

# LLMScore: Unveiling the Power of Large Language Models in Text-to-Image Synthesis Evaluation

UC SANTA BARBARA

UNIVERSITY of WASHINGTON

Yujie Lu, Xianjun Yang, Xiujun Li, Xin Eric Wang, William Yang Wang

# Motivation

## **Existing Metrics**

- Fail to distinguish object-level alignment
- Single-aspect
- Non-interpretable

Text Prompt: A red book and a yellow vase.





	Left Right	LLMScore - Overall Rationale
Human Overall	1.00 0.45	The overall quality of the image is quite
Error Counting	1.00 0.55	low due to the <u>significant discrepancies</u> between the objects described in the tex
Baseline CLIP	0.27 0.31	prompt and those portrayed in the image
NegCLIP	0.26 0.32	LLMScore - Error Counting Rationale
BLIP-ITM	0.99 1.00	The <u>red book</u> from the prompt is not in
BLIP-ITC	0.48 0.49	image. The <u>vase</u> is described as <u>red</u> in the image. While the text prompt specified as
LLMScore Overall	1.00 0.50	image, while the text prompt specified a yellow vase. Over-specification of the
Error Counting	1.00 0.44	yellow flowers in the image.

#### LLMScore - Overall Rationale

The overall quality of the image is quite low due to the significant discrepancies between the objects described in the text prompt and those portrayed in the image.

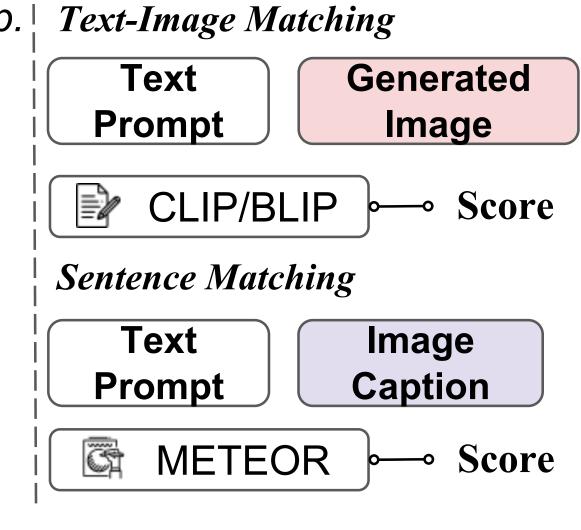
LLMScore - Error Counting Rationale The <u>red book</u> from the prompt is not in the image. The <u>vase</u> is described as <u>red</u> in the image, while the text prompt specified a

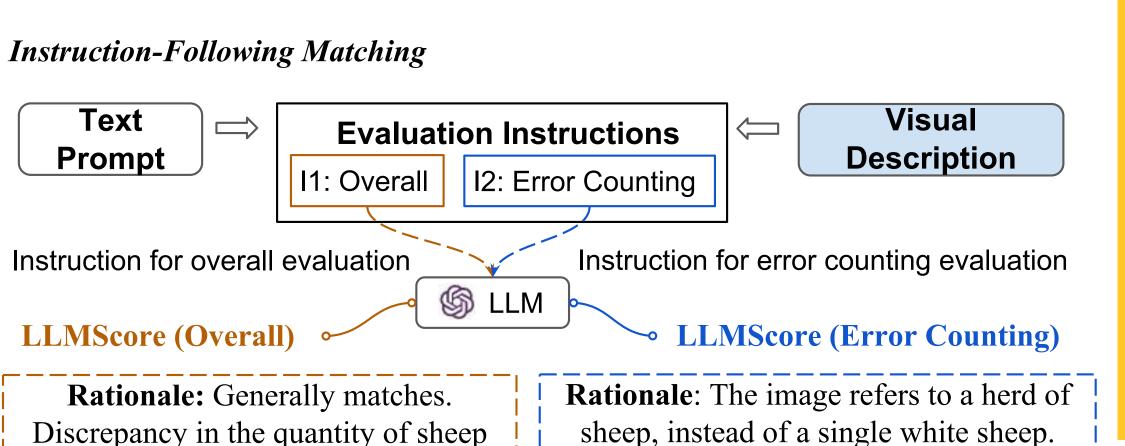
# Paradigm Comparison





Discrepancy in the quantity of sheep





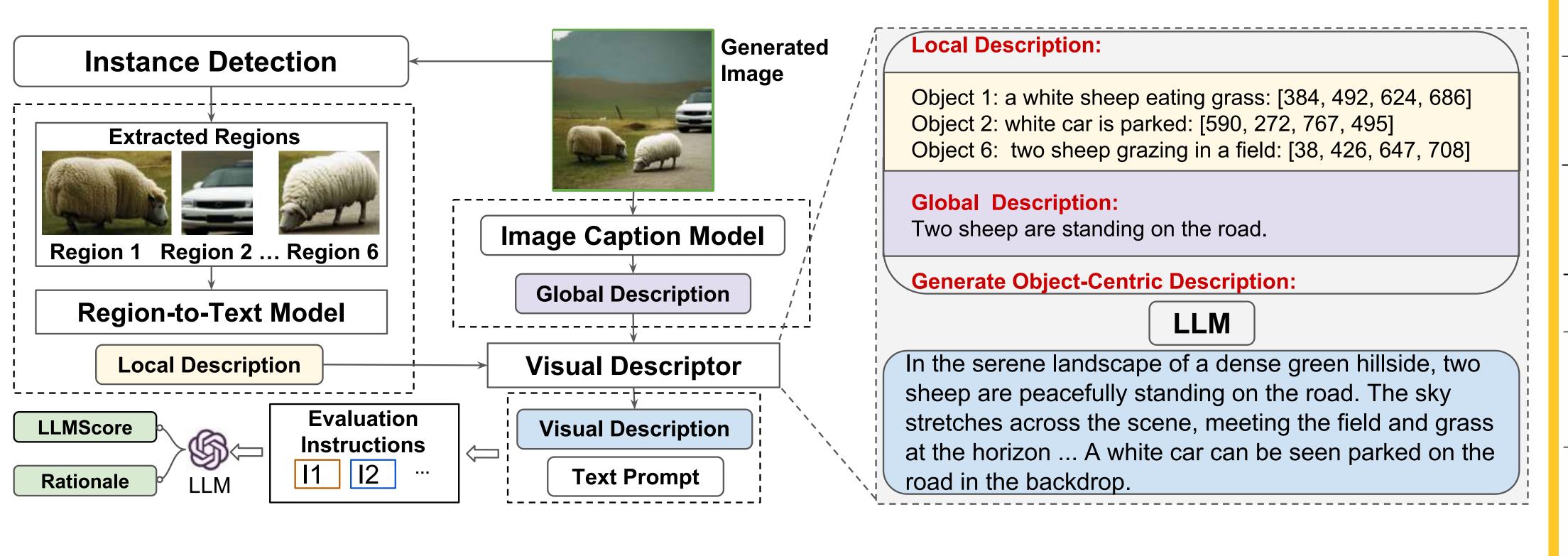
# LLMScore Pipeline for Text-to-Image Evaluation

LLMs As Multi-Granularity Visual Descriptor

- Global Image Description
- Local Region Descriptions
- Object-Centric Visual Descriptions

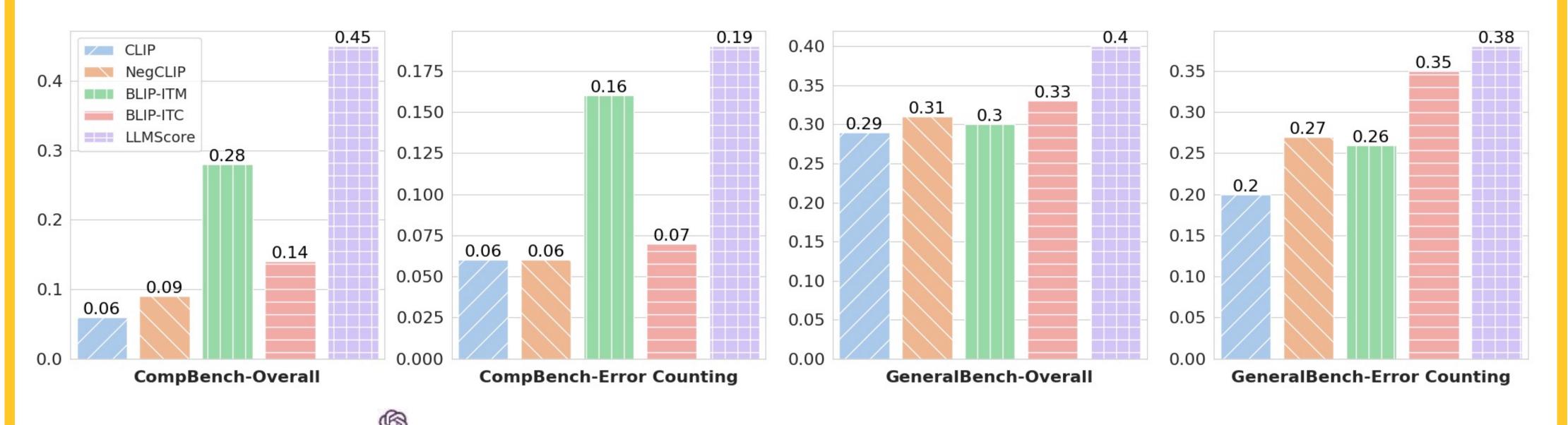
LLMs As Text-to-Image Evaluator

- Instruction Following Rating
- Generating Rationale



# Main Results

Averaged Kendall's t Ranking Correlation with Human Ratings.



Example showing the LLMScore captures the object-level discrepancies.





#### **Overall Rationale** The image caption describes two red suitcases, a vintage clock on the wall, and a blue curtain in the background, but the text prompt only mentions a red clock and a gold suitcase. The alignment between the text prompt and image caption is

LLMScore (Error Counting) 0.55

#### **Error Counting Rationale**

LLMScore (Overall)

The composition errors include incorrect suitcase colors, incorrect clock color, and additional elements not mentioned in the text prompt (a second suitcase and

## Ablation

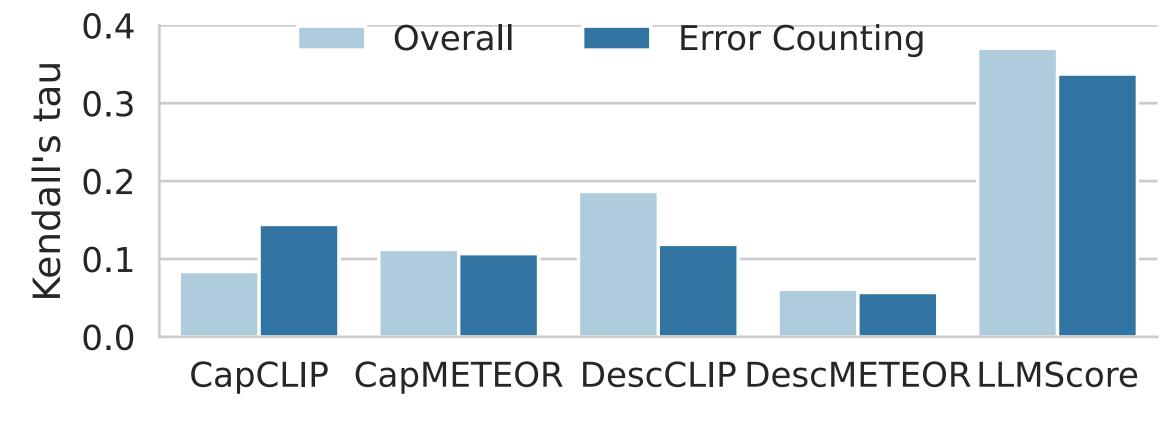
### Composition-focused Prompt Bench

	Metric	Concept Conjunction				Attribute Binding Contrast				
Human		<b>Stable Diffusion</b>		DALLE		Stable Diffusion		DALLE		
		$ au(\uparrow)$	$\rho(\uparrow)$	$ au(\uparrow)$	$\rho(\uparrow)$	$ au(\uparrow)$	$\rho(\uparrow)$	$ au(\uparrow)$	$\rho(\uparrow)$	
Overall	CLIP	0.1698	0.2459	-0.0049	-0.0058	0.0186	0.0320	0.0396	0.0548	
	<b>NegCLIP</b>	0.1724	0.2504	0.0682	0.0995	0.0151	0.0211	0.1145	0.1634	
	<b>BLIP-ITM</b>	0.4058	0.5618	0.3768	0.5266	0.1799	0.2559	0.1500	0.2134	
	<b>BLIP-ITC</b>	0.2378	0.3398	0.0991	0.1413	0.1982	0.2814	0.0252	0.0344	
	LLMScore	0.4871	0.6956	0.5167	0.7230	0.4005	0.5480	0.3955	0.5506	
Error Counting	CLIP	0.2012	0.2864	-0.0782	-0.1107	0.0061	0.0071	0.0914	0.1286	
	<b>NegCLIP</b>	0.2245	0.3240	-0.0353	-0.0502	-0.0339	-0.0418	0.0796	0.1130	
	<b>BLIP-ITM</b>	0.3341	0.4561	0.1105	0.1668	0.0696	0.0968	0.1249	0.1783	
	BLIP-ITC	0.2210	0.3124	-0.0755	-0.1071	0.0895	0.1315	0.0533	0.0786	
	LLMScore	0.3779	0.5443	0.2880	0.4428	0.1863	0.2821	0.2326	0.3351	

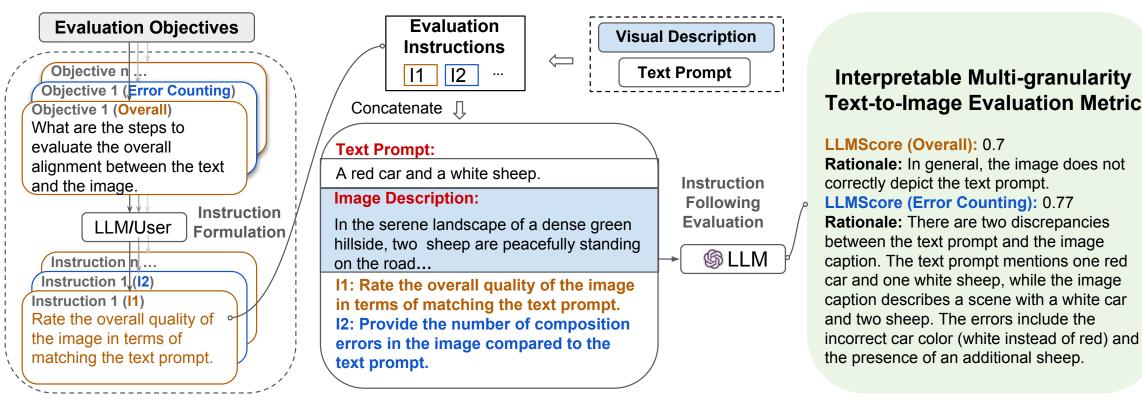
### General-purpose Prompt Bench

Human	Metric	COCO2014		<b>COCO2017</b>		DrawBench		<b>PaintSkills</b>	
		$ au(\uparrow)$	$ ho(\uparrow)$	$ au(\uparrow)$	$ ho(\uparrow)$	$ au(\uparrow)$	$ ho(\uparrow)$	$ au(\uparrow)$	$ ho(\uparrow)$
	CLIP	0.1971	0.2655	0.2227	0.2771	0.1530	0.2143	0.4715	0.5869
	NegCLIP	0.2164	0.2905	0.2793	0.3523	0.1463	0.1999	0.4911	0.6313
Overall	<b>BLIP-ITM</b>	0.3252	0.4255	0.0928	0.1155	0.1044	0.1455	0.4755	0.6214
	BLIP-ITC	0.3465	0.4535	0.1703	0.2121	0.1569	0.2171	0.4743	0.5864
	LLMScore	0.3629	0.4612	0.3357	0.4275	0.2230	0.3023	0.5600	0.6853
Error Counting	CLIP	0.1464	0.2142	0.1888	0.2677	0.1360	0.1910	0.3052	0.2891
	NegCLIP	0.2116	0.3061	0.1795	0.2581	0.1179	0.1596	0.4563	0.4908
	<b>BLIP-ITM</b>	0.2251	0.3289	0.1137	0.1635	0.0871	0.1189	0.4622	0.4997
	<b>BLIP-ITC</b>	0.2636	0.3739	0.1849	0.2620	0.1506	0.2029	0.6178	0.6511
_	LLMScore	0.2830	0.3992	0.2038	0.3027	0.2134	0.2865	0.6437	0.7325

### Comparison of Matching Paradigms



### Effects of Large Language Models



Human	LLM	Desc	CLIP	DescM	<b>1eteor</b>	LLMScore	
		$ au(\uparrow)$	$ ho(\uparrow)$	$ au(\uparrow)$	$ ho(\uparrow)$	$ au(\uparrow)$	$ ho(\uparrow)$
Overall	GPT-3.5 GPT-4	$0.1479 \\ 0.1128$	$0.1956 \\ 0.1485$	$0.0042 \\ 0.0297$	$0.0073 \\ 0.0374$	$0.2480 \\ 0.2793$	$0.3285 \\ 0.3649$
Error Counting	GPT-3.5 GPT-4	$0.0467 \\ 0.0149$	$0.0670 \\ 0.0228$	$-0.0597 \\ -0.1087$	-0.0835 $-0.1494$	$0.2205 \\ 0.2131$	$0.3013 \\ 0.2981$