

Do You Keep an Eye on What I Ask? Mitigating Multimodal Hallucination via Attention-Guided Ensemble Decoding

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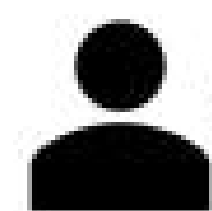
Yeongjae Cho, Keonwoo Kim, Taebaek Hwang, Sungzoon Cho

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Problem Definition

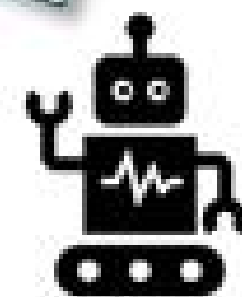
- Growing interest in Large Vision-Language Models (LVLMs) with advancements in language models
- Object Hallucination: Describing non-existent objects or incorrect details
- Reduced reliability in Visual Question Answering and Image Captioning tasks



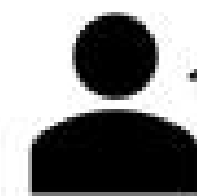
*What is the color of the **pot**?*



Red



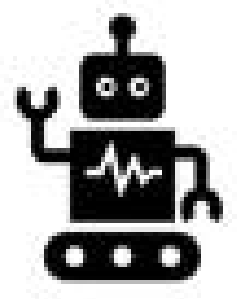
LVLM



What does the image describe?



*The image features ... several **people** ... **boat** ...*



LVLM

Fig. Example of Object Hallucination in Visual Question Answering Task

Fig. Example of Object Hallucination in Image Captioning Task

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Motivation

- Some Object Hallucination cases can be easily resolved using the Crop & Resize technique.
- Established two assumptions to mitigate Object Hallucination:
 - a. Reducing the number of unnecessary objects
 - b. Ensuring high resolution

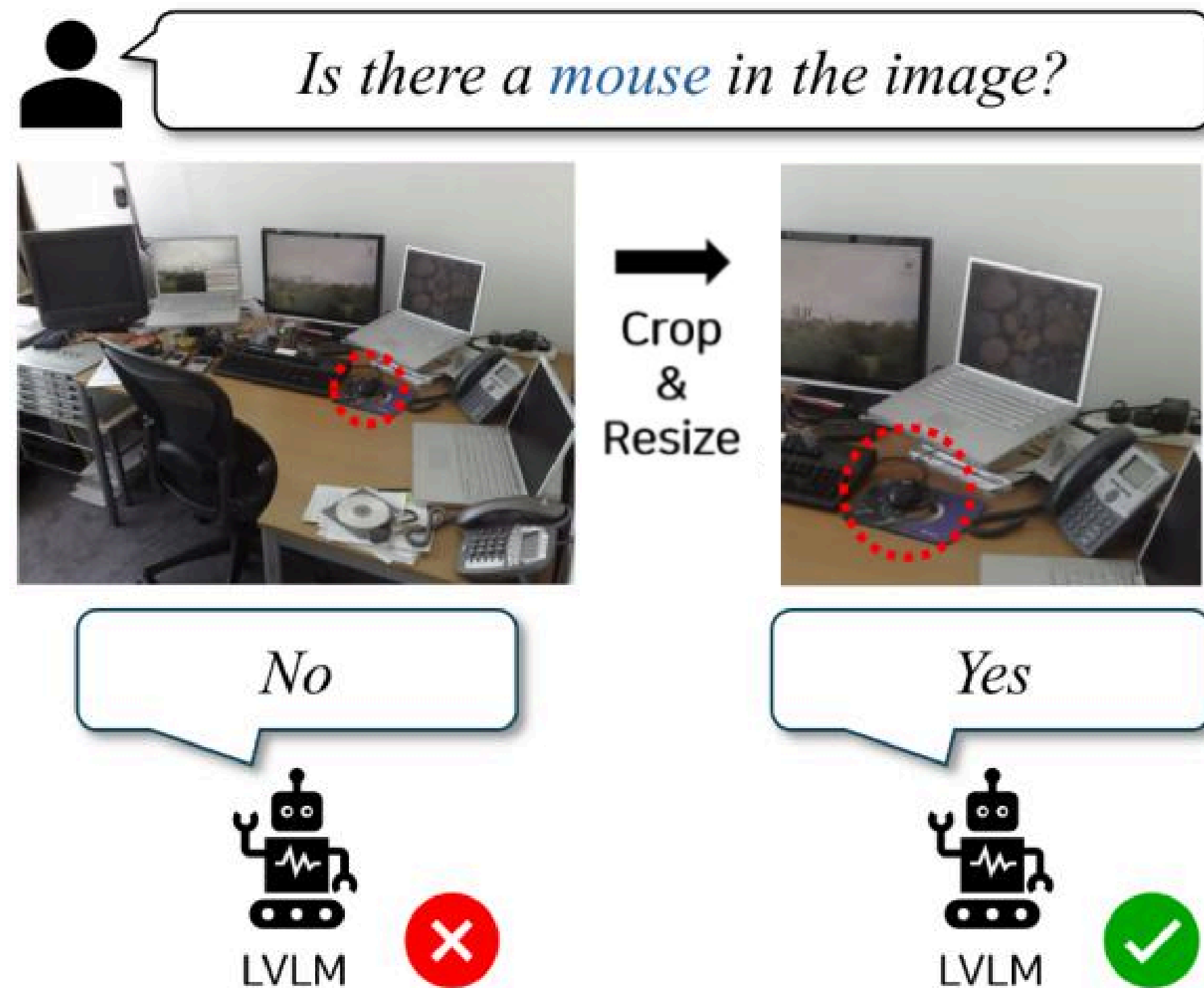


Fig. Example of Object Hallucination and its Modified Case

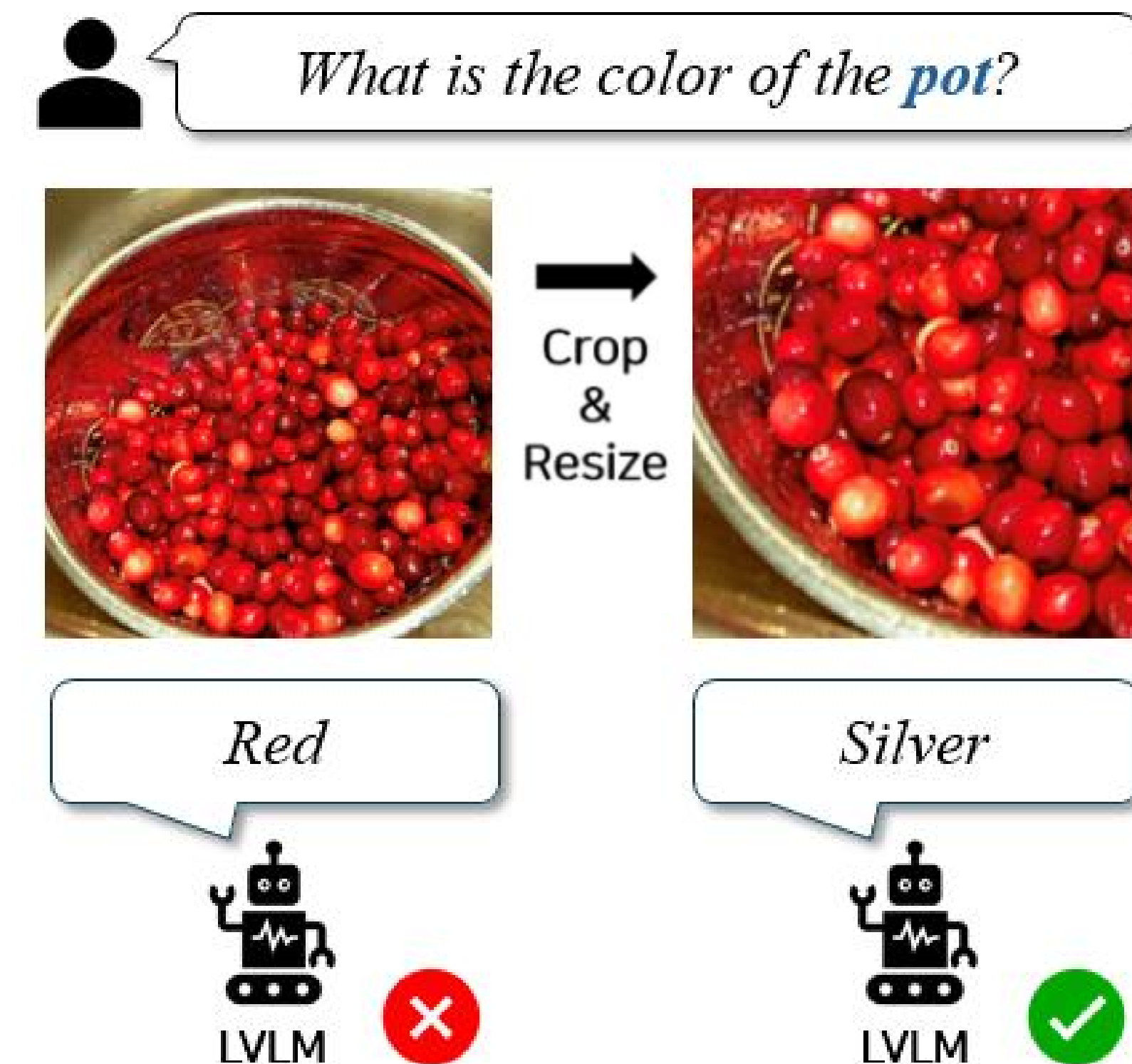


Fig. Example of Object Hallucination and its Modified Case

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Method

- Proposed Ensemble Decoding (ED) utilizing attention-guided weights and sub-image logit distribution.
- Introduced an optimized version (FastED) and ED Adaptive Plausibility Constraint.

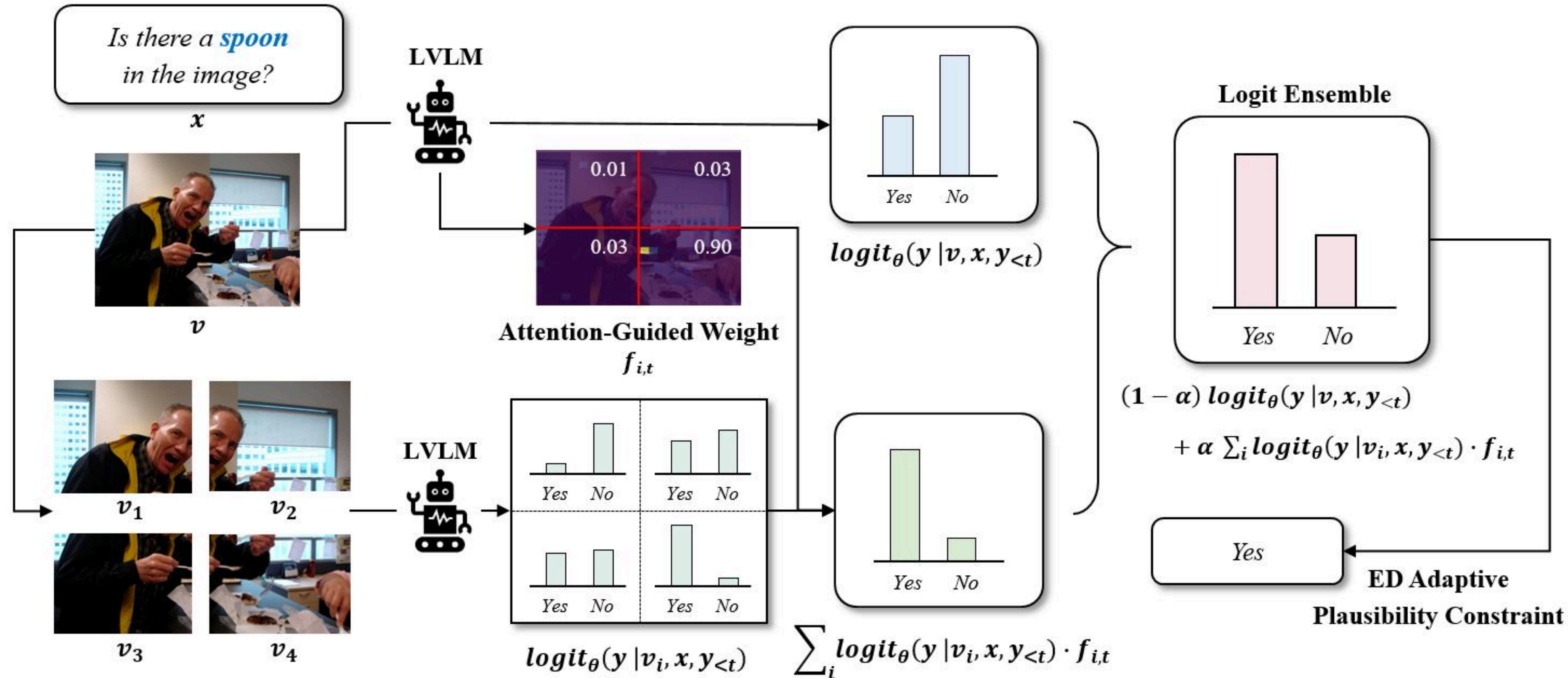


Fig. Overall Pipeline of Ensemble Decoding

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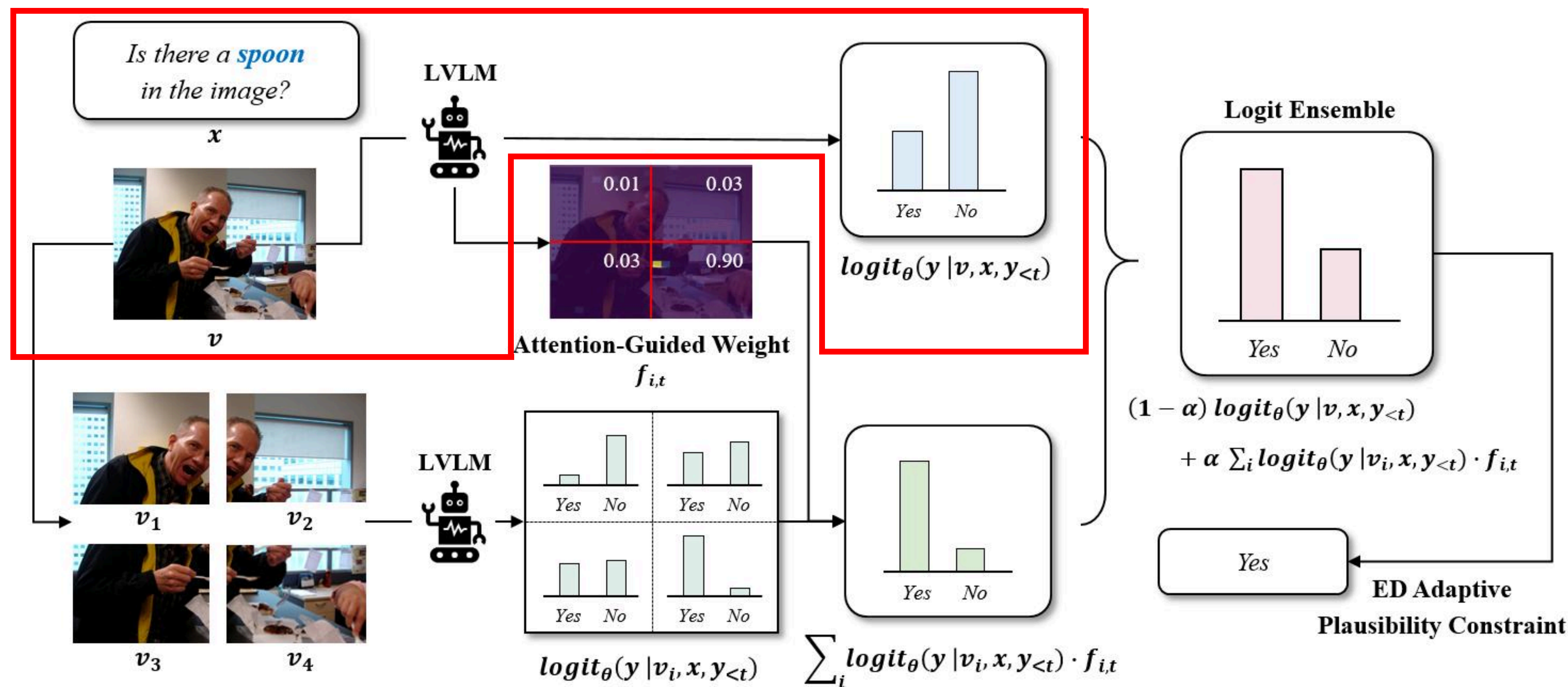


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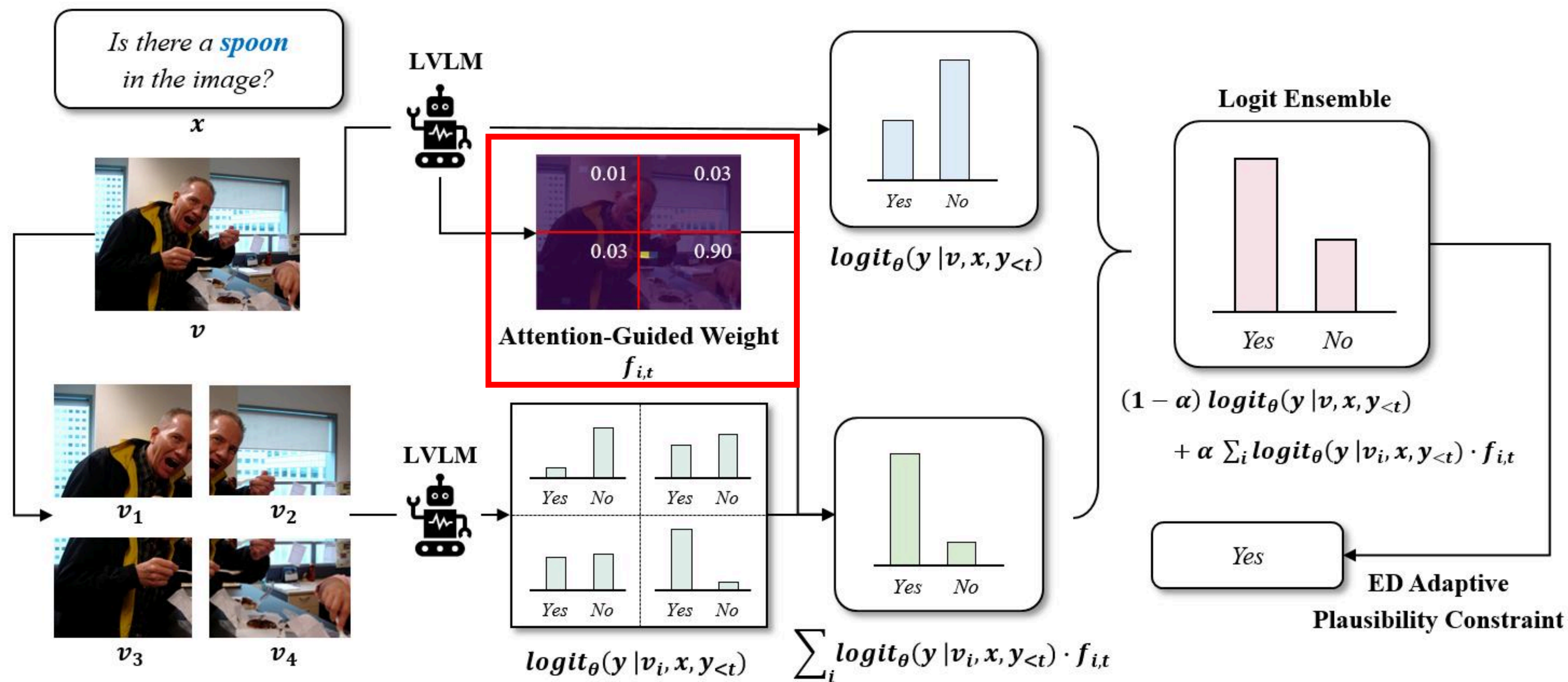


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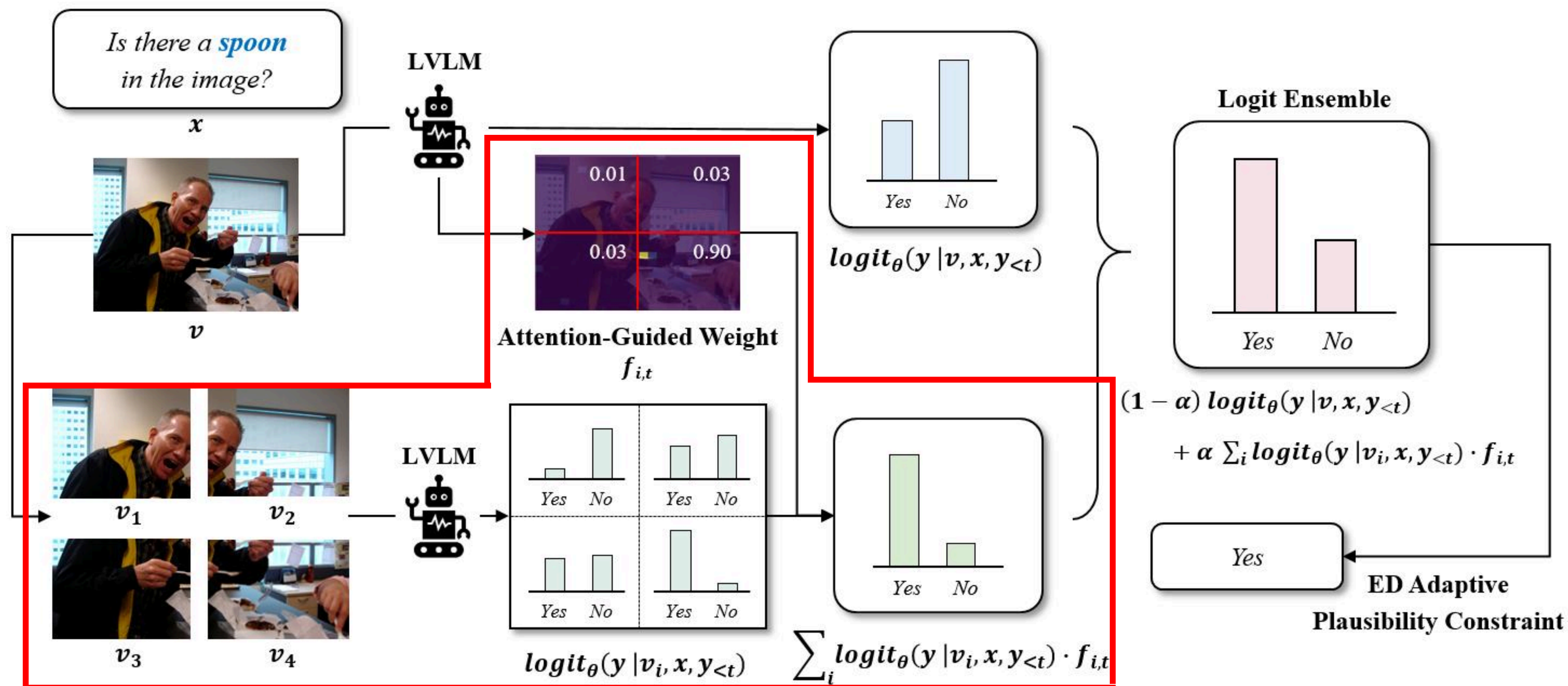


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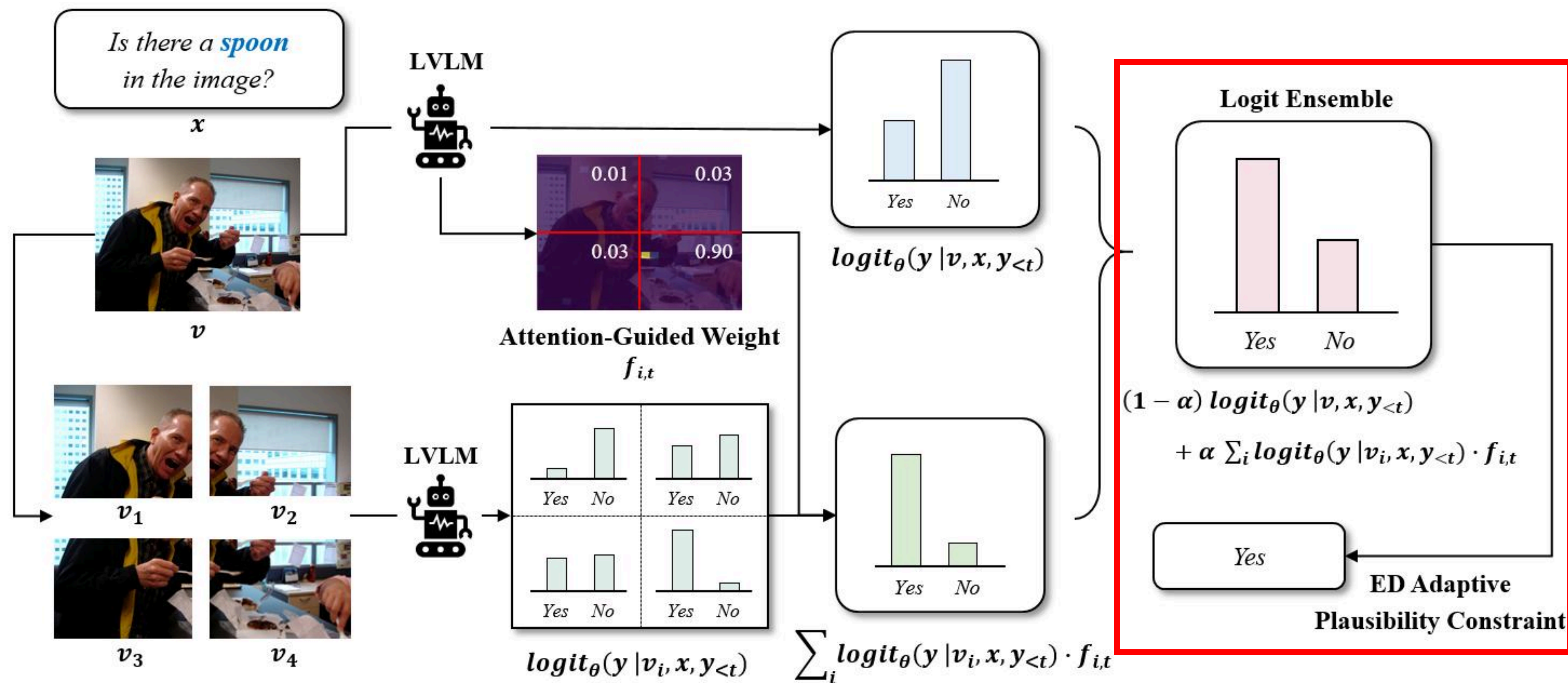


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Experimental Results

- Achieved the highest F1 Score and Accuracy on the hallucination benchmark (POPE).
- Outperformed other decoding strategies across all metrics in CHAIR, which requires generating long-form answers.

Tab. Experimental Results of VQA Hallucination Dataset (POPE)

Setting	Decoding	Precision	Recall	F1 Score	Accuracy
<i>Random</i>	Regular	88.84	76.76	82.28	83.49
	DOLA	87.59	81.27	84.19	84.78
	OPERA	94.52	79.80	86.45	87.53
	VCD	87.15	86.68	86.83	86.84
	AGLA	94.41	82.08	87.71	88.54
	ED	93.40	86.41	89.68	90.08
<i>Popular</i>	Regular	82.47	76.76	79.34	79.98
	DOLA	84.11	76.22	80.61	79.75
	OPERA	88.00	79.80	83.50	84.21
	VCD	87.15	80.59	83.37	82.65
	AGLA	87.88	82.08	84.68	85.14
	ED	86.12	86.41	86.00	86.09
<i>Adversarial</i>	Regular	76.11	76.80	76.26	76.03
	DOLA	77.27	75.47	76.16	76.32
	OPERA	82.16	79.76	80.69	80.88
	VCD	73.43	86.47	79.28	77.31
	AGLA	81.20	82.10	81.36	81.13
	ED	79.75	86.47	81.90	82.75

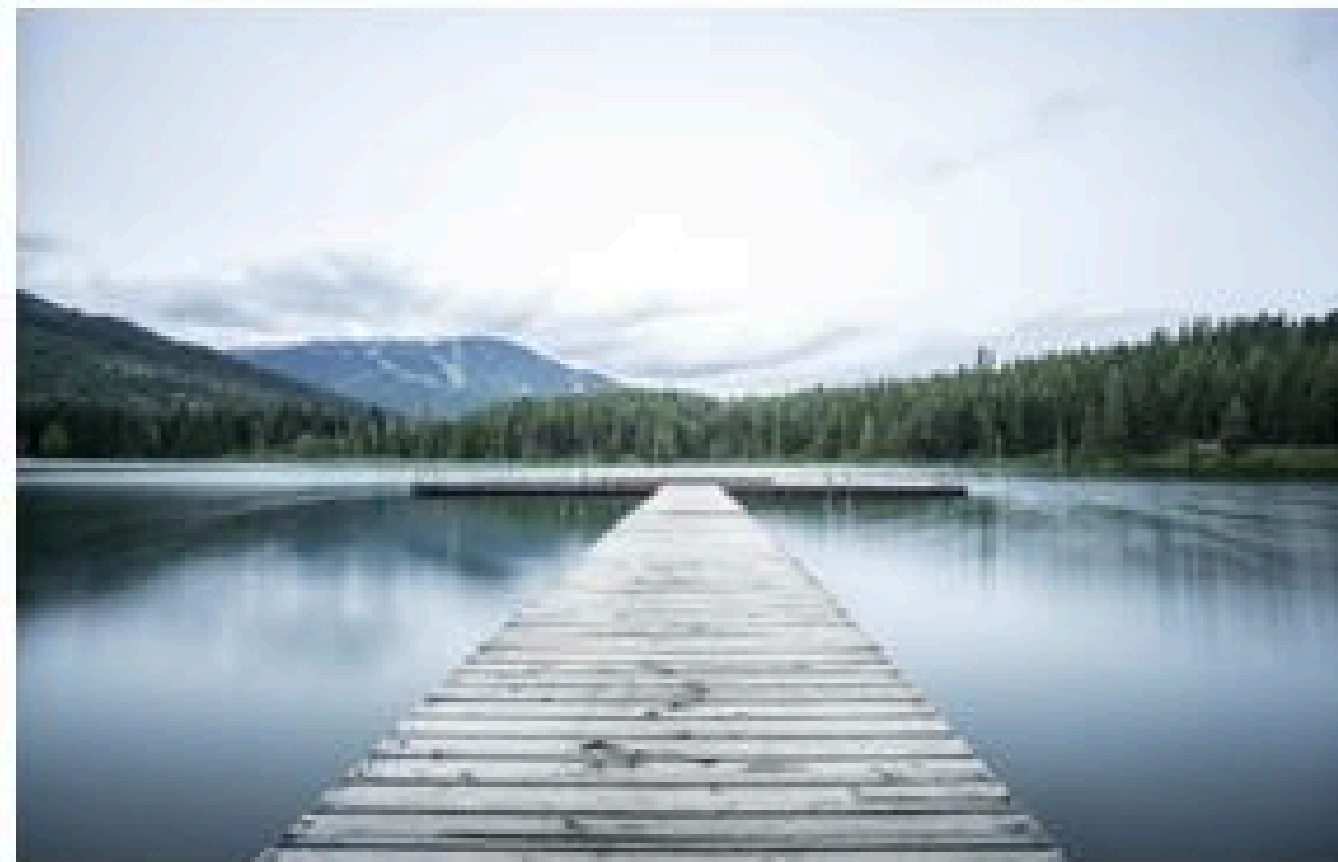
Tab. Experimental Results of Image Captioning Dataset (CHAIR)

Decoding	CHAIR _s ↓	CHAIR _l ↓	Recall↑	Average Length
Regular	51.0	15.2	75.2	102.2
DOLA	57.0	15.9	78.2	97.5
OPERA	47.0	14.6	78.5	95.3
VCD	51.0	14.9	77.2	101.9
AGLA	43.0	14.1	78.9	98.8
ED	43.0	14.0	82.5	100.1

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Qualitative Evaluation



(Regular) The image presents a pier extending into a mountain lake, with a simple boat dock next to it ... Along the pier, there is a **bench** where one can sit and enjoy the serene atmosphere. In the background, a cloudy sky adds depth to the scene, making the lake the main focal point of the image ...

(AGLA) The image features a pier extending out into a large body of water ... There are several **people** scattered along the pier, with some standing closer to the edge and others further back. A **boat** can be seen in the water near the pier, adding to the serene atmosphere ...

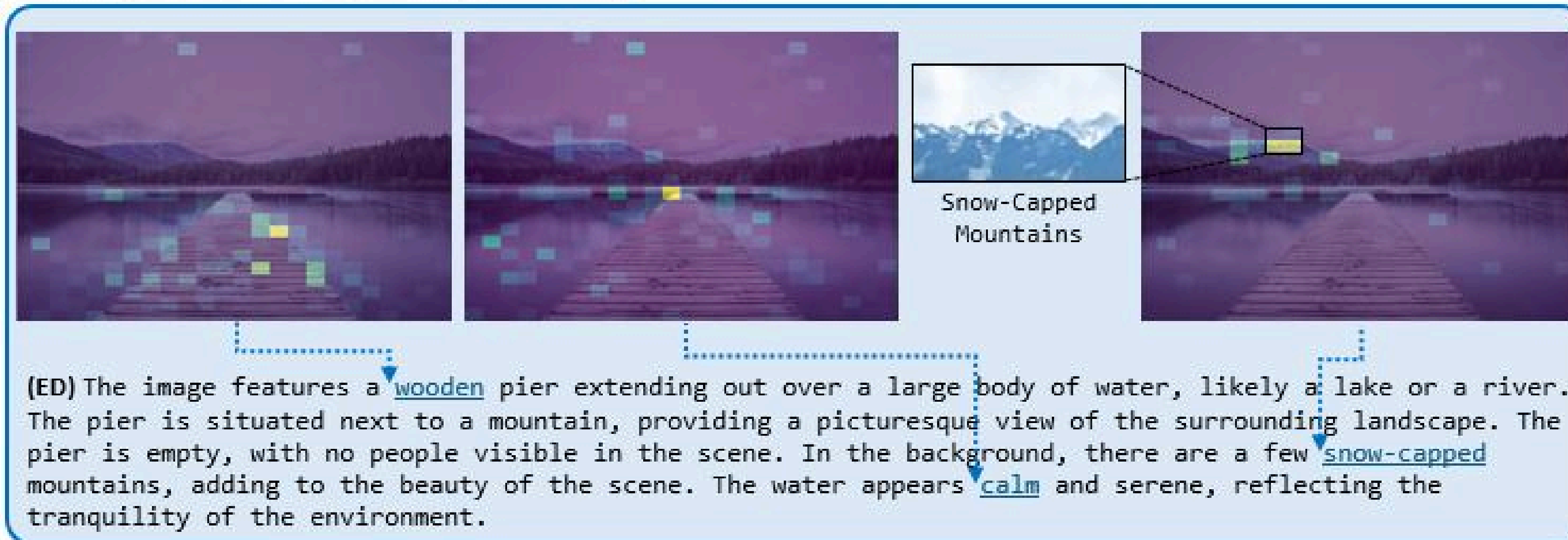


Fig. Generated captions using Regular, AGLA, and ED decoding strategies

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Conclusion

- Confirmed the superior performance of ED and FastED in hallucination benchmarks and image captioning tasks.
- FastED improves speed and accuracy, while ED is advantageous for detailed tasks, allowing selective use based on user needs.
- Proposed ED Adaptive Plausibility Constraint, better suited for ED and FastED compared to previous constraints.
- Minimized external dependencies by actively leveraging the model's inherent visual capabilities without external modules.
- Applicable to models without additional training and offers scalability in terms of model size.

Thank You!

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