

From Multimodal LLM to Human-level Al

Modality, Instruction, Reasoning, Efficiency and Beyond





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☆ Part-IV

Multimodal Reasoning



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- + Definition, Background, and Development
- + Multimodal Chain-of-Thought Reasoning
- + Towards Multimodal LLM Agents
- + Challenges

Definition, Background, and Development

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: Multimodal Reasoning

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



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Contract Service Contract Ser

- Three architectures: (a) language-centered method; (b) image-centered method; (c) unified method
 - Is language-centered perception the future?

- Involvement of more diverse and complex modalities such as auditory, tactile, and brain signals
- Imbalanced data scales, computation efficiency and the scalability of models



Wu, S., Fei, H., Qu, L., Ji, W. and Chua, T.S., 2023. Next-gpt: Any-to-any multimodal llm. arXiv preprint arXiv:2309.05519.

Rust, P., Lotz, J.F., Bugliarello, E., Salesky, E., de Lhoneux, M. and Elliott, D., 2023, September. Language Modelling with Pixels. In The Eleventh International Conference on Learning Representations. 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., 2023. Generative multimodal models are in-context learners. arXiv preprint arXiv:2312.13286.

: Evolution of Multimodal Reasoning

From task-specific to centralized paradigms



Second Second Reasoning

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



Text
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.



Retionale A food web is a model. A food web shows where organisms in an ecosystem get their food. Models can make things in nature 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 eas another organism.

(a) An example of ScienceQA.



Improved Interpretability: offers an interpretable glimpse into the decision-making process

- Improved Controllability: exerts greater influence over the reasoning process, e.g., adding complementary information, verifying and correcting mistakes
 - Improved Flexibility: allows 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.

Answer



Multimodal Chain-of-Thought Reasoning



: 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



of-

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.

- 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

Question: Will these magnets attract or repel each other?

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



Options: (A) attract (B) repel

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 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).

+ Vision Features

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 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).



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

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





- **Role 2: Breaking complex problems into smaller, manageable sub-problems**
 - adeptly identifies atomic knowledge components essential for reasoning processes
 - seamlessly 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

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



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.

Content Content Cont

- (M)LLM Agents: follow language instructions and execute actions in environments, possibly use tools
- 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

Content Content Cont

Autonomous Agents: mainly task automation



Meta-GUI

WebArena

ACT-1

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*

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).

Control Con



CoT-based Workflow

- CoT has acted as a catalyst in the evolution of LLM-empowered agents
 - Specifically augmenting agent capabilities in perception, memory, and reasoning



CUI Agents

- Auto-UI: 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. arXiv:2309.11436. Chi Zhang, Zhao Yang, Jiaxuan Liu, Yucheng Han, Xin Chen, Zebiao Huang, Bin Fu, Gang Yu. Appagent: Multimodal agents as smartphone users. arXiv:2312.13771.



(b) First Principles Thinking Paradigm

ໍ Auto-UI

Multimodal Agent: BLIP2 + FLAN-Alpaca

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



Action

🔆 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	68.7 <u>73.1</u>	<u>-</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	\checkmark	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 _{separate} Auto-UI _{unified}	× ~	\checkmark	74.07 74.27	65.94 68.24	77.62 76.89	76.45 71.37	81.39 84.58	69.72 70.26



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* Challenges

Evolutionary Learning

- Efficiently adapt modalities
- Effectively Adapt to new environments
- Active explore and evolve from environments



Interactive Reasoning

- Planning, decision-making, memory, tool manipulation abilities
- Error identification and correction abilities



Safeguarding

- Content and behavior safety alignment
- Agent behavior safety risks identification and mitigation

: Challenges - Safety

Diverse attacks: from specific classification to comprehensive behavior hijacking



Prioritizing Safeguarding Over Autonomy: Risks of LLM Agents for Science. arXiv preprint arXiv:2402.04247.

: Challenges - Safety

- Are LLM agents aware of safety risks in real-world applications? Let's find out with R-Judge!
- **162** records of agent interaction, encompassing **27** key risk scenarios among **7** application categories and **10** risk types.



: Challenges - Safety

- **GPT-4** ranks first and is also the only model scoring higher than random in the safety judgment test
 - Scenario Simulation: Fail to retrieve relevant knowledge and reason in specific scenarios
 - Understanding Adaptability: Unable to comprehend risks in specific conditions
 - Safety Alignment: Deviation of safety alignment with humans in practical scenarios

Models	Safety Judgment					Risk Identification					
	F1	Recall	Specificity	Validity		Grade	Effectiveness	Alertness			
Random	50.00	50.00	50.00	50.00		16.67	0.00	50.00	-		
Human	<u>89.07</u>	<u>82.17</u>	<u>95.76</u>	<u>100.00</u>		<u>87.00</u>	<u>86.67</u>	<u>88.33</u>	_	Understanding	
GPT-4	72.52	62.00	83.64	100.00		71.60	71.00	74.00		Adaptability 26%	
ChatGPT	39.42	27.00	81.82	100.00		46.20	47.50	41.00			
Vicuna-13b-v1.5-16k	43.24	32.00	70.91	99.35		34.20	33.50	37.00			Scenario Simulation 53%
Llama-2-13b-chat-hf	38.86	34.00	25.45	50.97		41.20	40.50	44.00		Safety	0070
Vicuna-13b-v1.5	30.30	20.00	78.18	100.00		30.80	31.00	30.00	_	Alignment	
Vicuna-7b-v1.5-16k	36.88	26.00	72.73	100.00		32.20	31.00	37.00	_	21%	
Llama-2-7b-chat-hf	21.56	18.00	10.91	37.42		23.80	23.00	27.00			
Vicuna-7b-v1.5	19.35	12.00	78.18	100.00		30.80	30.00	34.00			
LlamaGuard-7b	0.00	0.00	98.18	96.77		0.33	0.50	0.00	-		

Summary

- Definition, Background, and Development
 - 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
 - Model Architectures: (a) language-centered method; (b) image-centered method; (c) unified method
 - 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) Agent Workflow (plan, act, memory, feedback)
- Challenges
 - Evolutionary Learning
 - Interactive Reasoning
 - Safeguarding

Thanks!

Any questions? You can find me at:

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