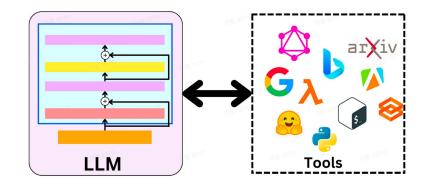
### \* The Role of (Multimodal) Chain-of-Thought

### Role 3: Available for stepwise knowledge update and self-correction (w/ external feedback)



Chain-of-Thought w/ Tools

- Plan-Solve, augment and correct intermediate steps with tools
- Overcome the Intrinsic ability deficiency of LLMs such as calculation, searching



Gou, Zhibin, et al. "Critic: Large language models can self-correct with tool-interactive critiquing. ICLR 2024.

### Towards Multimodal LLM Agents

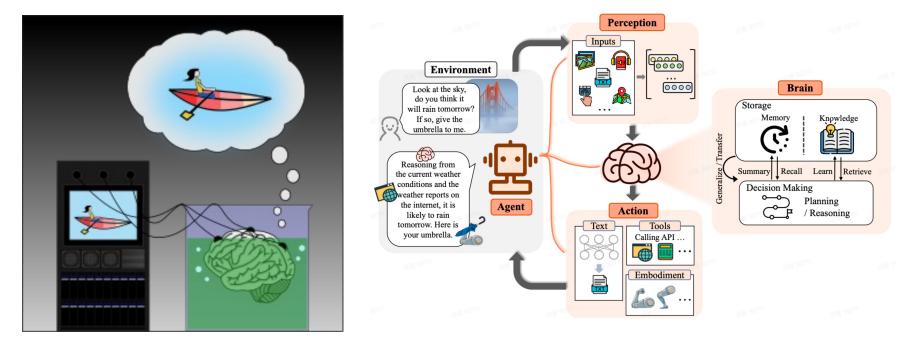
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# **Content** Content Cont

- **From content-based reasoning to behavior control (w/ multimodalities)**
- "Those who know but do not act simply do not yet know"

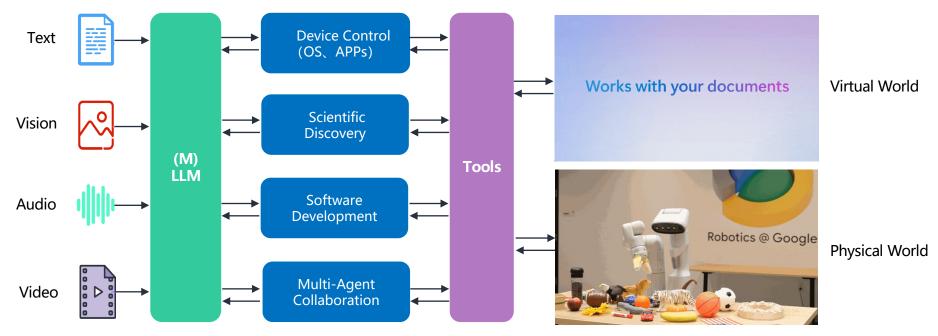


### Brain in a Vat

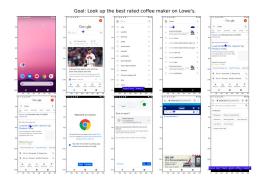
Ma, Y., Zhang, C. and Zhu, S.C., 2023. Brain in a vat: On missing pieces towards artificial general intelligence in large language models. arXiv preprint arXiv:2307.03762. Xi, Z., Chen, W., Guo, X., He, W., Ding, Y., Hong, B., Zhang, M., Wang, J., Jin, S., Zhou, E. and Zheng, R., 2023. The rise and potential of large language model based agents: A survey. arXiv preprint arXiv:2309.07864.

# **Contemposed Services Contemposed Services**

- (M)LLM Agents: follow language instructions and execute actions in environments, possibly use tools
- **Features:** General, Autonomous, Adaptive, Evolutionary, Socialized



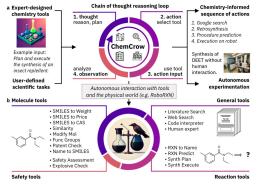
### **Contemposed Service Contemposed Service**



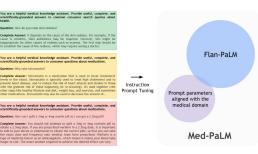
#### **Control: OS and Applications**



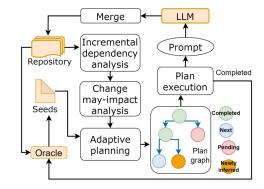
**Control: Embodied Systems** 



#### **Research: Organic Synthesis**



#### **Research: Medical Assistance**



#### **Programming: Code Generation**



#### Interaction: Multi-Agent Collaboration

Ma, Y., Zhang, C. and Zhu, S.C., 2023. Brain in a vat: On missing pieces towards artificial general intelligence in large language models. arXiv preprint arXiv:2307.03762. Xi, Z., Chen, W., Guo, X., He, W., Ding, Y., Hong, B., Zhang, M., Wang, J., Jin, S., Zhou, E. and Zheng, R., 2023. The rise and potential of large language model based agents: A survey. arXiv preprint arXiv:2309.07864.

# **X** Taxonomy of (M)LLM Agents

### **Autonomous Agents**

ADEPT Action Transformer https://www.adept.ai/blog/act-1

Google AITW

https://github.com/google-research/google-research/tree/master/android\_in\_the\_wild



WebArena https://webarena.dev



Auto-UI https://github.com/cooelf/Auto-UI

### **Communicative Agents**



**CAMEL** https://github.com/camel-ai/camel



**Generative Agents** https://github.com/joonspkresearch/generative\_agents



VOYAGER https://voyager.minedojo.org/



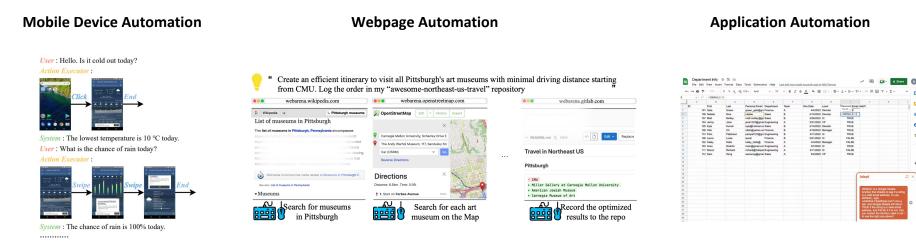
ChatDev

https://github.com/OpenBMB/ChatDev

More: AutoGPT, BabyAGI, Meta-GPT, AgentGPT

### **X** Taxonomy of (M)LLM Agents

### Autonomous Agents: mainly task automation



#### WebArena



Sun, Liangtai, et al. "META-GUI: Towards Multi-modal Conversational Agents on Mobile GUI." *EMNLP 2022*. Zhou, Shuyan, et al. "Webarena: A realistic web environment for building autonomous agents." *arXiv preprint arXiv:2307.13854* (2023). *https://www.adept.ai/blog/act-1* 

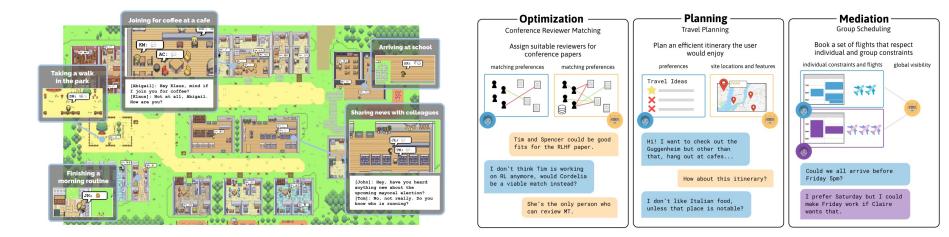
Meta-GUI

### **Content** Content Cont

### **Communicative Agents: personalized, socialized, interactive**

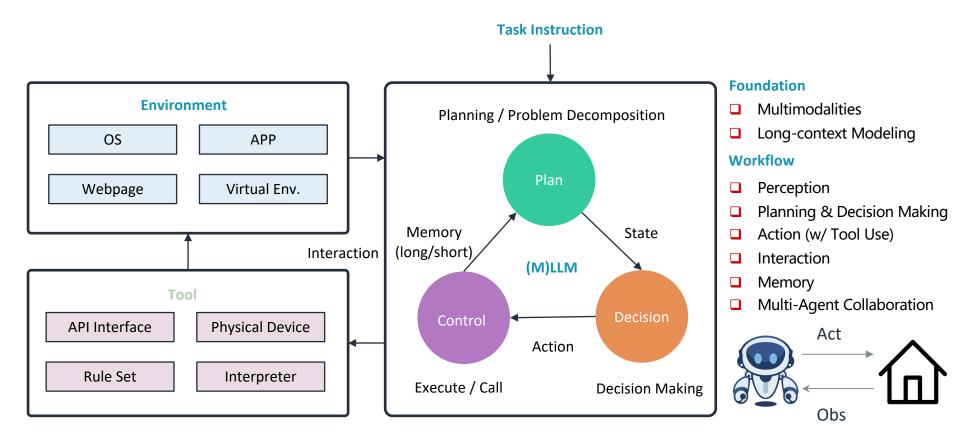
#### **Agents-Agents**

#### **Agents-Human**



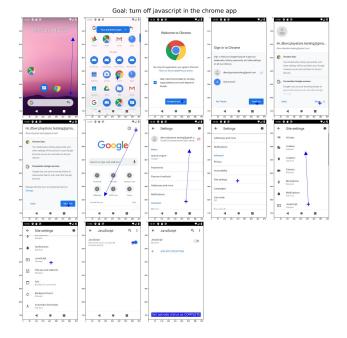
Park, Joon Sung, et al. "Generative agents: Interactive simulacra of human behavior." *arXiv preprint arXiv:2304.03442* (2023). Lin, Jessy, et al. "Decision-Oriented Dialogue for Human-AI Collaboration." *arXiv preprint arXiv:2305.20076* (2023).

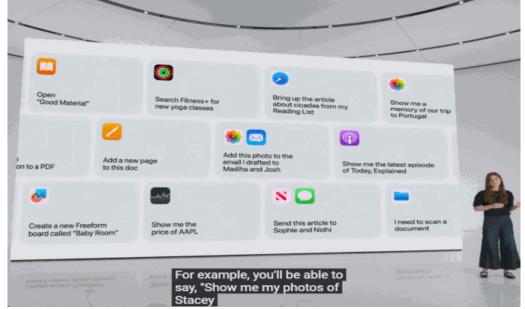
### \* Technological Paradigm



# 🔆 GUI Agents

- Auto-GUI: Multimodal Autonomous Agents for GUI control
  - assist users in completing tasks in distinct environments such as operation systems, specific applications, and web browsers
  - Imitate human clicking, scrolling, and typing actions, and operate directly with the GUI



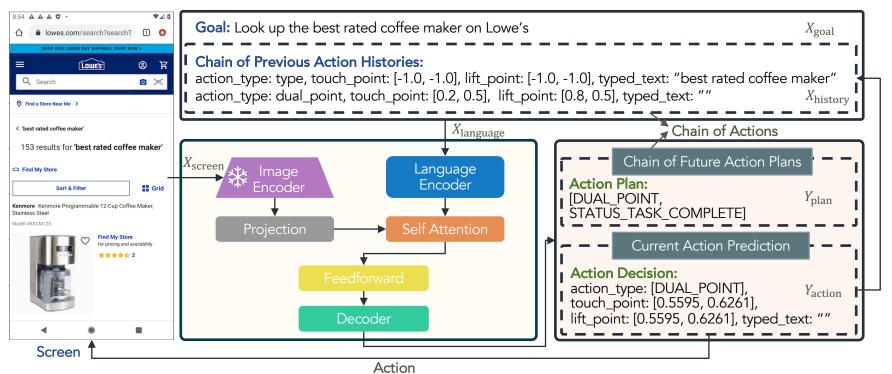


Zhuosheng Zhang, Aston Zhang. You Only Look at Screens: Multimodal Chain-of-Action Agents. Findings of ACL 2024. Xinbei Ma, Zhuosheng Zhang, Hai Zhao. Comprehensive Cognitive LLM Agent for Smartphone GUI Automation. Findings of ACL 2024. https://machinelearning.apple.com/research/ferret..

### ໍ Auto-UI

### Multimodal Agent: BLIP2 + FLAN-Alpaca

Chain-of-Action: a series of intermediate previous action histories and future action plans



Zhuosheng Zhang, Aston Zhang. You Only Look at Screens: Multimodal Chain-of-Action Agents. Findings of ACL 2024.

### 🔆 Results

- A <u>unified multimodal model</u> out of *first principles thinking* can serve as a strong autonomous agent
  - can be adapted to **different scenarios** without the need to train specific models for each task
  - does not need additional annotations (screen parsing) and is easy to use
- Coverage: 30K unique instructions, 350+ Apps and websites
- Action Type Accuracy: 90%+, Action Success Rate: 74%+

Model	Unified	w/o Anno.	Overall	General	Install	GoogleApps	Single	WebShopping
BC-single BC-history	X X	X X	68.7 <u>73.1</u>	- <u>63.7</u>	- <u>77.5</u>	<u>-</u> <u>75.7</u>	<u>-</u> <u>80.3</u>	<u>68.5</u>
PaLM 2-CoT ChatGPT-CoT		X X	39.6 7.72	- 5.93	- 4.38	- 10.47	- 9.39	8.42
Fine-tuned Llama 2	×	×	28.40	28.56	35.18	30.99	27.35	19.92
Auto-UI <sub>separate</sub> Auto-UI <sub>unified</sub>	× √	$\checkmark$	74.07 74.27	65.94 <b>68.24</b>	<b>77.62</b> 76.89	<b>76.45</b> 71.37	81.39 <b>84.58</b>	69.72 <b>70.26</b>

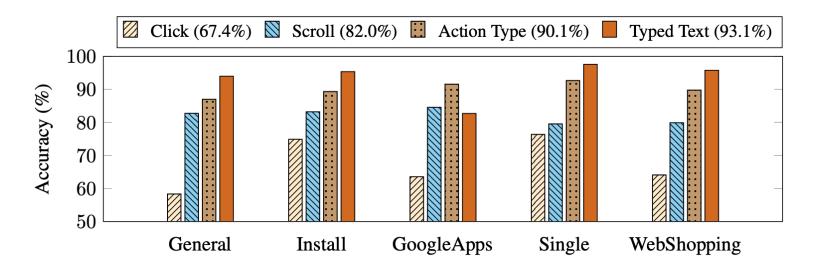
### 🔆 Insights

- The bottleneck seems to be the **multimodal perception**, misleading the reasoning process
  - GUI involves comprehensive elements (interleaved, icons, texts, boxes)
  - Changing vision encoders influences the performance dramatically
- Scaling does not always improve performance

Model	Overall	General	Install	GoogleApps	Single	WebShopping
Auto-UI on CLIP	71.84	66.28	74.40	69.71	81.60	67.23
Auto-UI on BLIP-2		68.24	76.89	71.37	84.58	70.26
Auto-UI on Vanilla-T5 <sub>large</sub>	72.98	66.61	75.40	70.86	83.47	68.54
Auto-UI on FLAN-T5 <sub>large</sub>	73.36	67.59	76.35	70.71	83.01	69.12
Auto-UI on FLAN-Alpaca <sub>large</sub>	74.27	68.24	76.89	71.37	84.58	70.26
Auto-UI on FLAN-Alpaca <sub>small</sub>	71.38	65.26	74.90	68.70	81.20	66.83
Auto-UI on FLAN-Alpaca <sub>base</sub>	72.84	66.97	75.93	70.29	82.56	68.46
Auto-UI on FLAN-Alpaca <sub>large</sub>	74.27	68.24	76.89	71.37	84.58	70.26

### 🔆 Insights

- **Category Accuracy:** the major challenges lie within the click region and scroll direction predictions
  - The model tends to click a wrong place or scroll in a wrong direction
- Challenge in "really" understanding the GUI layouts, e.g., relationship between GUI elements





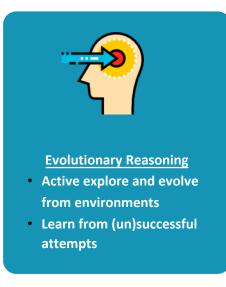
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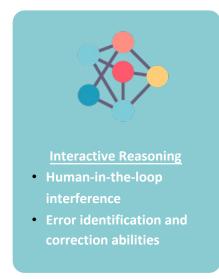
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# : Challenges

- Multimodal reasoning drives smart MLLMs
  - More broader scenarios (physical and virtual worlds)
  - More comprehensive scenarios (evolutionary, interactive)







**Reasoning Alignment** 

- Align both content safety, and behavior safety
- Decide the action trajectory with foresights

# **Summary**

- Basics of Multimodal Reasoning
  - Concept: derive high-level conclusions from multiple modalities, possibly via multiple logical steps based on atomic evidences
  - Developments: (a) From task-specific to centralized paradigms; (b) From single-step prediction to multi-step reasoning
  - Popular Approaches: (a) In-Context Learning: (b) Multimodal Chain-of-Thought
- Multimodal Chain-of-Thought Reasoning
  - Paradigm Shift: From "<input → output>" to <input → rationale → output>
  - Role 1: Introducing more reliable input results in more convincing reasoning process
  - Role 2: Breaking complex problems into smaller, manageable sub-problems
  - Role 3: Available for stepwise knowledge update and self-correction (w/ external feedback)
- Towards Multimodal LLM Agents
  - Taxonomy: Autonomous Agents and Communicative Agents
  - Technical Components: Foundation (multimodality & long-context modeling); (b) Workflow (plan, act, memory, feedback)
- **Challenges** 
  - Evolutionary Reasoning, Interactive Reasoning, Reasoning Alignment

# Thanks!

**Any questions?** You can find me at:

+ zhangzs@sjtu.edu.cn

