Multimodal Perception and Comprehension of Corner Cases in Autonomous Driving

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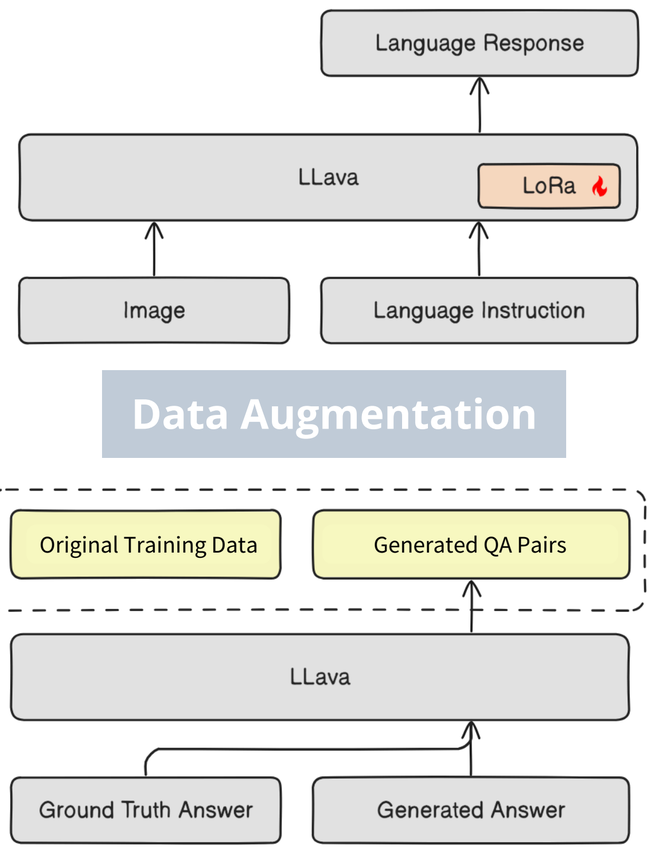
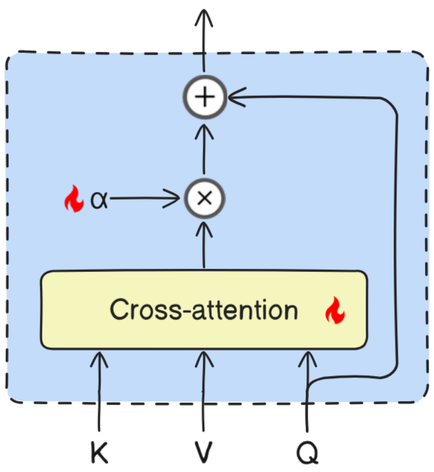
Methodology

Phase 1





Data Augmentation

Example: Prompt with Ground Truth and Generated Text

Prompt.
Given a reference text and a predicted text from an autonomous driving AI assistant, perform the following steps:

1. Evaluate the semantic similarity and relevance of the predicted text compared to the reference text.
2. Identify key details present in the reference text but missing or inaccurately represented in the predicted text.
3. Formulate a question-answer pair starting with 'Q:' for the question and 'A:' for the answer, addressing the missing or misrepresented details. This question-answer pair will be used as additional training data for the AI assistant to improve its reasoning and contextual accuracy.

Reference text:
{**Ground Truth.**}

Generated text:
{**Generated Text.**}

Example: QA Pair on "Train_general_71"

Question.
What is the presence of the maintenance truck with flashing lights, and how does it impact the driving decisions of the ego car?

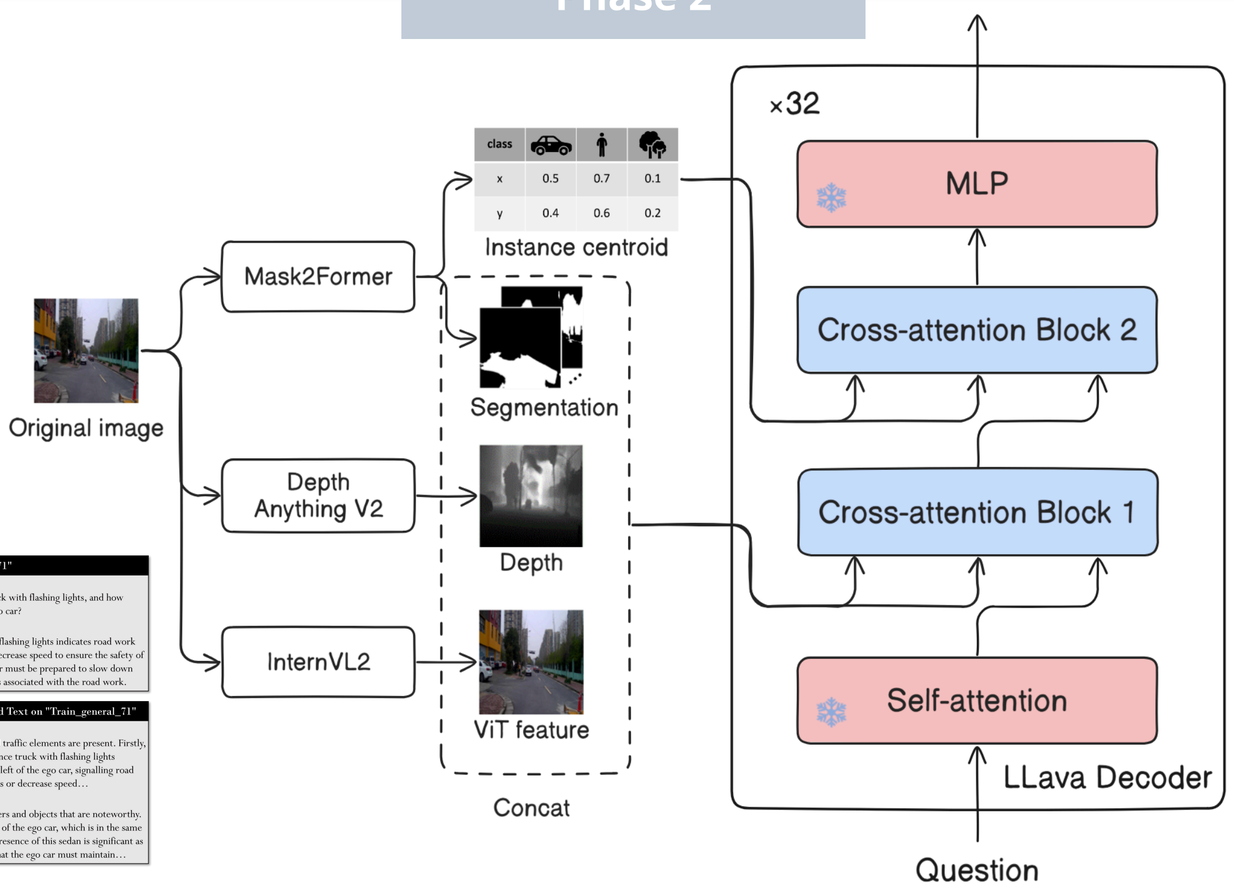
Answer.
The presence of the maintenance truck with flashing lights indicates road work and requires the ego car to change lanes or decrease speed to ensure the safety of the workers and other road users. The ego car must be prepared to slow down or stop if necessary to avoid potential hazards associated with the road work.

Example: Ground Truth and Generated Text on "Train_general_71"

Ground Truth.
In the visual provided, various road users and traffic elements are present. Firstly, there are two significant vehicles; a maintenance truck with flashing lights accompanied by workers is positioned to the left of the ego car, signalling road work and a potential necessity to change lanes or decrease speed…

Generated Text.
In the traffic image, there are several road users and objects that are noteworthy. Firstly, there is a black sedan directly in front of the ego car, which is in the same lane and moving in the same direction. The presence of this sedan is significant as it dictates the speed and following distance that the ego car must maintain…

Phase 2



Introduction

To tackle **Multimodal Perception and Comprehension of Corner Cases in Autonomous Driving**, a challenging problem defined in Track 1 of the ECCV 2024 Workshop on Corner Case Scene Understanding, we propose a two-phase approach:

- In **Phase 1**, we **fine-tune LLaVA with LoRA** to enhance its ability in processing driving scene inputs and aligning the model's output style with the ground truth annotations.
- In **Phase 2**, we extract comprehensive scene information from images using multiple encoders to obtain **segmentation, instance, depth, and vision transformer (ViT) features**. These features are integrated into LLaVA through new cross-attention layers added during second-stage fine-tuning, enabling the model to reason over diverse visual cues.

Furthermore, we also performed **Data Augmentation**. We used the results produced by the fine-tuned model as the **generated text** and fed them, along with the **ground-truth text**, into the LLaVA model. By identifying inaccuracies and gaps, the model generates multiple new QA pairs, which can then be used in Phase 1 or Phase 2 to further **enhance training**.

Experiment Result

Table 1. Experiment results across **different LoRA ranks**

LoRA Rank	Bleu 1	Bleu 2	Bleu 3	Bleu 4	General	Reginal	Suggestion	LLM judge	Final score
32	1.49	**0.86**	**0.51**	0.03	3.00	3.09	4.44	3.51	2.91
64	**1.28**	0.75	0.45	**0.28**	**5.08**	**5.39**	**4.89**	**5.12**	**4.19**

Table 2. Experiment results across **different settings**

Index	Setting	Bleu 1	Bleu 2	Bleu 3	Bleu 4	General	Reginal	Suggestion	LLM judge	Final score
1	LoRA only (rank=64)	1.28	0.75	0.45	0.28	5.08	5.39	4.89	5.12	4.19
2	cross-attn only (all features)	1.28	0.75	0.46	0.29	5.06	5.18	4.55	4.93	4.04
3	1 + vit	1.30	0.76	0.47	**0.30**	5.01	5.55	**4.95**	5.17	4.23
4	1 + segmentation	1.31	0.77	0.47	0.30	5.57	5.51	4.53	5.20	4.26
5	1 + depth	1.31	0.76	0.46	0.29	5.07	5.48	4.82	5.12	4.19
6	1 + instance	**1.31**	**0.77**	**0.47**	**0.30**	5.55	5.48	4.42	5.15	4.21
7	1 + all features	1.30	0.76	0.46	0.29	**5.72**	**5.56**	4.64	**5.31**	**4.34**

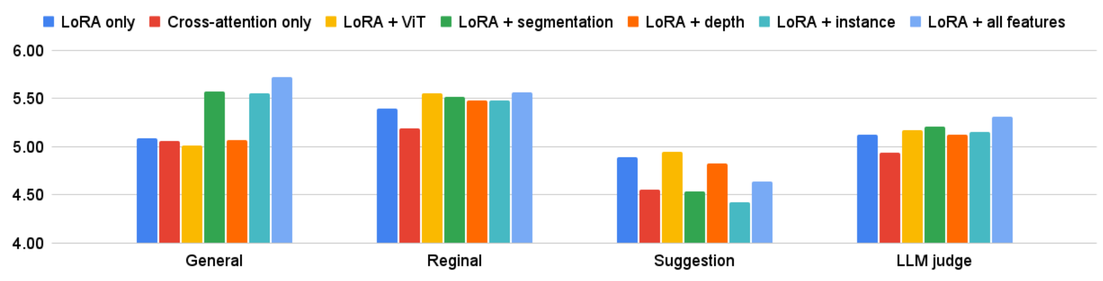


Fig 1. Bar chart comparing different settings

In Table 2, we take the LoRA only model (rank=64) as a **baseline**, as it has the best performance in Table 1, to further examine the importance of Phase 2 and the contributions of each feature individually.

- We consider that using **cross-attention only** for fine-tuning results in **suboptimal** performance, as the model tends to allocate excessive capacity to **adapting text styles** rather than **leveraging the additional visual cues** for enhanced reasoning. This limitation emphasizes the effectiveness of LoRA in facilitating alignment between the model's outputs and the ground truth.
- In addition, we observed the following relationships:
  - **Segmentation** and **instance** features strengthen **General Perception**.
  - **ViT** and **depth** features enhance **Driving Suggestion**.

Finally, based on the results discussed above, we utilized **all features** under the application of LoRA, effectively **combining their strengths** to achieve the optimal model performance.

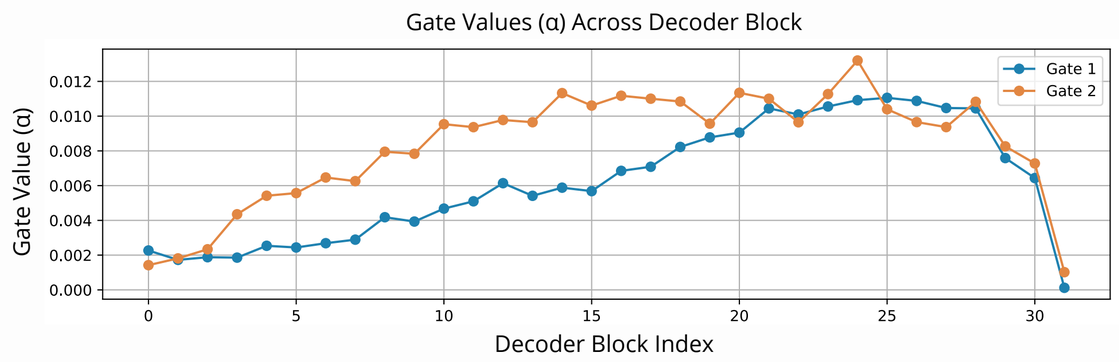


Fig 2. indicate that gate values are **largest in the latter layers** of the decoder, suggesting that **allocating more parameters to these layers** could enhance efficiency by **better utilizing the model's capacity** where it is most impactful.

Table 3. Experimental results before and after **applying augmentation**

Index	Setting	General	Reginal	Suggestion	LLM judge	Final score
1	LoRA only (rank=64)*	4.35	5.02	4.73	4.70	3.86
2	w/ Augmentation*	4.70	5.26	4.56	4.84	3.97
3	w/ Augmentation					

* Trained on 4812 samples, with additional 5425 augmented QA-pairs

Reference

1. Hu et al. LoRA: Low-Rank Adaptation of Large Language Models. ICLR 2021.
2. Bachlechner et al. Rezero is all you need: Fast convergence at large depth. PMLR 2021.
3. Bowen Cheng et al. Masked-attention Mask Transformer for Universal Image Segmentation. CVPR 2022.
4. Lihe Yang et al. Depth Anything V2. NeurIPS 2024.
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