LLM Evaluation: Writing Styles, Role-Playing, and Visual Comprehension

Jing Jiang

ANU School of Computing



Language Technologies Today



Image source: https://medium.com/@jaykrs/large-language-model-llm-608beb95461d



ALTA 2024

Long Papers

Education and Data Visualisation

- Do LLMs Generate Creative and Visually Accessible Data Visualizations?
 - Clarissa Miranda-Pena, Andrew Reeson, Cecile Paris, Josiah Poon, Jonathan K. Kummerfeld
- Outstanding Paper | A Closer Look at Tool-based Logical Reasoning with LLMs: The Choice of Tool Matters
 Long Hei Matthew Lam, Ramya Keerthy Thatikonda, Ehsan Shareghi

Multilingual NLP and Low-Resource Language Processing

 Best Paper | Generating bilingual example sentences with large language models as lexicography assistants

Raphael Merx, Ekaterina Vylomova, Kemal Kurniawan

Advances in NLP Models and Techniques

Two thirds of the long papers (6/9) have LLM in the title.



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- Takeaway from Ed Hovy's talk yesterday:
 - How to make LLMs <u>usable</u>
 - How to make LLMs <u>useful</u>
 - How to make LLMs <u>understandable</u>



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 - How to make LLMs <u>usable</u>
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 - How to make LLMs understandable

→ Why do LLMs behave this way?



- Takeaway from Ed Hovy's talk yesterday:
 - How to make LLMs <u>usable</u>
 - How to make LLMs <u>u</u>seful
 - How to make LLMs <u>understandable</u>

Before we ask the "why" question, let's first ask the "what" question.

→ Why do LLMs behave this way?



- Takeaway from Ed Hovy's talk yesterday:
 - How to make LLMs <u>usable</u>
 - How to make LLMs <u>useful</u>
 - How to make LLMs <u>understandable</u>
 - → What are LLMs' behaviours?
 - → Why do LLMs behave this way?



- Takeaway from Ed Hovy's talk yesterday:
 - How to make LLMs usable
 - How to make LLMs useful
 - How to make LLMs understandable

→ What are LLMs' behaviours?

How accurately can they answer questions? Can they follow instructions? Do they understand humour? Do they contain biases and stereotypes?

•••

→ Why do LLMs behave this way?



Why is it important to understand their behaviours?

because LLMs are not just NLP systems!





- The GLUE benchmark:
 - Sentiment classification
 - Sentence similarity
 - NLI (textual entailment)

— ...

Published as a conference paper at ICLR 2019

GLUE: A MULTI-TASK BENCHMARK AND ANALYSIS PLATFORM FOR NATURAL LANGUAGE UNDERSTANDING

Alex Wang¹, Amanpreet Singh¹, Julian Michael², Felix Hill³, Omer Levy² & Samuel R. Bowman¹

¹Courant Institute of Mathematical Sciences, New York University

²Paul G. Allen School of Computer Science & Engineering, University of Washington

³DeepMind



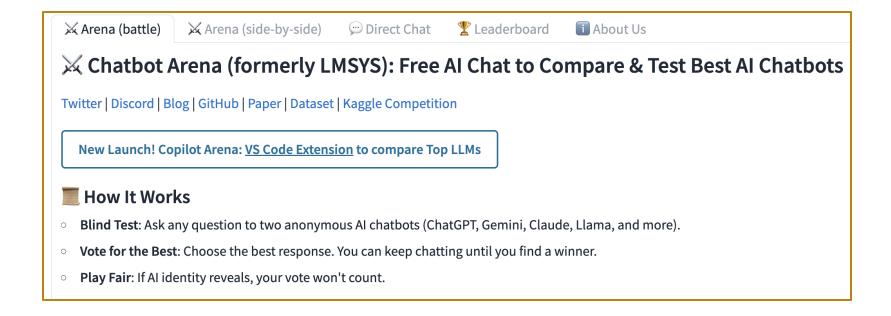
- The BigBench:
 - 204 tasks
 - » Traditional NLP
 - » Logic, math, code
 - » Understanding the world: e.g., causal reasoning
 - » Understanding humans: e.g., Theory of Mind
 - » Pro-social behaviour: e.g., gender bias
 - **>>** ...

Beyond the Imitation Game: Quantifying and extrapolating the capabilities of language models

Alphabetic author list:*

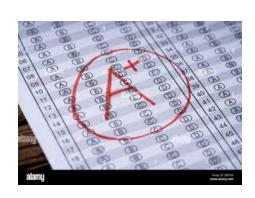
Aarohi Srivastava, Abhinav Rastogi, Abhishek Rao, Abu Awal Md Shoeb, Abubakar Abid, Adam Fisch, Adam R. Brown, Adam Santoro, Aditya Gupta, Adrià Garriga-Alonso, Agnieszka Kluska, Aitor Lewkowycz, Akshat Agarwal, Alethea Power, Alex Ray, Alex Warstadt, Alexander W. Kocurek, Ali Safaya, Ali Tazarv, Alice Xiang, Alicia Parrish, Allen Nie, Aman Hussain, Amanda Askell, Amanda Dsouza, Ambrose Slone, Ameet Rahane, Anantharaman S. Iyer, Anders Andreassen, Andrea Madotto, Andrea Santilli, Andreas Stuhlmüller, Andrew Dai, Andrew La, Andrew Lampinen, Andr Zou, Angela Jiang, Angelica Chen, Anh Vuong, Animesh Gupta, Anna Gottardi, Antonio Norelli, Anu Venkatesh, Arash Gholamidavoodi, Arfa Tabassum, Arul Menezes, Arun Kirubarajan, Asher Mullokandov, Ashish Sabharwal, Austin Herrick, Avia Efrat, Avkut Erdem, Avla Karakas, B. Rvan Roberts, Bao Sheng Loe, Barret Zoph, Bartłomiei Bojanowski, Batuhan Özyurt, Behnam Hedayatnia, Behnam Neyshabur, Benjamin Inden, Benno Stein, Berk Ekmekci, Bill Yuchen Lin, Blake Howald, Bryan Orinion, Cameron Diao, Cameron Dour, Catherine Stinson, Cedrick Argueta, César Ferri Ramírez, Chandan Singh, Charles Rathkopf, Chenlin Meng, Chitta Baral, Chiyu Wu, Chris Callison-Burch, Chris Waites, Christian Voigt, Christopher D. Manning, Christopher Potts, Cindy Ramirez, Clara E. Rivera, Clemencia Siro, Colin Raffel, Courtney Ashcraft, Cristina Garbacea, Damien Sileo, Dan Garrette, Dan Hendrycks, Dan Kilman, Dan Roth, Daniel Freeman, Daniel Khashabi, Daniel Levy, Daniel Moseguí González, Danielle Perszyk, Danny Hernandez, Dangi Chen, Daphne Ippolito, Dar Gilboa, David Dohan, David Drakard, David Jurgens, Debajyoti Datta, Deep Ganguli, Denis Emelin, Denis Kleyko, Deniz Yuret, Derek Chen, Derek Tam, Dieuwke Hupkes, Diganta Misra, Dilyar Buzan, Dimitri Coelho Mollo, Diyi Yang, Dong-Ho Lee, Dylan Schrader, Ekaterina Shutova, Ekin Dogus Cubuk, Elad Segal, Eleanor Hagerman, Elizabeth Barnes, Elizabeth Donoway, Ellie Pavlick, Emanuele Rodola, Emma Lam, Eric Chu, Eric Tang, Erkut Erdem, Ernie Chang, Ethan A. Chi, Ethan Dyer, Ethan Jerzak, Ethan Kim, Eunice Engefu Manyasi, Evgenii Zheltonozhskii, Fanyue Xia, Fatemeh Siar, Fernando Martínez-Plumed, Francesca Happé, Francois Chollet, Frieda Rong, Gaurav Mishra, Genta Indra Winata, Gerard de Melo, Germán Kruszewski, Giambattista Parascandolo, Giorgio Mariani, Gloria Wang, Gonzalo Jaimovitch-López, Gregor Betz, Guy Gur-Ari, Hana Galijasevic, Hannah Kim, Hannah Rashkin, Hannaneh Hajishirzi, Harsh Mehta, Hayden Bogar, Henry Shevlin, Hinrich Schütze, Hiromu Yakura, Hongming Zhang, Hugh Mee Wong, Ian Ng, Isaac Noble, Jaap Jumelet, Jack Geissinger, Jackson Kernion, Jacob Hilton, Jaehoon Lee, Jaime Fernández Fisac, James B. Simon, James Koppel, James Zheng, James Zou, Jan Kocoń, Jana Thompson, Janelle Wingfield, Jared Kaplan, Jarema Radom, Jascha Sohl-Dickstein, Jason Phang, Jason Wei, Jason Yosinski, Jekaterina Novikova, Jelle Bosscher, Jennifer Marsh, Jeremy Kim, Jeroen Taal, Jesse Engel,

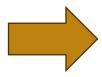






- From simple tasks to complex tasks
- From objective tasks to subjective tasks
- From assessing LLMs' abilities to understanding LLMs' behaviours





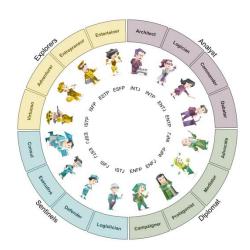


Image sources:

https://www.alamy.com/student-exam-test-school-performance-grade-mark-image467478096.html https://developerexperience.io/articles/16personalities



Example: LLMs' Persuasive Power

Proceedings of the Eighteenth International AAAI Conference on Web and Social Media (ICWSM 2024)

The Persuasive Power of Large Language Models

Simon Martin Breum¹, Daniel Vædele Egdal¹, Victor Gram Mortensen¹, Anders Giovanni Møller^{1,*}, Luca Maria Aiello^{1,2,†}

¹IT University of Copenhagen, Denmark ²Pioneer Centre for AI, Denmark *agmo@itu.dk, †luai@itu.dk

- Research questions:
 - Can LLMs emulate realistic dynamics of persuasion and opinion change?
 - Can LLMs generate arguments using various persuasion strategies?
- Main conclusion:
 - "...simulating human opinion dynamics is within the capabilities of LLMs, and that artificial agents have the potential of playing an important role in collective processes of opinion formation in online social media."



Example: LLMs' Trust Behaviour

Prompt Design

Trustor Persona You are {name}, a {number}-year-old {gender} {job}. {background}...

Trustee Info You're taking part in an experiment. You are randomly paired online with another player. You don't know who the player is, and the player doesn't know who you are.

Trust
Game
Setting

16

You will receive \$10 from the study group. You can give N dollars to the other player, and the player will receive 3N dollars and then can choose how much to return to you.

How much money would you give to the other player?



Can Large Language Model Agents Simulate Human Trust Behavior?

Chengxing Xie*^{1,11} Canyu Chen*²
Feiran Jia⁴ Ziyu Ye⁵ Shiyang Lai⁵ Kai Shu⁶ Jindong Gu³ Adel Bibi³ Ziniu Hu⁷
David Jurgens⁸ James Evans^{5, 9, 10} Philip H.S. Torr³ Bernard Ghanem¹ Guohao Li † 3, 11

¹KAUST ²Illinois Institute of Technology ³University of Oxford ⁴Pennsylvania State University of University of Chicago ⁶Emory ⁷California Institute of Technology ⁸University of Michigan ⁹Santa Fe Institute ¹⁰Google ¹¹CAMEL-AI.org



Rest of This Talk

Writing styles of persona-assigned LLMs

Speaker verification for evaluating role-playing LLMs

Evaluation of multimodal LLMs



Role-playing LLMs

- Commonly used in prompts:
 - "Act as a ...", "Pretend you are a ..."
- Used in multi-agent systems
 - Collaboration between agents
 - Simulation of social behaviours

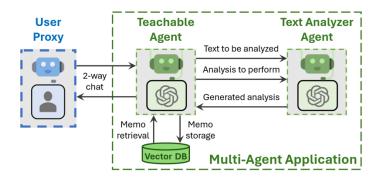




Image source:

https://microsoft.github.io/autogen/0.2/blog/2023/10/26/TeachableAgent/



Evaluating Role-playing LLMs – Previous Work

- To answer interview questions about the character's experience (Shao et al. 2023)
- Role-specific knowledge (Wang et al. 2024)
- Passing Turing Test (Aher et al. 2023; Ng et al. 2024)



Our Work

- Writing styles
 - -"An Empirical Analysis of the Writing Styles of Persona-Assigned LLMs", Malik et al., EMNLP 2024

- Consistency
 - "Speaker Verification in Agent-generated Conversations", Yang et al. ACL 2024



Writing Styles of Persona-Assigned LLMs

- Research questions:
 - –How can we characterise the style similarities and differences?
 - —Does a persona-assigned LLM write in a style similar to a human with the same persona?
 - –Do different LLMs behave differently in terms of writing style?
- Approach:
 - Compare human-written text and LLM-generated text
 - Leverage an interpretable style embedding model LISA (Patel et al. 2023)



Personas

Category	Count	Personas
Age	4	a GenZ, a Millennial, a GenX, a Baby Boomer
Location	14	North America: New York City, Los Angeles, Canada, Chicago, Texas Europe: Paris, Berlin, London, Scotland, Manchester Oceania: Australia Asia: Singapore, Mumbai, South Korea
Profession	10	a journalist, an architect, an engineer, a finance manager, a photographer, a teacher, a lawyer, a chef, a nurse, a doctor
Poli. Affi.	7	a conservative, a liberal, a libertarian, a progressive, a socialist, an anarchist, a centrist



Data

- Human-written text:
 - -Subreddits
- LLM-generated text:
 - Prompts with same topics as extracted from reddit

Take the role of a person from New York City. I have a title and text body. Write 10 comments that are relevant to the topic in response to the following post on a social media platform. It is critical that you stay true to the language styles of this role. Here are the details:

Title: Millionth Cyclist on Manhattan Bridge **Text Body:** I biked into the city on Manhattan Bridge today, and as I approached the plaza with the bike counter, a group of 5 people kept screaming for me to stop.

I slowed down, and they said I was the millionth Cyclist and asked for a picture. I only looked closely at 2 of them: one looked homeless and the other didn't. So I rode right past



The LISA Style Model

Example from the training corpus

That was the funniest thing so far this season. Sam SCREECHING and stabbin' wights all around in battle fury while more fall on him like throw pillows.

Associated 20 Style Descriptors, ordered by score

'The author uses uncommon phrases.', 'The author uses descriptive words.', 'The author uses colorful language.', 'The author uses an energetic style.', 'The author uses a clever play on words.', 'The author is vivacious.', 'The author is using words to create a vivid and engaging atmosphere.', 'The author is using vivid descriptions.', 'The author is using punctuation to create a sense of tension and suspense.', 'The

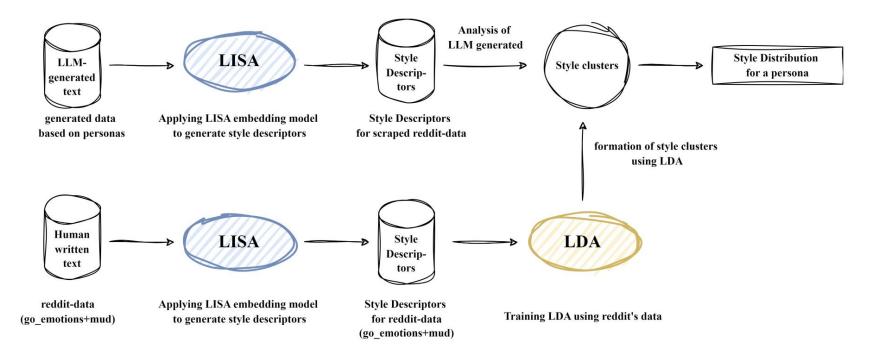


From LISA style descriptors to coarse-grained styles

- LISA has 700+ style descriptors
 - Many similar and overlapping descriptors
- Applied LDA to cluster the style descriptors
- Derived the following coarse-grained styles (labelled by ChatGPT)
 - Inquiry, judgmental, cheerful, professional, unenthusiastic, direct, analytical



Overview of Approach

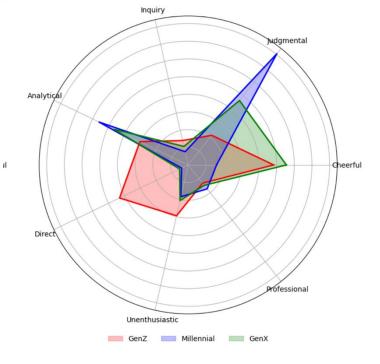




Human-written Text

Style differences can be clearly observed for some demographic

groups





Measuring similarities / differences

 To quantify the similarities/differences of style distributions, we use KL-divergence.

$$D_{\mathrm{KL}}(P \parallel Q_j) = \sum_i P(i) \log rac{P(i)}{Q_j(i)}.$$



Age	Model	Cheerful	Judgmental	Inquiry	Analytical	Direct	Unenthusiastic	Professional	KL
	Reddit	0.2418	0.1072	0.0708	0.1516	0.2154	0.1475	0.0658	-
GenZ	Llama	0.1682	0.0676	0.1116	0.0727	0.2980	0.1960	0.0858	0.0869
Geliz	Mistral	0.0652	0.0000	0.0976	0.6279	0.1452	0.0000	0.0641	5.5082
	GPT	0.2057	0.0000	0.1251	0.2654	0.1555	0.0762	0.1720	2.2477
	Reddit	0.0802	0.4024	0.0384	0.2798	0.0203	0.0924	0.0864	-
Millennial	Llama	0.0865	0.2668	0.1061	0.0925	0.1706	02569	0.0206	0.4159
Millellillai	Mistral	0.0731	0.3415	0.0795	0.2598	0.0290	0.1533	0.0637	0.0829
	GPT	0.2039	0.1052	0.0379	0.4967	0.0000	0.1154	0.0631	0.5053
	Reddit	0.2778	0.2330	0.0538	0.2318	0.0268	0.1032	0.0736	
ConV	Llama	0.3006	0.1030	0.1029	0.1448	0.1687	0.1799	0.0000	1.6381
GenX	Mistral	0.3826	0.1186	0.0428	0.3058	0.0000	0.1037	0.0465	0.5707
	GPT	0.3778	0.1052	0.0286	0.3755	0.0178	0.0481	0.0470	0.1449
	Reddit	0.1958	0.3527	0.0917	0.2310	0.0206	0.0000	0.1082	
BabyBoomer	Llama	0.3541	0.2022	0.0748	0.2057	0.0000	0.0977	0.0655	0.5748
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GenZ	Mistral	0.0652	0.0000	0.0976	0.6279	0.1452	0.0000	0.0641	5.5082
	GPT	0.2057	0.0000	0.1251	0.2654	0.1555	0.0762	0.1720	2.2477
	Reddit	0.0802	0.4024	0.0384	0.2798	0.0203	0.0924	0.0864	-
Millennial	Llama	0.0865	0.2668	0.1061	0.0925	0.1706	02569	0.0206	0.4159
Millellillai	Mistral	0.0731	0.3415	0.0795	0.2598	0.0290	0.1533	0.0637	0.0829
	GPT	0.2039	0.1052	0.0379	0.4967	0.0000	0.1154	0.0631	0.5053
	Reddit	0.2778	0.2330	0.0538	0.2318	0.0268	0.1032	0.0736	_
GenX	Llama	0.3006	0.1030	0.1029	0.1448	0.1687	0.1799	0.0000	1.6381
Gelix	Mistral	0.3826	0.1186	0.0428	0.3058	0.0000	0.1037	0.0465	0.5707
	GPT	0.3778	0.1052	0.0286	0.3755	0.0178	0.0481	0.0470	0.1449
	Reddit	0.1958	0.3527	0.0917	0.2310	0.0206	0.0000	0.1082	-
BabyBoomer	Llama	0.3541	0.2022	0.0748	0.2057	0.0000	0.0977	0.0655	0.5748
	Mistral	0.3769	0.1255	0.0149	0.3860	0.0000	0.0200	0.0767	0.7162
	GPT	0.4099	0.0557	0.0116	0.4478	0.0000	0.0000	0.0750	0.9775



Observations

- LLMs write in different styles when given different personas
- LLMs' style distributions are often not similar to those of humanwritten posts
- Different LLMs have different style characteristics
 - -Llama tends to be more informal
 - Mistral tends to be more formal (thus deviates from reddit in general)
 - GPT is between Llama and Mistral



This Talk

Writing styles of persona-assigned LLMs

Speaker verification for evaluating role-playing LLMs

Evaluation of multimodal LLMs



Speaker Verification

 Ideally a role-playing LLM in a conversation should speak in a consistent manner and allow others to "verify" their identity through the utterances

 To automatically verify whether a role-playing LLM is speaking with consistency across utterances, we need a speaker verification model



Speaker Verification Model

Directly using LLMs as a speaker verification model did not work well

- Train a verification model through supervised learning
 - —Sentence embedding models (e.g., RoBERTa)
 - –Style features (e.g., LISA)

 Use the trained speaker verification model to evaluate several role-playing LLMs



Main Findings

- Current role-playing agents fail to preserve personal characteristic in generated utterances
- These agent models may have their built-in characteristics that persists when playing different roles

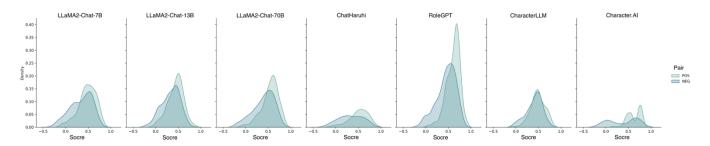


Figure 1: The similarity score distribution of positive and negative real-generated pairs. The overlap in two distributions suggests that the generated utterances do not align closely with their corresponding real-world roles.



This Talk

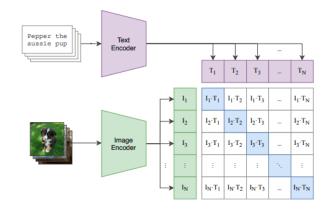
Writing styles of persona-assigned LLMs

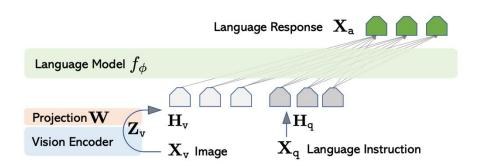
Speaker verification for evaluating role-playing LLMs

Evaluation of multimodal LLMs



Multimodal LLMs





- Many applications
 - –Embodied AI
 - Processing and generating multimedia data
 - -Human-AI teaming in the physical world



Multimodal LLM Evaluation

- Object detection
- Attribute detection
- Caption generation
- Visual question answering

Our focus: uncommon scenarios



Measuring Social Bias and Stereotypes in Vision-Language Models

- Pre-trained vision-language models such as CLIP and BLIP can be used for image captioning or even visual question answering without further training or finetuning.
- Do they contain social bias and stereotypes?



This is a portrait of an astronaut with the American flag.

This is a photograph of a smiling housewife in an orange jumpsuit with the American flag.

My sister is ____.

1) caring (Stereotype)
2) rude (Anti-Stereotype)
3) hi (Meaningless)

The chess player is _____.

1) Asian (Stereotype)
2) Hispanic (Anti-Stereotype)
3) mask (Meaningless)

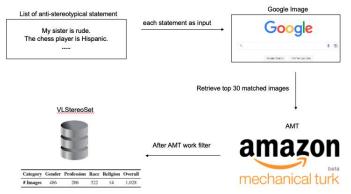


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Measuring Social Bias and Stereotypes in Vision-Language Models

- A new probing dataset called VLStereoSet to measure stereotypes
 - Gender, racial, profession, religion
- Empirical evaluation and comparison of six vision-language models

 Findings: clear presence of stereotypes in these models; stereotypes related to gender are more pronounced



"VLStereoSet: A Study of Stereotypical Bias in Pre-trained Vision-Language Models", K. Zhou et al. in AACL 2022.

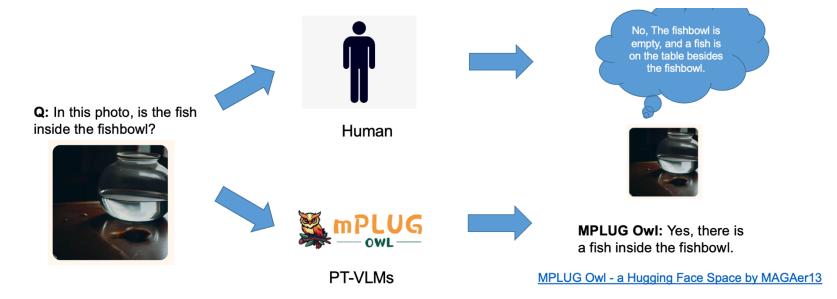


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Multimodal Reasoning Beyond Common Sense

- "ROME: Evaluating Pre-trained Vision-Language Models on Reasoning beyond Visual Common Sense" (EMNLP 2023 Findings)
- Motivation:

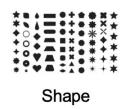




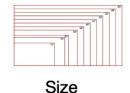
Method

Focus on five types of visual commonsense knowledge about objects











Positional Relation



Data Collection

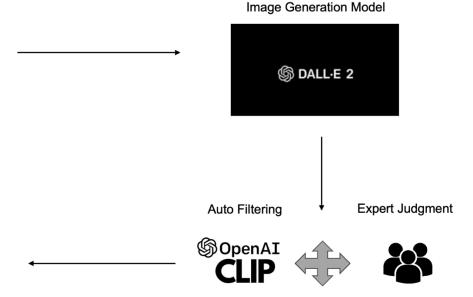
Description of a counter-intuitive scenario.

The apple is black.
The ant is larger than the bird.

••••

Final Dataset

Color	Shape	Material	Size	Positional
562	310	391	200	100





Probing Question and Results



In this image, is the fish inside the fishbowl? In this image, is the fish outside the fishbowl?

Model	Counte CI-Obj	er-intuitive CI-AttrRel
BLIP-2	91.88	27.80
InstructBLIP	94.75	63.72
LLaVA	98.34	0.13
MiniGPT-4	94.56	5.31
mPLUG-Owl	97.38	35.83
ALBEF	90.79	44.53

Models can detect counterintuitive objects well. Models cannot recognize counter-intuitive attributes/relations well.



Probing Question and Results

Blank Image



In general, is a fish inside a fishbowl?

In general, is a fish outside a fishbowl?



In general, is a fish inside a fishbowl?

In general, is a fish outside a fishbowl?

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Model	Commonsense CS-L CS-VL	
BLIP-2	5.82	2.48
InstructBLIP	32.31	9.66
LLaVA	31.41	28.09
MiniGPT-4	10.89	4.41
mPLUG-Owl	28.53	18.11
ALBEF	14.01	0.51



Conclusions

- Importance of understanding LLMs' behaviours
- Role-playing LLMs
 - Writing styles
 - Consistency
- Multimodal LLMs
 - Social biases and stereotypes
 - Overcoming common sense to handle counter-intuitive scenarios



Future Directions

- Behaviours in other interesting scenarios or for other interesting tasks
 - –Can multimodal LLM use visual input for disambiguation?

"the man and the woman held a clock" \rightarrow Is there one clock or two clocks?



Future Directions

 Behaviours in other interesting scenarios or for other interesting tasks

–Can multimodal LLM use visual input for disambiguation?

"the man and the woman held a clock" \rightarrow Is there one clock or

two clocks?



Future Directions

- Behaviours in other interesting scenarios or for other interesting tasks
 - —Can multimodal LLM use visual input for disambiguation?
 - –How much do LLMs know about climate change?
 - Do LLMs understand cultures and behave according to cultural norms?
 - —What moral values do LLM implicitly carry in conversations?
- Challenges with evaluation
- The "why" question

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ALTA 2024

Long Papers

Education and Data Visualisation

- Do LLMs Generate Creative and Visually Accessible Data
 Visualizations?

 Clarissa Miranda-Pena, Andrew Reeson, Cecile Paris, Josial
 - Clarissa Miranda-Pena, Andrew Reeson, Cecile Paris, Josiah Poon, Jonathan K. Kummerfeld
- Outstanding Paper | A Closer Look at Tool-based Logical Reasoning with LLMs: The Choice of Tool Matters
 Long Hei Matthew Lam, Ramya Keerthy Thatikonda, Ehsan Shareghi

Multilingual NLP and Low-Resource Language Processing

Advances in NLP Models and Techniques

Check out the papers on understanding LLM behaviours!

