2025/05/22 Stanford NLP Seminar

Closing the Modality Gap: Benchmarking and Improving Visual Understanding in Multimodal LLMs

Deqing Fu
University of Southern California

Hunt for Meaningful Failures

- (Multimodal) LLMs work quite well, but they can still fail in some situations.
- How can we **understand** these failures and potentially **mitigate** some of them?
- How to build meaningful **evaluations** beyond ranking models?

Failures Covered In This Talk

- LLMs Are **Bad at Arithmetics**

- Multimodal LLMs **Hallucinate**

Overview

LLMs are Bad At Arithmetics.

Can we find a family of embeddings to bypass tokenization?

Evaluating Multimodal LLMs Beyond Ranking Models.

Humans have pictorial superiority. How about MLLMs?

Adjacency Matrix: $\begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$. Query Nodes: 4 and 8.

Text LLMs are Teachers for MLLMs.

Fine-Grained Rewards.

Train Text Backbone to be Token-Level Reward Models.

O O O X O O X
O X O X O

MLLM

O O O X O O X
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TLDR

Text Steering Vectors.

Leverage Text-Based Interpretability Tools for MLLMs.

Overview

LLMs are Bad At <u>Arithmetics</u>.

Can we find a family of embeddings to bypass <u>tokenization</u>?

USC University of Southern California

FoNE: Precise Single-Token Number Embeddings via Fourier Features

[In Submission]

Tianyi Zhou

Deqing Fu

Mahdi Soltanolkotabi

Vatsal Sharan

Robin Jia

A Famous Tweet

- **Tokenization** seems like a reason why LLMs are natively bad at simple arithmetics.

Tokenization Comparison for "12345.6789"	
GPT-4, Llama-3.2 (BPE)	123 45 . 678 9
Llama-2, Qwen2.5 (Digitwise tokenization)	1 2 3 4 5 . 6 7 8 9

- Can we design a number embedding to <u>**bypass**</u> tokenization?

Andrej Karpathy
@karpathy

We will see that a lot of weird behaviors and problems of LLMs actually trace back to tokenization. We'll go through a number of these issues, discuss why tokenization is at fault, and why someone out there ideally finds a way to delete this stage entirely.

Tokenization is at the heart of much weirdness of LLMs. Do not brush it off.

- Why can't LLM spell words? **Tokenization**.
- Why can't LLM do super simple string processing tasks like reversing a string? **Tokenization**.
- Why is LLM worse at non-English languages (e.g. Japanese)? **Tokenization**.
- Why is LLM bad at simple arithmetic? **Tokenization**.
- Why did GPT-2 have more than necessary trouble coding in Python? **Tokenization**.
- Why did my LLM abruptly halt when it sees the string "<|endoftext|>"? **Tokenization**.
- What is this weird warning I get about a "trailing whitespace"? **Tokenization**.
- Why the LLM break if I ask it about "SolidGoldMagikarp"? **Tokenization**.
- Why should I prefer to use YAML over JSON with LLMs? **Tokenization**.
- Why is LLM not actually end-to-end language modeling? **Tokenization**.
- What is the real root of suffering? **Tokenization**.

9:40 AM · Feb 20, 2024 · **744.5K** Views

59 402 2.7K 1K

Zhou et. al. *Pre-trained Large Language Models Use Fourier Features to Compute Addition*. NeurIPS 2024

Pre-trained Number Tokens Are Embedded in a Fourier Space.

Can we Hard-Code Numbers?

FoNE: Fourier Number Embedding

- We hard-code embeddings for any number as the following,

$$\mathrm{FoNE}(x) = \begin{bmatrix} \cos\left(\frac{2\pi}{10}\cdot x\right) \\ \sin\left(\frac{2\pi}{10}\cdot x\right) \\ \cos\left(\frac{2\pi}{100}\cdot x\right) \\ \sin\left(\frac{2\pi}{100}\cdot x\right) \\ \vdots \end{bmatrix} = \left[\begin{bmatrix} \cos\left(\frac{2\pi}{T_j}\cdot x\right) \\ \sin\left(\frac{2\pi}{T_j}\cdot x\right) \end{bmatrix}_j\right]$$

- You may choose the periods T_j to be any number. For floating numbers, we can choose $T_j = 0.1,\ 0.01,\ 0.001,\ \cdots$

FoNE Enables Efficient Arithmetic Training

- We train a Transformer model with only **38M** parameters with FoNE number embedding.
- Task: 6-digit decimal addition.
- FoNE can achieve 100% accuracy.
- To achieve >99% accuracy, FoNE requires much less data. FoNE is **data efficient.**

(a) 6-digit decimal addition: Acc. vs. Training Data Size

FoNE Enables Efficient Arithmetic Training

- We ablate # **parameters** of Transformers for training FoNE.
- FoNE is **parameter efficient.**
- We extend tasks to addition, subtraction, and multiplication. The conclusions are similar.

(b) 6-digit decimal addition: Acc. vs. Model Size

FoNE Can Handle Large Numbers

- Train and test on **60-digit addition,** FoNE could achieve 97% accuracy on average.
- It demonstrates the effectiveness of FoNE in handling **long sequences**.

(a) Test accuracy of 60-digit addition with FoNE

FoNE Enables Better Length Generalization

- We integrate FoNE with the Abacus embedding method [MBSJ+24], which operates on digit-wise tokenization.
- In this setup, the embeddings for each digit (0–9) are replaced with their corresponding Fourier Number Embeddings.
- Complementary benefits of combining FoNE with other positional embedding strategies.

(b) Impact of combining FoNE with Abacus embedding

McLeish et al. *Transformers Can Do Arithmetic with the Right Embeddings*. NeurIPS 2024

FoNE Could Fix Tokenization Issues for Numbers

Conclusion

- Leveraging Fourier features, FoNE directly maps numbers into a compact and precise representation.
- FoNE bypasses tokenization — a commonly believed root cause for arithmetic failures.
- **Future Plans** for FoNE:
  - Training a foundation model with FoNE for numbers.
  - Unleashing FoNE's efficiency and precision for science and time-series tasks.

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IsoBench: Benchmarking Multimodal Foundation Models on *Isomorphic Representations*

[COLM 2024]

Deqing Fu★

Ruohao Guo★

Ghazal Khalighinejad★

Ollie Liu★

Bhuwan Dhingra

Dani Yogatama

Robin Jia

Willie Neiswanger

In a hypothetical perfect world

The Platonic Representation Hypothesis

"Neural networks, trained with different objectives on different data and modalities, are converging to a shared statistical model of reality in their representation spaces."

Huh et. al. *The Platonic Representation Hypothesis.* ICML 2024

Prompts

Problem: Check Function Parity

<Definition of Function Parity>

***Image* Representation**

Prompts

Problem: Check Function Parity

<Definition of Function Parity>

***Image* Representation**

Responses

The plot of the function f(x) **shows symmetry about the y-axis**. **This symmetry indicates that f(x) = f(-x)** for all x in the domain of the function, which is the **definition of an even function**. Therefore, based on the plot, **f(x) is an even function**.

Prompts

Problem: Check Function Parity

<Definition of Function Parity>

***Image* Representation**

Responses

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Prompts

Problem: Check Function Parity

<Definition of Function Parity>

***Image* Representation**

***Text* Representation**

Here is the expression $f(x)$:

$$f(x) = \frac{7x^6 - 3x^5 + x^2 - 21.76}{2x^6 + 4x^4 + 3x^2 + 11.34}$$

Responses

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***Text* Representation**

Here is the expression $f(x)$:

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Responses

The plot of the function f(x) **shows symmetry about the y-axis**. **This symmetry indicates that f(x) = f(-x)** for all x in the domain of the function, which is the **definition of an even function**. Therefore, based on the plot, **f(x) is an even function**.

Substituting $-x$ into the original function, we get

$$f(-x) = \frac{7(-x)^6 - 3(-x)^5 + (-x)^2 - 21.76}{2(-x)^6 + 4(-x)^4 + 3(-x)^2 + 11.34} = \frac{7x^6 + 3x^5 + x^2 - 21.76}{2x^6 + 4x^4 + 3x^2 + 11.34}$$

This expression is **not equal to the original function** $f(x)$, indicating that the function is **not even**. Additionally, the expression is **not the negative of the original function**, indicating that the function is **not odd**. Therefore, $f(x)$ **is neither even nor odd.**

Prompts

Problem: Check Function Parity

<Definition of Function Parity>

***Image* Representation**

***Text* Representation**

Here is the expression $f(x)$:

$$f(x) = \frac{7x^6 - 3x^5 + x^2 - 21.76}{2x^6 + 4x^4 + 3x^2 + 11.34}$$

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IsoBench Tasks

Task: Function Parity

Text Representation

$$f(x) = -\frac{18x}{2x^{10} + 16x^4 - 10x^2 + 29.34}$$

Image Representation

Mathematical Functions

Graph Algorithms

Task: Connectivity

Text Representation

Adjacency Matrix: $\begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$. Query Nodes: 4 and 8.

Image Representation

Answer: Not Connected

Task: Winner Identification

Text Representation

```
. . . r . . k .
p R . . . p p p
. . . . . . . .
Q . . . . . . .
P . P . p . . .
. . P . K q . .
. . . B . P . P
. . . . R . . .
```

Image Representation

Answer: Black Wins

Chess Games

Science Questions

Task: Physics QA

Text Representation

Question: Consider the given circuit. What is the current in amperes if 9.9 Coulombs of charge flow past point A in 1.1 seconds?

(A) 6 (B) 7 (C) 8 (D) 9

Description: The circuit consists of a single battery connected to three light bulbs arranged in a parallel configuration. A, B, C, D, and E are points in the circuit. The battery provides the electrical energy that powers the light bulbs.

Image Representation

Answer:(D) 9 Amps

In total, IsoBench comprises 10 tasks, spanning these four sub-categories.

Significant Modality Gap

On average, GPT-4-Turbo has a **modality gap of 18.7**; Claude-3-Opus **14.9**; and Gemini-1.0-Pro **28.7**.

Image

Text

Significant Modality Gap

	Gemini 1.5				Claude						GPT			
	Pro		Flash		Opus		Sonnet		Haiku		4o		4o-mini	
Modality	Perf.	Δ	Perf.	Δ	Perf.	Δ	Perf.	Δ	Perf.	Δ	Perf.	Δ	Perf.	Δ
Text	77.5	-	69.9	-	77.7	-	77.4	-	72.5	-	71.5	-	72.6	-
Image	57.3	20.2↓	36.3	33.6↓	26.9	50.8↓	18.8	58.6↓	9.9	62.6↓	60.1	11.4↓	48.5	24.1↓
Audio	56.6	20.9↓	53.9	16.0↓	-	-	-	-	-	-	-	-	-	-
Video	36.3	41.2↓	15.1	54.8↓	-	-	-	-	-	-	53.1	18.4↓	18.6	54.0↓
Extract-Then-Answer (ETA) Prompting														
Image	73.5	4.0↓	68.1	1.8↓	62.6	15.1↓	48.1	29.3↓	43.2	29.3↓	66.7	4.8↓	58.4	14.2↓
Audio	69.9	7.6↓	63.6	6.3↓	-	-	-	-	-	-	-	-	-	-
Video	48.6	28.9↓	42.8	27.1↓	-	-	-	-	-	-	25.0	46.5↓	59.3	13.3↓

Chen et. al. *OmniXR: Evaluating Omni-modality Language Models on Reasoning across Modalities.* ICLR 2025

We can design *simple* and *deliberately contrived* mechanisms to further study the performance of MLLMs on tasks with *isomorphic representations*

IsoCombination

Instruction about the Task: Graph Isomorphism

Definition of Graph Isomorphism

Image Representation

Text Representation 1

Adjacency Matrices:

$$G = \begin{bmatrix} 0 & 1 & 0 & 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$H = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

Text Representation 2

Description of Graph G:

There are 8 nodes in the graph.
Node 0 is connected to Node 1 and Node 3 and Node 5.
[….]

Description of Graph H:

There are 8 nodes in the graph.
Node 0 is connected to Node 6 and Node 7.
Node 1 is connected to Node 2 and Node 3.
[…]

Instruction on Output Format

IsoCombination

- Combining **Text and Image** inputs could improve the model significantly.

- Sometimes IsoCB is better than text-only inputs.

- However, it's "*cheating*" in the sense that the text inputs are given.

GPT-4-Turbo on MaxFlow Problems

IsoScratchPad

1

IsoScratchPad

1

Instruction: Describe the Image

Image Representation

IsoScratchPad

1

Instruction: Describe the Image

***Image* Representation**

IsoScratchPad

1

Instruction: Describe the Image

Image Representation

Model Scratch Pad

The image displays two graphs.
The Left Graph consists of eight nodes numbered 0 to 7, with the following connections:
- 0 is connected to 1, 3, and 5.
- 1 is connected to 6.
- 2 is connected to 3, 4 and 5.
- 7 is an isolated node.

The Right Graph consists of eight nodes numbered 0 to 7, with the following connections:
- 0 is connected to 6 and 7.
- 1 is connected to 2 and 3.
- 2 is connected to 3.
- 4 is connected to 6, 7.
- 5 is an isolated node.

IsoScratchPad

2

Instruction about the Task: Graph Isomorphism

Definition of Graph Isomorphism

Model Scratch Pad

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Instruction on Output Format

IsoScratchPad

2

Instruction about the Task: Graph Isomorphism

Definition of Graph Isomorphism

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Instruction on Output Format

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2

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Instruction on Output Format

Model Final Response

No, the two graphs G (Left Graph) and H (Right Graph) are not isomorphic.

Explanation:
In graph G, there are two nodes (0 and 2) that each have a degree of 3, meaning they are connected to three other nodes. However, in graph H, there is no node with a degree of 3. The nodes in graph H have the following degrees:

- Nodes 0, 1, 2, 3, 4, 6, 7 have a degree of 2
- Node 5 has a degree of 0

For two graphs to be isomorphic, they must have the same number of nodes with each degree. Since graph G has two nodes with a degree of 3 and graph H has no nodes with a degree of 3, the two graphs cannot be isomorphic.

Furthermore, graph H has a node (Node 3) that is connected to two nodes (Node 1 and Node 2) which are also connected to each other, forming a triangle. In graph G, there is no such triangle structure.

These structural differences between the two graphs prove that they are **not isomorphic**, as there is no bijection that can preserve the edge relationships between the nodes while mapping one graph to the other.

IsoScratchPad

- Prompting MLLMs to generate texts as *scratchpad* could fill in the modality gap slightly.
- Due to model ***hallucinations*** in the modality transferring steps, IsoScratchPad is still worse than the text-only variant.

GPT-4-Turbo on MaxFlow Problems

Conclusions

- Humans have pictorial superiority but MLLMs seem to have textual superiority.
- [Hu et al. *Visual Sketchpad: Sketching as a Visual Chain of Thought for Multimodal Language Models*. NeurIPS 2024] Proposes tool usage to draw auxiliary lines to help MLLMs reason over images.
- [Li et al. *Zebra-CoT: A Dataset for Interleaved Vision Language Reasoning*. 2025] collects a dataset with 148,000 samples with interleaved text-image reasoning chains.
- Can we use MLLMs' textual superiority to improve their visual understanding?

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TLDR

TLDR: Token-Level Detective Reward Model for Large Vision Language Models

[ICLR 2025]

Deqing Fu

Tong Xiao

Rui Wang

Wang Zhu

Pengchuan Zhang

Guan Pang

Robin Jia

Lawrence Chen

Multimodal LLMs Hallucinate over Images

Describe the image in detail.

The image captures a bustling scene on a highway, where the flow of traffic is disrupted by a construction zone. The highway, a four-lane road, is filled with a variety of vehicles, including cars, trucks, and buses. The cars are predominantly black and white, while the trucks are white and red. The buses, painted in shades of blue and white, add a splash of color to the scene. The construction zone, marked by orange cones, is located on the right side of the highway. It's a busy area with several construction vehicles and workers diligently at work. The highway is surrounded by lush green fields and trees, providing a stark contrast to the concrete structures. The sky above is a clear blue, dotted with fluffy white clouds. The image is taken from an aerial perspective, providing a comprehensive view of the highway and its surroundings. This perspective allows for a detailed analysis of the traffic flow and the ongoing construction work.

Multimodal LLMs Hallucinate over Images

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Let's Build Models to Detect Hallucinations

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Synthetic Data Collection

- I. *Spatial Relationship*: A is **left** to B. ↔ A is **right** to B.
- II. *Visual Attribute*: A is **yellow**. ↔ A is **blue**.
- III. *Attribute Binding*: A is **blue** and B is **yellow**. ↔ A is **yellow** and B is **blue**.
- IV. *Object Identification*: A **dog** chasing a ball. ↔ A **cat** chasing a ball.
- V. *Counting*: **One** duck is swimming. ↔ **Four** ducks are swimming.
- VI. *Small Object*: **Cirrostratus cloud** in the sky. ↔ **Clear** sky.
- VII. *Text OCR*: A shirt writes **heavy fog**. ↔ A shirt writes **happy frog**.
- VIII. *Counterfactual*: A soldier. ↔ A soldier has **no sword** in hand.

Synthetic Data Collection

- Two datasets:
  - Visual Genome (VG100K)
    - Visual Question Answering (**VQA**)
    - **Image Captioning** by Grouping VQA to Captions
  - DOCCI for **dense image captions**
- Synthetic Generation Steps:
  - Prompt LLMs (Llama-3.1-70B) to **generate wrong answers/captions**
  - Model ***never sees the image*** (text-only perturbation)
  - Filter out paraphrases, unnatural perturbations, etc.
  - Compare to gold-standard to obtain **token-level labels**

Task	Data Source	Taxonomy	# Positive	# Negative	Train Set Proportion (%)
VQA	VG100K	—	1,179,007	1,179,007	80%
Image Caption	Synthetic Caption from VG100K	Spatial Relation	94,684	45,225	
		Visual Attribute		86,366	
		Attribute Binding		59,219	
		Object Identification		75,328	
		Counting		75,156	
		Small Object		80,455	
		Text OCR		84,164	
		Counterfactual		57,153	
Image Caption	DOCCI	Spatial Relation	14,639	8,867	65%
		Visual Attribute		13,811	
		Attribute Binding		13,561	
		Object Identification		10,618	
		Counting		10,491	
		Small Object		11,680	
		Text OCR		13,366	
		Counterfactual		12,844	

TLDR as Hallucination Evaluation Tool

The image captures a bustling scene on a highway, where the flow of traffic is disrupted by a **construction** zone.

The highway, a **four**-lane road, is filled with a variety of vehicles, including cars, trucks, and **buses**.

The cars are predominantly black and white, while the trucks are white and red.

The **buses**, painted in shades of **blue** and white, add a splash of color to the scene.

The **construction** zone, marked by **orange cones**, is located on the right side of the highway.

It's a busy area with several **construction vehicles and workers** diligently at work.

The highway is surrounded by lush green fields and trees, providing a stark contrast to the concrete structures.

The sky above is a clear blue, dotted with fluffy white clouds.

The image is taken from an aerial perspective, providing a comprehensive view of the highway and its surroundings.

This perspective allows for a detailed analysis of the traffic flow and the ongoing **construction** work.

Hallucination Rate (%)

Token-Level

Tokens: **208**
Bad Tokens: **15**

Token-Level Rate:

$$\frac{15}{208} \approx 0.072\,\%$$

Sentence-Level

Sentences: **10**
Bad Sentences: 6

Sentence-Level Rate:

$$\frac{6}{10} \approx 60\,\%$$

Response-Level

This is a **bad** response.

TLDR as Hallucination Evaluation Tool

Model	Token-Level (%)	Sentence-Level (%)	Response-Level (%)	MMMU	MEGA-Bench
GPT-4o	**0.016**	0.23	1.62	**69.1**	**54.1**
Llama-3.2-90B-Vision	0.017	**0.19**	**1.23**	60.3	/
GPT-4o-mini	0.030	0.38	2.12	59.4	43.0
GPT-4-Turbo-Vision	0.033	0.62	3.12	56.8	/
Qwen2-VL-7B	0.061	0.48	1.96	54.1	35.9
Qwen2-VL-2B	0.066	0.72	1.70	41.1	22.3
MiniCPM-Llama-3-V2.5	0.067	0.81	3.62	45.8	22.8
Llama-3.2-11B-Vision	0.073	0.85	1.88	50.7	18.0
Phi-Vision-3.5-Instruct	0.261	2.65	9.25	43.0	25.3
PaliGemma-3B	4.444	5.96	17.50	27.3	/

Conjecture

TLDR as Hallucination Evaluation Tool

$$\text{ModelPerformance} = -\log \mathscr{H}_{\text{TokenLevel}} + \text{Constant}$$

TLDR Guided Self-Correction

Image	GPT-4V Synthetic Caption **Flagged by TLDR Model**	GPT-4V **Self-Correction** with TLDR's Guidance
	The image depicts a stack of **six** books, each varying in color and size, arranged in a slightly staggered formation. [...]	The image depicts a stack of **five** books, each varying in color and size, arranged in a slightly staggered formation. [...]
	In the image, a young woman is seated at a dining table, [...] focused expression as she uses **chopsticks** to pick up food from her plate.	In the image, a young woman is seated at a dining table, [...] focused expression as she uses **a fork** to pick up food from her plate.
	[...] The dog's face is characterized by its deep wrinkles and big, soulful eyes, which give it a somewhat melancholic yet cute appearance. On top of its head, there are **three** biscuits stacked neatly, adding a playful and whimsical touch to the scene. [...]	[...] The dog's face is characterized by its deep wrinkles and big, soulful eyes, which give it a somewhat melancholic yet cute appearance. On top of its head, there are **four** biscuits stacked neatly, adding a playful and whimsical touch to the scene. [...]
	[...] Surrounding the map are essential travel items: a digital camera, suggesting the intention to capture memories; a pair of sunglasses, indicating sunny travel conditions; and a smartphone, likely used for additional navigation or communication. To the side, there's a cup of **tea**, providing a comforting element to the planning process. [...]	[...] Surrounding the map are essential travel items: a digital camera, suggesting the intention to capture memories; a pair of sunglasses, indicating sunny travel conditions; and a smartphone, likely used for additional navigation or communication. To the side, there's a cup of **coffee**, providing a comforting element to the planning process. [...]

TLDR Automatically Trains Token-Level *Likelihood Optimization*

TLDR Automatically Trains Token-Level *Likelihood Optimization*

TLDR Automatically Trains Token-Level *Likelihood Optimization*

TLDR Automatically Trains Token-Level *Likelihood Optimization*

TLDR Automatically Trains Token-Level *Likelihood Optimization*

TLDR Automatically Trains Token-Level *Likelihood Optimization*

TLDR Automatically Trains Token-Level *Likelihood Optimization*

Model	Token-Level (%)	Sentence-Level (%)	Response-Level (%)
PaliGemma-3B	4.444	5.96	17.50
+ TLDR (τ=0.10)	0.991	3.80	10.53
+ TLDR (τ=0.25)	**0.172**	**1.13**	**3.96**
Llama-3.2-11B-Vision	0.073	0.85	1.88
+ TLDR (τ=0.10)	0.078	**0.69**	2.71
+ TLDR (τ=0.25)	**0.066**	0.74	**1.72**

- Training with TLDR Automatically **Reduces Model Hallucinations** Rates.
- Evaluations in this table are **cross-evaluation** with two TLDR models (i.e., using PaliGemma to evaluation Llama)

TLDR Automatically Trains Token-Level *Likelihood Optimization*

Model	BLINK			IsoBench	
	Count	Spatial Relation	Object Localize	Function Parity	Chess Winner
PaliGemma-3B	69.2	78.3	45.9	41.4	45.1
+ TLDR (τ=0.25)	**71.7**	80.4	**47.5**	**45.1**	45.1
+ TLDR (τ=0.50)	**71.7**	**81.1**	42.6	44.3	**47.5**
+ TLDR (τ=1.00)	12.5	2.1	42.6	34.4	44.8
Llama-3.2-11B-Vision	55.0	61.5	60.7	34.9	45.5
+ TLDR (τ=0.25)	**67.5**	65.0	**67.2**	**35.4**	43.6
+ TLDR (τ=0.50)	65.8	**65.7**	59.0	33.3	**47.9**
+ TLDR (τ=1.00)	61.7	65.7	56.6	35.1	39.4

- Training with TLDR Automatically **Improves** MLLM's **Visual Understanding.**
- Llama-3.2-11B-Vision improves at most **+12.5** on counting.
- BLINK is "in-distribution" in terms of taxonomy, IsoBench is "out-of-distribution".

Conclusions

- TLDR introduces token-level reward modeling that offers fine-grained, interpretable annotations to each generated token.
- TLDR offers diverse use cases: hallucination evaluation, guided self-correction, and human annotation speedup.
- TLDR's LoRA training coupled with its architecture design implicitly improve the backbone model.
- Tuning the text backbone LLM could teach the MLLM.
- Future work: Extend the token-level reward framework to broader safety and alignment tasks, and integrate it into token-level DPO/PPO policy optimization for more robust multimodal generation.

Overview

LLMs are Bad At Arithmetics.

Can we find a family of embeddings to bypass tokenization?

Evaluating Multimodal LLMs Beyond Ranking Models.

Humans have pictorial superiority. How about MLLMs?

Adjacency Matrix: $\begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$. Query Nodes: 4 and 8.

Text LLMs are Teachers for MLLMs.

Fine-Grained Rewards.

Train Text Backbone to be Token-Level Reward Models.

O O O X O O X
O X O X O

MLLM

O O O X O O X
O X O X O

TLDR

Text Steering Vectors.

Leverage Text-Based Interpretability Tools for MLLMs.

Overview

Text LLMs are Teachers for MLLMs.

Text Steering Vectors.

Leverage Text-Based Interpretability Tools for MLLMs.

USC University of Southern California

Textual Steering Vectors Can Improve Visual Understanding in Multimodal Large Language Models

[In Submission]

Haosheng Gan★

Deqing Fu★

Julian Asilis★

Ollie Liu★

Dani Yogatama

Vatsal Sharan

Robin Jia

Willie Neiswanger

Let’s Ponder: Why TLDR Works?

Let's Ponder: Why TLDR Works?

- Conditional Activation Steering [LPRM+25]: $h' \leftarrow h + \alpha \cdot f(\mathrm{sim}(h, \mathrm{proj}_c h)) \cdot v$
- h is the activation, c is the condition vector, and v is the **steering vector.**

Lee et. al. *Programming Refusal with Conditional Activation Steering*. ICLR 2025

Let's Ponder: Why TLDR Works?

- Conditional Activation Steering [LPRM+25]: $h' \leftarrow h + \alpha \cdot f(\mathrm{sim}(h, \mathrm{proj}_c h)) \cdot v$
- h is the activation, c is the condition vector, and v is the **steering vector.**
- Let's assume f is an identity mapping, and c and h are unit length. We have

$$h' \leftarrow h + \alpha \cdot h^\top \left(cc^\top h\right) \cdot v = (I + \alpha \underbrace{h^\top c}_{\tau} vc^\top)\, h = (I + \tau\alpha \cdot \underbrace{vc^\top}_{\text{rank-1 update}})\, h$$

Lee et. al. *Programming Refusal with Conditional Activation Steering*. ICLR 2025

Let's Ponder: Why TLDR Works?

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- In TLDR's setting, LoRA with rank-r implies r **steering vectors** at each layer.

Lee et. al. *Programming Refusal with Conditional Activation Steering*. ICLR 2025

Toy Experiment: Color Intervention

Toy Experiment: Color Intervention

What's the color of the image?

Red

Orange

Yellow

Toy Experiment: Color Intervention

What's the color of the image?

Red

Orange

Yellow

Toy Experiment: Color Intervention

What's the color of the image?

Steering Method: *SparseAutoencoder (Gemma-2-9B)*
Layer Index: *20;* ***Feature ID***: *13864*
Feature Explanation: *"color-related terms, specifically highlighting the color red"*

$$h^{(20)}_{\text{ImageToken}} \leftarrow h^{(20)}_{\text{ImageToken}} + \alpha \cdot v^{(SAE)}_{13864}$$

Red

Orange

Yellow

Toy Experiment: Color Intervention

What's the color of the image?

Steering Method: *SparseAutoencoder (Gemma-2-9B)*
Layer Index: *20;* ***Feature ID***: *13864*
Feature Explanation: *"color-related terms, specifically highlighting the color red"*

Red
Orange
Yellow

Toy Experiment: Color Intervention

What's the color of the image?

Steering Method: *SparseAutoencoder (Gemma-2-9B)*
Layer Index: *20;* ***Feature ID***: *13864*
Feature Explanation: *"color-related terms, specifically highlighting the color red"*

Red
Orange
Yellow

Toy Experiment: Color Intervention

Toy Experiment: Color Intervention

Toy Experiment: Color Intervention

Toy Experiment: Color Intervention

Identify Textual Representations of Visual Concepts from Text-Only LLMs

Identify Textual Representations of Visual Concepts from Text-Only LLMs

Visual Concepts

Spatial Relationship

Counting

Object Entity

Attribute

Identify Textual Representations of Visual Concepts from Text-Only LLMs

Visual Concepts

Spatial Relationship

Counting

Object Entity

Attribute

Sentences and Anchor Words

He placed the shoes **beneath** the bed

A tree fell during the storm

She won seven medals in the competition

The red car stopped at the light

Identify Textual Representations of Visual Concepts from Text-Only LLMs

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Identify Textual Representations of Visual Concepts from Text-Only LLMs

Textual Vectors with SAE

Sentences and Anchor Words

He placed the shoes **beneath** the bed

A tree fell during the storm

She won seven medals in the competition

The red car stopped at the light

Textual Vectors with SAE

Sentences and Anchor Words

He placed the shoes **beneath** the bed

Textual Vectors with SAE

Sentences and Anchor Words

He placed the shoes **beneath** the bed

Layer ℓ

Pretrained SAE:
GemmaScope(Gemma-2-9B)

Textual Vectors with SAE

Sentences and Anchor Words

He placed the shoes **beneath** the bed

Layer ℓ

Pretrained SAE:
GemmaScope(Gemma-2-9B)

***Layer Index**: 10;*
***Feature ID**: 17692*
***Feature Explanation**:*
"spatial relationships and proximity between objects or locations"

. . . . . .

***Layer Index**: 10;*
***Feature ID**: 6725*
***Feature Explanation**:*
"spatial relations or proximity between objects or concepts"

Textual Vectors with SAE

Sentences and Anchor Words

He placed the shoes **beneath** the bed

Layer ℓ

Pretrained SAE:
GemmaScope(Gemma-2-9B)

***Layer Index**: 10;*
***Feature ID**: 17692*
***Feature Explanation**:*
"spatial relationships and proximity between objects or locations"

***Layer Index**: 10;*
***Feature ID**: 6725*
***Feature Explanation**:*
"spatial relations or proximity between objects or concepts"

$v^{(\ell)}_{\text{Spatial},1}$ .... $v^{(\ell)}_{\text{Spatial},K}$

Textual Vectors with SAE

Textual Vectors with MeanShift

Sentences and Anchor Words

He placed the shoes **beneath** the bed

A tree fell during the storm

She won seven medals in the competition

The red car stopped at the light

Textual Vectors with MeanShift

Sentences and Anchor Words

He placed the shoes **beneath** the bed

Textual Vectors with MeanShift

Sentences and Anchor Words

He placed the shoes **beneath** the bed

Textual Vectors with MeanShift

Sentences and Anchor Words

He placed the shoes **beneath** the bed

Anchor Words
(Relevant Tokens)

$h^{(\ell)}(w_1)$ $h^{(\ell)}(w_2)$ ... $h^{(\ell)}(w_n)$

Non-Anchor Words
(Irrelevant Tokens)

$h^{(\ell)}(w_1)$ $h^{(\ell)}(w_2)$ ... $h^{(\ell)}(w_n)$

Textual Vectors with MeanShift

Sentences and Anchor Words

He placed the shoes **beneath** the bed

Non-Anchor Words (Irrelevant Tokens)

$h^{(\ell)}(w_1)$ $h^{(\ell)}(w_2)$ $\cdots$ $h^{(\ell)}(w_n)$

$\bar{h}^{(\ell)}_{+}$

Textual Vectors with MeanShift

Sentences and Anchor Words

He placed the shoes **beneath** the bed

$\bar{h}_+(\ell)$

$\bar{h}_-(\ell)$

Textual Vectors with MeanShift

Sentences and Anchor Words

He placed the shoes **beneath** the bed

Steering MLLMs using Text Representations

Steering MLLMs using Text Representations

Multimodal Query

How many red buses are there?

Tokenization

Steering MLLMs using Text Representations

Multimodal Query

How many red buses are there?

Tokenization

how

many

red

buses

are

there

Steering MLLMs using Text Representations

Steering MLLMs using Text Representations

Steering MLLMs using Text Representations

Steering MLLMs using Text Representations

Steering MLLMs using Text Representations

Steering MLLMs using Text Representations

Steering Can Improve Visual Understanding

Spatial Relationships

Considering the relative positions of the fork and the cup in the image provided, where is the fork located with respect to the cup? Select from the following choices.

(A) left

(B) right

Counting

Answer the multiple choice question by only responding the letter of the correct answer. How many beds are in the image? Select from the following choices.

(A) 0

(B) 2

(C) 1

(D) 3

(E) 4

Steering Can Improve Visual Understanding

Visual Concepts

CV-Bench Tasks

	Counting	Spatial Relationship	Entity	Attribute
Count	+0.7% (L7@0.8)	+1.3% (L14@1)	+0.0% (L9@0.8)	+0.0% (L16@0.6)
Relation	+3.3% (L9@1)	+7.3% (L5@1)	+0.0% (L9@0.6)	+2.7% (L6@1)
Distance	+1.3% (L6@0.8)	+0.7% (L16@0.6)	+0.7% (L6@0.1)	+0.7% (L5@0.2)
Depth	-0.7% (L11@0.6)	-1.3% (L11@0.4)	+0.7% (L10@0.8)	-0.7% (L10@0.4)

Interven Text Tokens

	Counting	Spatial Relationship	Entity	Attribute
Count	+2.7% (L5@0.4)	+1.3% (L5@1)	+2.0% (L11@0.8)	+1.3% (L10@1)
Relation	+0.7% (L10@0.8)	+2.7% (L10@1)	+3.3% (L14@1)	+4.0% (L13@1)
Distance	+0.0% (L19@0.8)	+0.0% (L9@0.6)	-0.7% (L6@0.2)	-2.0% (L10@0.4)
Depth	+0.7% (L11@1)	+2.7% (L10@1)	+0.7% (L11@0.8)	+0.7% (L10@1)

Intervene Image Tokens

	Counting	Spatial Relationship	Entity	Attribute
Count	+2.7% (L9@0.6)	+1.3% (L5@0.6)	-0.7% (L7@0.2)	+2.0% (L10@1)
Relation	+3.3% (L9@1)	+5.3% (L5@1)	+0.7% (L6@0.8)	+2.0% (L6@0.8)
Distance	-0.7% (L15@0.8)	+2.0% (L8@0.2)	+1.3% (L6@0.1)	+1.3% (L13@0.2)
Depth	+0.0% (L5@0.8)	+2.0% (L11@0.6)	+1.3% (L10@0.8)	+0.0% (L10@0.8)

Intervene Image + Text Tokens

Performance Improvements on **CV-Bench** tasks when steering `PaliGemma2-3B` with **MeanShift** vectors

Steering Can Improve Visual Understanding

Steering Can Improve Visual Understanding

- CV-Bench Spatial Relationship
- Idefics3-8B-Llama3

Steering Can Improve Visual Understanding

- CV-Bench Spatial Relationship
- Idefics3-8B-Llama3

Tokens to Intervene		Intervention Method		
TEXT	IMAGE	SAE	Probe	MeanShift

Steering Can Improve Visual Understanding

- CV-Bench Spatial Relationship
- Idefics3-8B-Llama3

Tokens to Intervene		Intervention Method		
TEXT	IMAGE	SAE	Probe	MeanShift
Baseline		***73.3***		

Steering Can Improve Visual Understanding

- CV-Bench Spatial Relationship
- Idefics3-8B-Llama3

Tokens to Intervene		Intervention Method		
TEXT	IMAGE	SAE	Probe	MeanShift
Baseline			***73.3***	
Prompting			*75.3*	

Steering Can Improve Visual Understanding

- CV-Bench Spatial Relationship
- Idefics3-8B-Llama3

Tokens to Intervene		Intervention Method		
TEXT	IMAGE	SAE	Probe	MeanShift
Baseline			*73.3*	
Prompting			*75.3*	
X		**76.0**	**78.0**	**80.0**

Steering Can Improve Visual Understanding

- CV-Bench Spatial Relationship
- Idefics3-8B-Llama3

Tokens to Intervene		Intervention Method		
TEXT	IMAGE	SAE	Probe	MeanShift
Baseline			*73.3*	
Prompting			*75.3*	
X		76.0	78.0	80.0
	X	78.0	72.7	76.7

Steering Can Improve Visual Understanding

- CV-Bench Spatial Relationship
- Idefics3-8B-Llama3

Tokens to Intervene		Intervention Method		
TEXT	IMAGE	SAE	Probe	MeanShift
Baseline			*73.3*	
Prompting			*75.3*	
X		76.0	78.0	80.0
	X	78.0	72.7	76.7
X	X	77.3	78.7	80.7

Steering Can Improve Visual Understanding

- CV-Bench Spatial Relationship
- Idefics3-8B-Llama3
- MeanShift gives the best steering improvements

Tokens to Intervene		Intervention Method		
TEXT	IMAGE	SAE	Probe	MeanShift
Baseline			*73.3*	
Prompting			*75.3*	
X		76.0	78.0	80.0
	X	78.0	72.7	76.7
X	X	77.3	78.7	80.7 ✓

Steering Generalizes Out-of-Distribution

Spatial Relationships

Please select the correct caption for the image:
(A) A toilet roll under a chair
(B) A toilet roll to the left of a chair
(C) A toilet roll to the right of a chair
(D) A toilet roll on a chair

What'sUp-A

Please select the correct caption for the image:
(A) A bowl behind a cup
(B) A bowl to the left of a cup
(C) A bowl to the right of a cup
(D) A bowl in front of a cup

What'sUp-B

Object Localization

BLINK Object Localization

A bounding box is an annotated rectangle surrounding an object. The edges of bounding boxes should touch the outermost pixels of the object that is being labeled. Given the two bounding boxes on the image, labeled by A and B, which bounding box more accurately localizes and encloses the teddy bear? Select from the following options.
(A) Box A
(B) Box B

Counting

CLEVR

Super-CLEVR

Steering Generalizes Out-of-Distribution

Connection to AxBench

[Wu et al. 2025] *AxBench: Steering LLMs? Even Simple Baselines Outperform Sparse Autoencoders.*

Connection to AxBench

[Wu et al. 2025] *AxBench: Steering LLMs? Even Simple Baselines Outperform Sparse Autoencoders.*

Connection to AxBench

[Wu et al. 2025] *AxBench: Steering LLMs? Even Simple Baselines Outperform Sparse Autoencoders.*

Conclusions

- We introduce a plug-and-play steering paradigm that repurposes text-only LLM representations—via SAEs, MeanShift, and linear probes—to guide multimodal LLMs with minimal extra data or compute. (All experiments were done with only *one* A6000.)
- **MeanShift** interventions on models like PaliGemma2-3B yield up to +7.3% improvement in spatial relation accuracy and +3.3% in counting tasks on CV-Bench, consistently outperforming direct prompting.
- These textual steering vectors generalize out-of-distribution.
- Future Work: Merging steering vectors of difference visual concepts across multiple layers.

Failures and Recipes In This Talk

- LLMs Are **Bad at Arithmetics**

Recipe: Better Representations

- Multimodal LLMs **Hallucinate**

Recipe: Leveraging the Power of Their Textual Backbone LLMs

Thank you!

- Questions? Comments? Ideas?
- Contact: deqingfu@usc.edu