

# Seeing the Image: Prioritizing Visual Correlation by Contrastive Alignment

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ByteDance.

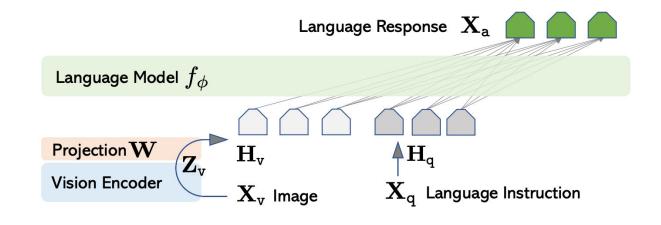
## Introduction to Vision Language Models



Motivation for Visual Correlation in Alignment

- Vision Language Models

   (VLMs): Emerging multimodal systems that combine visual and textual data.
- Challenges in Alignment: Existing VLMs often treat all text tokens equally, ignoring the varying relevance of tokens to image content



## Problem Statement: Existing Alignment Strategies



Limitations in Token Correlation in VLMs

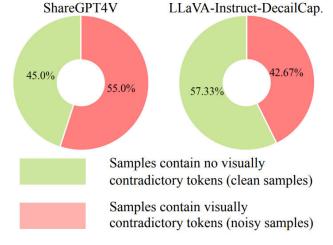


: visually contradictory tokens

- *Q*: *Please describe the image in detail.*
- A: The image features a unique ... The backdrop of the image provides context to the loca--tion of the traffic lights tree. It is situated on a busy street with a red truck and a black car captured in motion.

(a) Tokens correlate differently with the image.

Different text tokens have varying degrees of correlation with the image and should not be treated equally.



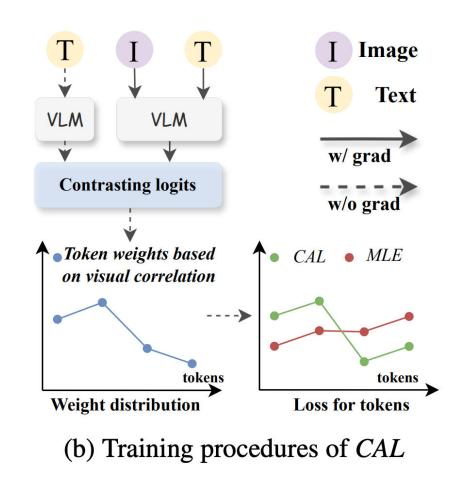
(b) Human evaluations.

Irrelevant or contradictory tokens can lead to poor alignment and degraded model performance.

# Proposed Method: Contrastive Alignment (CAL)



- **CAL**: A method to prioritize visually correlated tokens.
- **Process:** Re-weighting strategy based on prediction logit contrasts, distinguishing between visually relevant, irrelevant, and contradictory tokens.
- **Objective**: Enhances alignment with minimal computational overhead.





#### **Experiments and Results**



CAL achieved higher accuracy in OCR and image caption benchmarks.

Method	LLM	OCRB.	VQA <sup>Doc</sup>	VQA <sup>Chart</sup>	<b>VQA</b> <sup>Text</sup>	SQA	MMS.	MMT.	Win/All
LLaVA-NeXT	Vicuna- 7B	542	75.1	62.2	64.2	68.5	33.7	49.5	
LLaVA- NeXT+CAL	Vicuna- 7B	561	77.3	64.3	65.0	70.1	35.5	50.7	7/7
LLaVA-NeXT	Vicuna- 13B	553	78.4	63.8	67.0	71.8	37.5	50.4	
LLaVA- NeXT+CAL	Vicuna- 13B	574	80.1	67.2	67.1	71.5	38.1	52.4	6/7

#### **Experiments and Results**

CAL achieved cleaner attention map and better text alignment



(a) a white van on a highway from Monks & Crane.

	lles Price Der Unit	Variable Cost per Unit		
Junior Adult Expert	\$ 50 75 110	\$15 25 60		
	purch purch	0 0		
Baseline pt pt pt	unit unit Price purch			
CAL pt expert expert	unit unit	6 0		



#### **Conclusion and Future Directions**



- **Summary**: CAL enhances image-text alignment by focusing on visually correlated tokens.
- **Contribution**: Helps VLMs concentrate on relevant data, advancing multimodal performance.
- **Future Work**: Further refinement of token-weighting strategies and adaptive settings for token bounds.