

# SCRAMBLe: Enhancing Multimodal LLM Compositionality with Synthetic Preference Data LLV Compositionality with Synthetic Preference Data

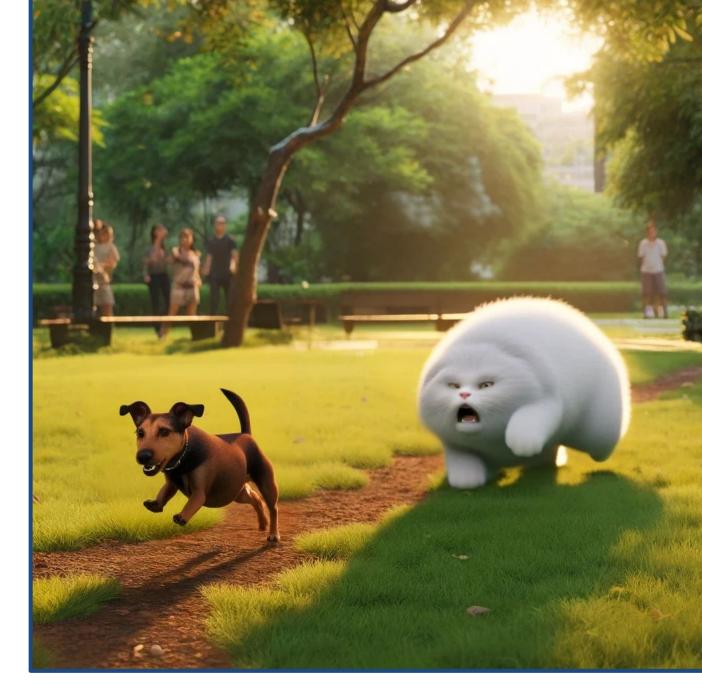
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### Can Multimodal LLMs distinguish between





a dog chasing a cat

a cat chasing a dog

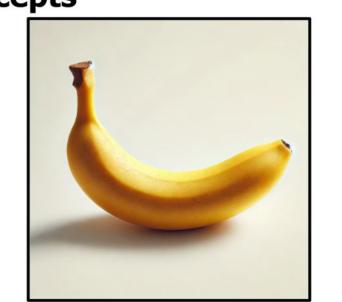
On Winoground, a benchmark of such questions, MLLM (GPT-4V) performance = 33% Human performance = 85%

# **Compositionality:**

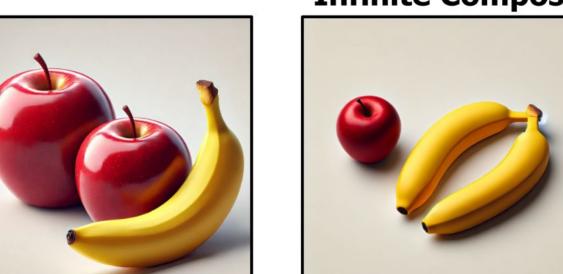
Identifying parts/concepts and how they are composed to give rise to a given scene

### **Atomic Concepts**





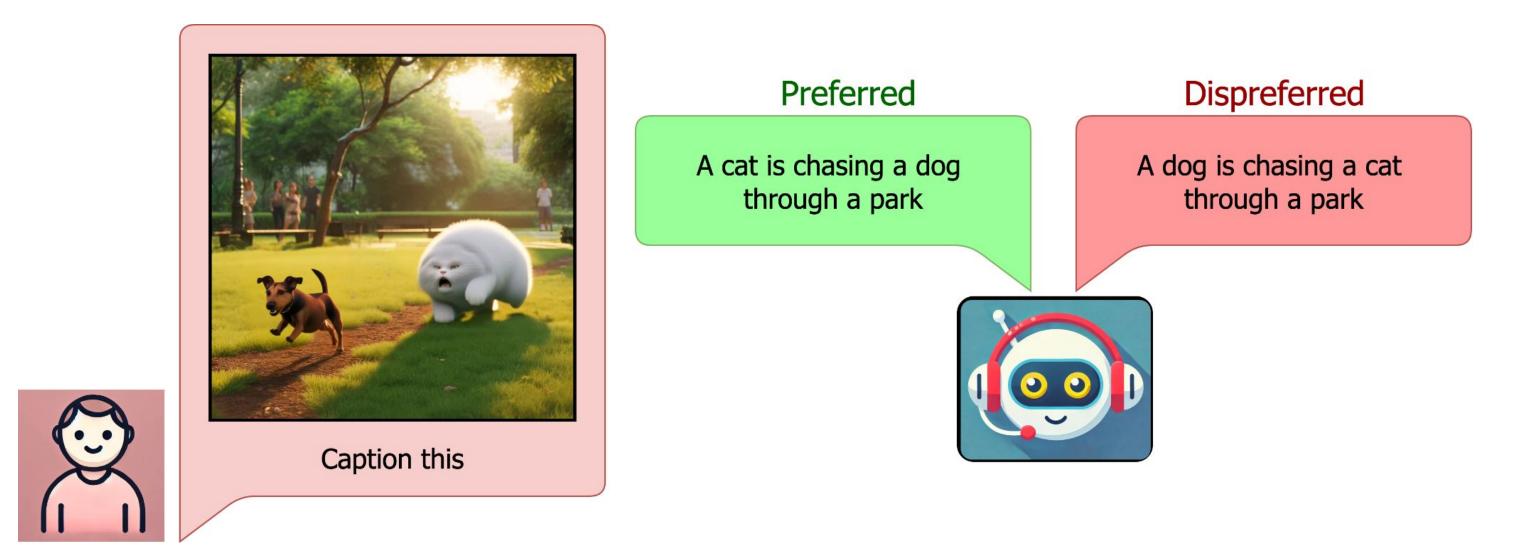
**Infinite Compositions - Nothing New** 



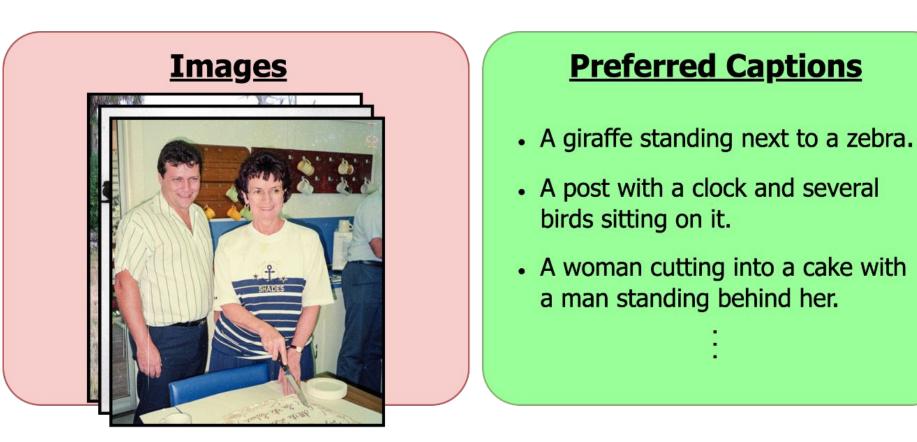
An apple and two bananas A banana on an apple

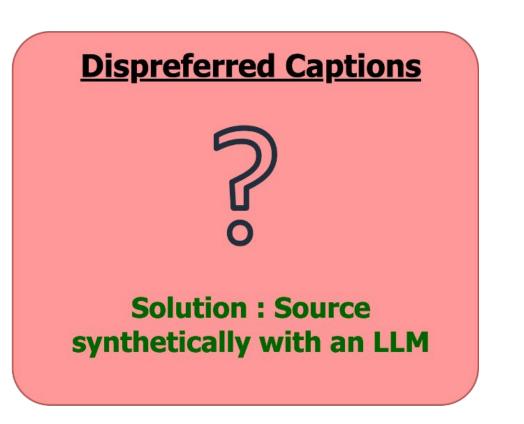


# **Improving Compositionality with Preference Tuning**

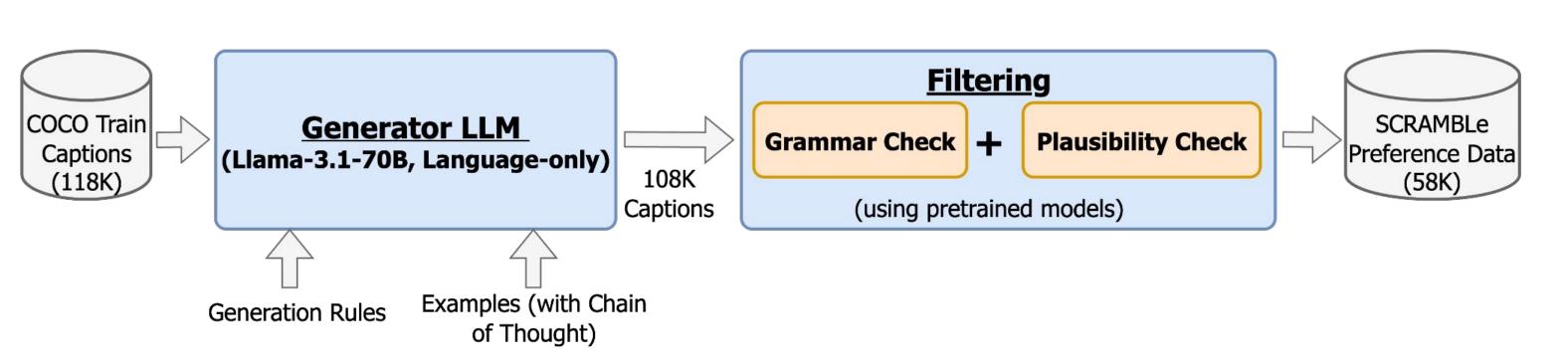


### Data Source: Existing Image Caption Dataset (COCO)





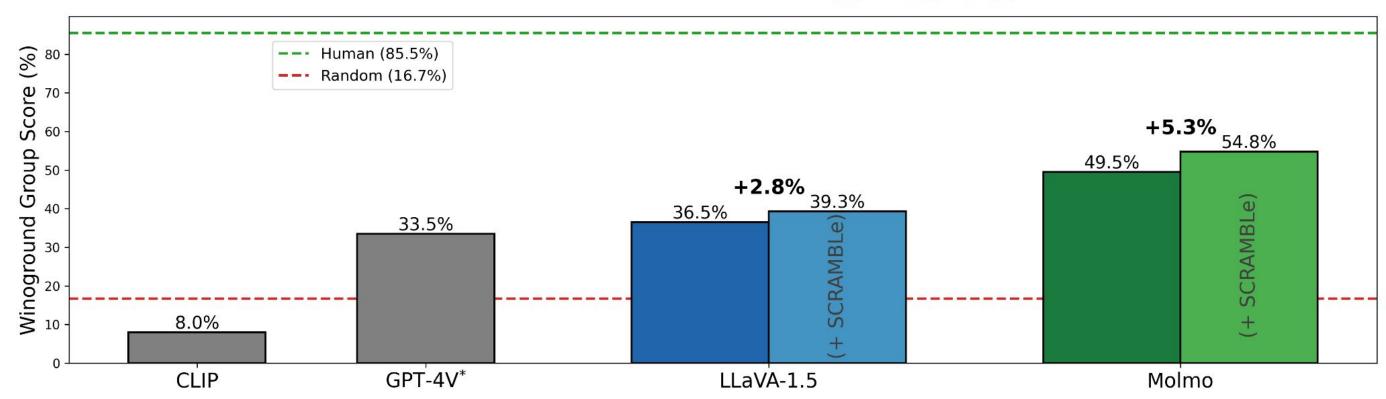
# **Synthetic Data Generation**



### References

[1] Mitra, Chancharik, et al. "Compositional chain-of-thought prompting for large multimodal models." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern [2] Lin, Zhiqiu, et al. "Evaluating text-to-visual generation with image-to-text generation." European Conference on Computer Vision. Cham: Springer Nature Switzerland, 2024.

## Winoground Accuracy



### Hmm, could this be overfitting?

Seemingly not. Models retain or improve general QA performance (on Control Benchmarks)

Model Name	Compositionality Benchmarks			Control Benchmarks	
	Winoground	COLA	ConMe	SEED-Bench	MM-Vet
LLaVA-1.5-13B	36.5	49.5	62.3	<b>68.23</b> 68.19	$36.2 \pm 0.3$
+ SCRAMBLe	<b>39.3</b>	<b>55.7</b>	<b>64.5</b>		$38.6 \pm 0.1$
MoLMo-7B	49.5	57.1	72.2	74.04	$59.3 \pm 0.2$ $60.9 \pm 0.4$
+ SCRAMBLe	<b>54.8</b>	<b>60.5</b>	<b>74.6</b>	<b>74.61</b>	

### **Chats with SCRAMBLe-Molmo**







Two apples and a banana