Can MLLMs Understand the Deep Implication Behind Chinese Images?



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Introduction

As the capabilities of Multimodal Large Language Models (MLLMs) improve, the need for higher-order evaluation of them is increasing. However, there is a lack of work evaluating MLLM for higher-order perception and understanding of Chinese visual content. To address this, we introduce the CII-Bench, which aims to assess MLLMs' such capabilities for Chinese images. To ensure the authenticity of the Chinese context, images in CII-Bench are sourced from the Chinese Internet and manually reviewed, with corresponding answers also manually crafted. Additionally, CII-Bench incorporates images that represent Chinese traditional culture, such as famous Chinese traditional paintings, which can deeply reflect the model's understanding of Chinese traditional culture. Through experiments on multiple MLLMs using CII-Bench, significant findings emerged. There is a large gap between MLLMs and humans in performance. The highest MLLM accuracy is 64.4%, while the human average is 78.2% and the peak is 81.0%. MLLMs perform poorly on traditional culture images, indicating limitations in understanding high-level semantics and lacking a deep knowledge base of Chinese traditional culture. Moreover, most models have higher accuracy when image emotion hints are added to the prompts. We believe CII-Bench will help MLLMs better understand Chinese semantics and specific images, and move forward the development of expert artificial general intelligence (AGI). Our project is publicly available at https://cii-bench.github.io.

Overview

We introduce the Chinese Image Implication Understanding Benchmark CII-Bench, a new benchmark measuring the higher-order perceptual, reasoning and comprehension abilities of MLLMs when presented with complex Chinese implication images. These images, including abstract artworks, comics, memes, posters and paintings, possess visual implications that require an understanding of visual details



中华传统文化 Chinese Traditional Culture

Question: 这张图片有什么隐喻? Option:

(A)萧瑟的冬景暗示了人物对于

春天到来、万物复苏的渴望。

(B)孤身赏雪景暗示了图片中

人物淡然、超脱世俗的心境。 (C)独自一人欣赏雪景暗示了人物内心的孤独和知己难求的悲伤。

(D)抬头的动作暗示了人物的思考。

(E)独身一人暗示了人物对于亲人和家乡的怀念。

(F)萧瑟的冬景暗示了人物内心的悲伤。

Rhetoric: 隐喻 Emotion: 积极 Difficulty Level: 困难

Image Type: 绘画(Painting)

Question: 这张图片有什么隐喻?

环境 Environment

Option: (A)象征着自然界的生物受到人类 活动的严重影响,甚至面临灭绝

的威胁。 (B)这张图片表现了工业技术的飞速

发展, 暗示着未来生活将更加便利和富裕。

(C)这张图片旨在宣传新型环保技术的应用,表现工业与自然和 谐共处的美好愿景。 (D)暗示了人们有能力通过改变行为模式、采用新技术、实施环

保政策等方式,来减轻对自然环境的破坏,实现可持续发展和 生态平衡的可能。 (E)表达了人类对自然界的彻底征服,通过技术改变地表环境。

(F)表达了对环境污染和生态破坏的深刻忧虑,它提醒观者在追 求工业发展的同时,不应忽视对自然环境的保护和珍惜。

Image Type: 海报(Poster) Rhetoric: 象征 Emotion: 消极 Difficulty Level: 中等

Difficulty Level: 简单

政治 Politics

Question: 这张图片有什么隐喻? Option:

(A)个体在面对群体或更高权威时, 所面临 的道德困境和选择。

(B)天使和士兵形象之间的冲突暗示了信仰 与现实之间的张力,以及个体在面对残酷

现实时, 如何坚持自己的信仰。 (C)图片象征了人类对宗教信仰的追求,表达了对精神世界的渴望。

达了对和平的渴望与对战争后果的担忧。 (E)个人的命运既受到外力的影响,也取决于个人的选择。 (F)即使在和平时期,战争的威胁也可能随时存在;而即使在战争

(D)图片可能讽刺了那些以战争干预其他国家或地区的行为,表

中,人们也可能怀抱着对和平的渴望。 Image Type: 插画(Illustration)

Rhetoric: 隐喻、对比 Emotion: 消极 Difficulty Level: 困难

Statistics

CII-Bench contains a total of 698 various Chinese images. These images are manually collected and annotated by 30 undergraduate students from various disciplines and institutions, with sources from multiple renowned Chinese illustration websites. Each image is manually designed with one to three multiple-choice questions, each with six options and only one correct answer. The questions cover the metaphors, symbolism, and detailed understanding of the images. The benchmark includes a total of 800 multiple-choice questions, with 765 questions used to construct the test set and 35 questions used to construct the development and validation set for few-shot tasks. Statistics **Statistics**

Statistics	
Total Questions	800
Total Images	698
Dev : Validation : Test	15:20:765
Easy: Medium: Hard	305 : 282 : 111
Average Question Length	10.54
Average Option Length	28.31
Average Explanation Length	121.06
Metaphor	562
Exaggerate	121
Symbolism	236
Visual Dislocation	42
Antithesis	13
Analogy	19
Personification	73
Contrast	87

Statistics	
Life	216 (30.95%)
Art	123 (17.62%)
Society	157 (22.49%)
Environment	51 (7.31%)
Politics	21 (3.01%)
Chinese Traditional Culture	130 (18.62%)
Positive	220 (31.52%)
Neutral	247 (35.39%)
Negative	231 (33.09%)
Illustration	178 (25.50%)
Meme	145 (20.77%)
Poster	87 (12.46%)
Multi-panel Comic	34 (4.87%)
Single-panel Comic	143 (20.49%)
Painting	119 (17.05%)
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Personification 73 Contrast 87	<u> </u>	Comic 143 (20.49%) 119 (17.05%)
Illustration	Meme	Poster
Life (19, 10.68%)	Life (138, 95.17%)	Life (8, 9.20%)
Art (79, 44.38%)	Mrt (0, 0%)	Art (33, 37.93%)
Society (58, 32.58%)	Society (4, 2.76%)	Society (3, 3.45%)
TCTC (0, 0%)	TCTC (0, 0%)	TCTC (7, 8.05%)
Environment (12, 6.74%)	Environment (3, 2.07%)	Environment (36,41.37%)
Politics (10, 5.62%)	Politics (0, 0%)	Politics (0, 0%)
Multi-panel Comic	Single-panel Comic	Painting
Life (25, 73.53%)	Life (27, 18.88%)	Life (0, 0%)
Art (0, 0%)	Art (11, 7.69%)	Art (0, 0%)
Society (8, 23.53%)	Society (88, 61.54%)	Society (0, 0%)
TCTC (0, 0%)	T CTC (4, 2.80%)	TCC (119, 100%)
Environment (0, 0%)	Environment (2, 1.40%)	Environment (0, 0%)

Politics (11, 7.69%)

Main Results

Overall	Life	Art	Society	Politics	Env.	CTC	Positive	Negative	Neutral	
(800)	(216)	(123)	(157)	(21)	(51)	(130)	(220)	(247)	(231)	
		Open-s	source Mod	dels						
34.3	27.9	34.7	32.5	45.8	55.2	36.5	34.0	35.1	33.6	
36.3	25.0	46.3	38.1	41.7	56.9	32.9	32.8	39.1	36.4	
40.4	36.3	45.6	37.1	50.0	51.7	40.2	43.2	37.0	41.3	
43.4	37.1	48.3	42.3	54.2	63.8	40.2	40.3	45.7	43.8	
45.0	37.5	47.6	49.5	58.3	55.2	42.3	45.6	44.6	44.9	
46.0	40.8	<u>55.1</u>	42.8	45.8	62.1	43.1	44.4	48.2	45.2	
48.0	43.8	48.3	49.5	<u>70.8</u>	60.3	43.8	41.5	52.5	49.2	
49.6	42.5	51.7	54.1	62.5	65.5	44.5	50.2	47.5	51.2	
50.3	46.7	48.3	53.6	54.2	62.1	48.2	51.9	52.9	46.3	
52.9	50.8	53.7	51.0	58.3	67.2	51.1	<u>54.8</u>	51.8	52.3	
53.1	49.2	53.1	55.7	62.5	63.8	50.4	50.6	53.3	55.1	
<u>57.9</u>	<u>55.8</u>	<u>55.1</u>	61.9	62.5	<u>70.7</u>	<u>52.6</u>	54.4	<u>58.0</u>	60.8	
64.4	61.7	61.2	68.0	79.2	75.9	59.9	62.7	63.8	66.4	
		Closed-	source Mo	odels						
54.1	54.1	55.8	52.1	50.0	63.8	51.8	51.9	56.2	54.1	
54.1	52.1	<u>61.9</u>	52.6	62.5	46.6	<u>53.3</u>	52.7	56.5	53.0	
56.9	53.3	59.2	58.8	62.5	<u>67.2</u>	52.6	53.9	58.3	58.0	
60.1	60.0	63.3	<u>62.4</u>	70.8	62.1	51.1	<u>54.8</u>	65.6	59.4	
60.9	<u>55.0</u>	59.9	66.5	<u>66.7</u>	79.3	55.5	58.5	<u>64.5</u>	59.4	
		Text-	Only Mode	els						
21.7	22.2	26.9	18.6	25.0	27.8	20.4	21.2	24.4	19.5	
27.1	26.6	32.7	30.9	20.0	35.2	18.2	25.7	$\overline{22.2}$	33.2	
32.5	33.2	34.6	30.9	35.0	40.7	28.5	33.6	30.4	33.6	
		1	Humans							
78.2	81.0	67.7	82.7	87.7	84.0	65.9	77.9	75.2	81.6	
81.0	83.2	73.6	87.2	89.5	86.0	66.7	78.2	78.8	83.3	
	(800) 34.3 36.3 40.4 43.4 45.0 46.0 48.0 49.6 50.3 52.9 53.1 57.9 64.4 54.1 56.9 60.1 60.9	34.3 27.9 36.3 25.0 40.4 36.3 43.4 37.1 45.0 37.5 46.0 40.8 48.0 43.8 49.6 42.5 50.3 46.7 52.9 50.8 53.1 49.2 57.9 55.8 61.7 54.1 52.1 56.9 53.3 60.1 60.0 55.0 21.7 22.2 27.1 26.6 32.5 33.2	(800) (216) (123) Open-s 34.3 27.9 34.7 36.3 25.0 46.3 40.4 36.3 45.6 43.4 37.1 48.3 45.0 37.5 47.6 46.0 40.8 55.1 48.0 43.8 48.3 49.6 42.5 51.7 50.3 46.7 48.3 52.9 50.8 53.7 53.1 49.2 53.1 57.9 55.8 55.1 64.4 61.7 61.2 Closed- 54.1 54.1 55.8 54.1 52.1 61.9 56.9 53.3 59.2 60.1 60.0 63.3 60.9 55.0 59.9 Text-0 21.7 22.2 26.9 27.1 26.6 32.7 32.5 33.2 34.6	Open-source Mode Open-source Mode 34.3 27.9 34.7 32.5 36.3 25.0 46.3 38.1 40.4 36.3 45.6 37.1 43.4 37.1 48.3 42.3 45.0 37.5 47.6 49.5 46.0 40.8 55.1 42.8 48.0 43.8 48.3 49.5 49.6 42.5 51.7 54.1 50.3 46.7 48.3 53.6 52.9 50.8 53.7 51.0 53.1 49.2 53.1 55.7 57.9 55.8 55.1 61.9 64.4 61.7 61.2 68.0 Closed-source Mode 54.1 54.1 55.8 52.1 54.1 54.1 55.8 52.1 54.1 54.1 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There is a notable performance gap between MLLMs and humans.

in the images.

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Models demonstrate the highest accuracy of 64.4%, while human accuracy average at 78.2% and best at 81.0%. - Disparity between Open-source and Closed-source Models

Closed-source models generally outperform open-source models,

but the best-performing open-source model surpasses the top closed source model, with a difference of more than 3%. - Model Performance across Different Domains and Emotions

Models perform significantly worse in Chinese traditional culture

compared to other domains, indicating that current models still lack sufficient understanding of Chinese culture. Further analysis shows that GPT-40 can only observe the surface-level information, it's difficult to deeply interpret the complex cultural elements contained in Chinese traditional painting.

- Analysis on different prompt skills Incorporating image emotion hints into prompts generally improves model scores, indicating that models struggle with emotional understanding, leading to misinterpretation of the implicit meanings

Politics (0, 0%)

Politics (1, 2.94%)