Label-Efficient Fine-Tuning of VLMs for Interpretable Autonomous Driving via RLOO Algorithm

Kai-Yuan Jeng [1] Pei-Hsun Wu [2] Chen-Fang Hu [2]

[1]National Tsing Hua University [2]National Yang Ming Chiao Tung University

Abstract

We develop an efficient approach for **fine-tuning Vision-Language Models (VLMs) in End-to-End Autonomous Driving (E2E-AD)**. This work addresses two distinct challenges: heavy labeled data dependency in E2E-AD applications [4] and computational overhead of critic networks in large model RL training [1]. Our solution adapts **REINFORCE Leave-One-Out (RLOO)** [2] from RLHF domains [1] to vision-language tasks. This **critic-free** algorithm enables **label-efficient** VLM fine-tuning using only semantic alignment rewards [3], eliminating both extensive human annotations (E2E-AD challenge) and expensive critic training (RLHF challenge).

Problem Formulation

Problem Definition: We formulate VLM fine-tuning as a **video understanding** task (extension of the image captioning) [3]. The model processes traffic scene image frames and generates natural language text containing both scene descriptions and appropriate AD control actions.

Bandit Setting: We then model this as a bandit problem [1] where

- **State:** Input image frames $\mathbf{I}$
- **Action:** Complete generated text sequence $\mathbf{T}$
- **Reward:** Semantic similarity $\mathcal{R}(\mathbf{I},\mathbf{T})$, measured by fine-tuned CLIP [3]

RLOO Optimization: Instead of training expensive critic networks, RLOO uses **multiple Monte-Carlo samples as baselines for unbiased policy gradient estimation**, enabling a critic-free training [2], with the policy gradient calculated as:

$$\nabla_\theta \mathcal{J}_{\text{RLOO}}(\theta) = \mathbb{E}_{\mathbf{I}\sim\mathcal{D}}\left[\sum_{i=1}^{k}\left(\mathcal{R}(\mathbf{I},\mathbf{T}^i) - \frac{1}{k-1}\sum_{j\neq i}\mathcal{R}(\mathbf{I},\mathbf{T}^j)\right)\nabla_\theta \log \mathbf{VLM}_\theta(\mathbf{T}^i \mid \mathbf{I})\right].$$

Methodology

Two-Stage Training Framework:

1. **Text Sequence Generation via Reinforcement Learning:** CLIP rewards + RLOO optimization for scene description generation.
2. **Action Selection and Formatting Alignment via Supervised Learning:** Format alignment using instructed prompts and BLEU score.

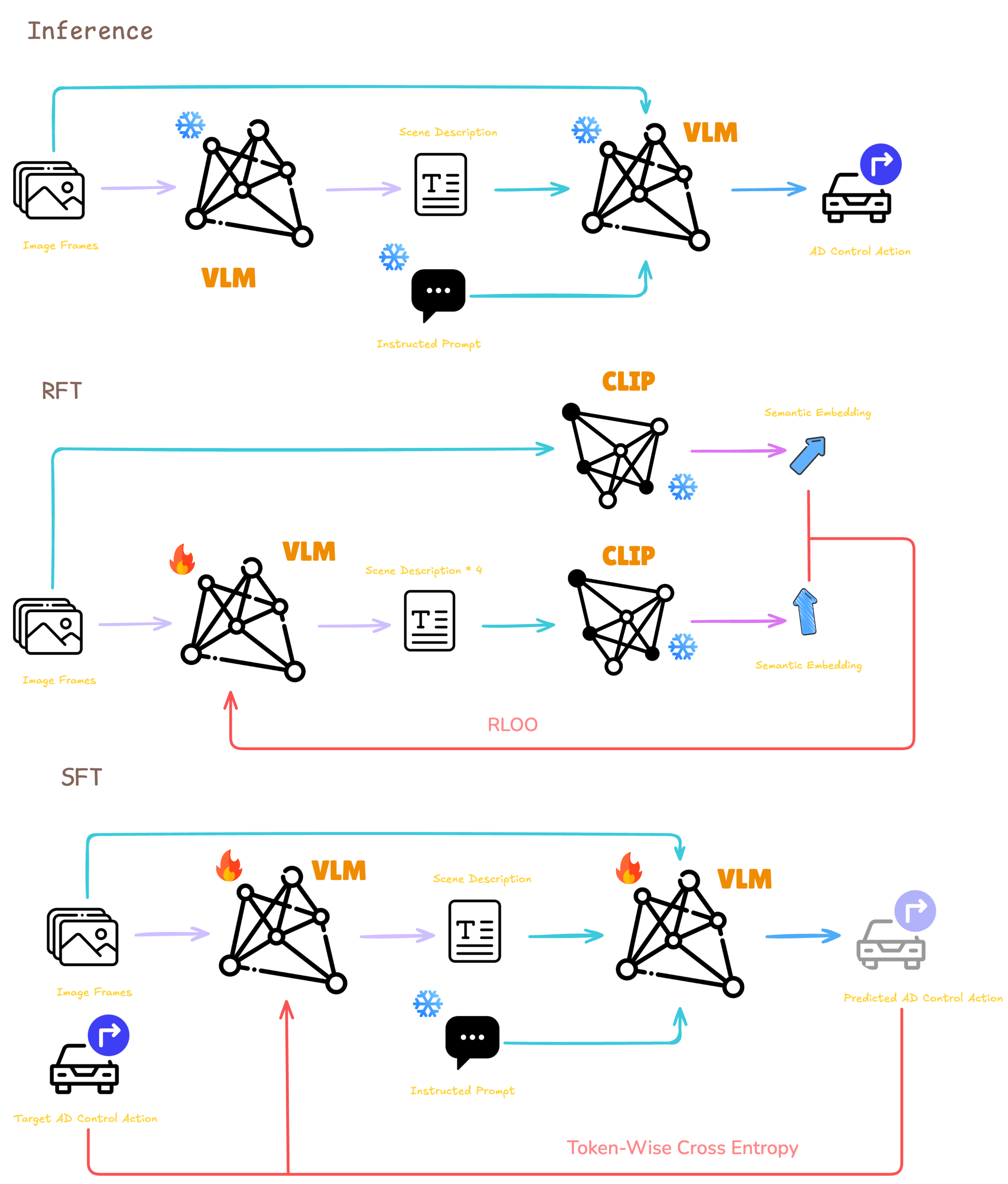


Figure 1. Complete training and inference pipeline.

Experiment

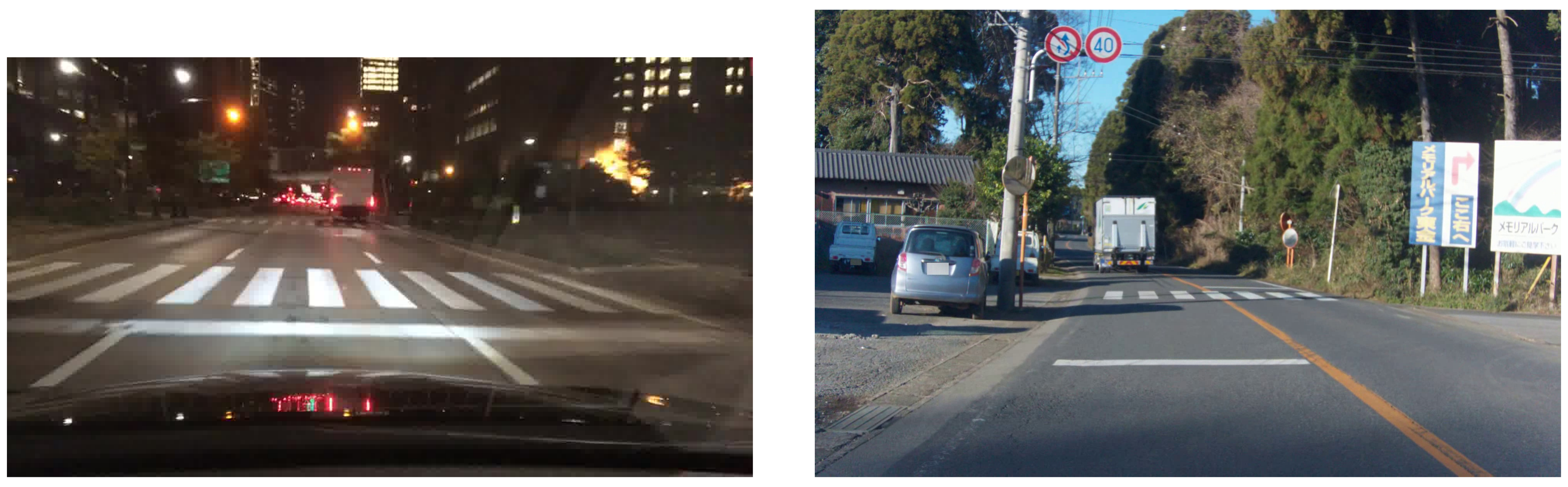
Setup: 1) **BDD-OIA** dataset [4] with traffic scenes, actions, and reasoning; 2) Fine-tuned **CLIP** as reward model; and 3) **Token-wise supervised** fine-tuning as baseline vs. our RLOO framework on **SmolVLM-256M**.

Key Findings: 1) Domain gap: Pretrained VLM with 0% performance; 2) Catastrophic forgetting: CLIP score 91% → 42%; 3) Model capacity: Cannot balance pretrained knowledge + reward optimization; 4) Action formatting issue: 84% action F1, but all predictions are `STOP`; and 5) Positive insight: **RLOO enhances scene description capability**.

Root Cause: High learning rate (2e-5) + insufficient model capacity (256M) → requires careful hyperparameter tuning.

Table 1. Experimental results.

Method	Action F1	Reason F1	CLIP Score
Ground Truth	100.00%	100.00%	91.32%
Pretrained VLM	0.00%	0.00%	0.00%
Baseline (SFT for 10 Epochs)	80.15%	66.75%	*N/A*
RFT (RLOO for 3 Epochs with $k=4$)	*N/A*	*N/A*	41.88%
RFT+SFT (Each with 3 Epochs)	84.12%	0.00%	*N/A*



(a) BDD-OIA (in-distribution) (b) OOD scenario

Figure 2. Sample model outputs comparison.

Left: (1) **Pretrained:** "Crosswalk." (2) **SFT Baseline:** "Action: stop. Reason: Traffic light is not green." (3) **RFT+SFT:** "Action: stop. Reason: The intersection of an asian city road is fully visible in this photo."

Right: (1) **Pretrained:** "There is a road sign that says 40." (2) **SFT Baseline:** "Action: stop. Reason: Traffic sign." (3) **RFT+SFT:** "Action: stop. Reason: A two way street sign says that there are 40 down."

Conclusion

Contribution and Future Work: We have successfully adapted RLOO from RLHF to vision-language tasks, providing a **critic-free, label-efficient** framework for VLM fine-tuning in autonomous driving. We will evaluate on larger VLMs and implement adaptive learning strategies for hyperparameter optimization in future work.

References

[1] Arash Ahmadian, Chris Cremer, Matthias Gallé, Marzieh Fadaee, Julia Kreutzer, Olivier Pietquin, Ahmet Üstün, and Sara Hooker. Back to basics: Revisiting REINFORCE-style optimization for learning from human feedback in LLMs. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 12248–12267, Bangkok, Thailand, August 2024. Association for Computational Linguistics.

[2] Wouter Kool, Herke van Hoof, and Max Welling. Buy 4 REINFORCE samples, get a baseline for free! In *Deep Reinforcement Learning Meets Structured Prediction, ICLR 2019 Workshop, New Orleans, Louisiana, United States, May 6, 2019*. OpenReview.net, 2019.

[3] Zhou Ren, Xiaoyu Wang, Ning Zhang, Xutao Lv, and Li-Jia Li. Deep reinforcement learning-based image captioning with embedding reward. In *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 1151–1159, 2017.

[4] Yiran Xu, Xiaoyin Yang, Lihang Gong, Hsuan-Chu Lin, Tz-Ying Wu, Yunsheng Li, and Nuno Vasconcelos. Explainable object-induced action decision for autonomous vehicles. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 9523–9532, 2020.