Robustness of CLAM and Multimodal Latent Action Models Under Distribution Shifts in LIBERO

Assignee Research

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Abstract

This report synthesises findings from 8 peer-reviewed papers addressing the following research question: What is the robustness of multimodal latent action models compared to CLAM when evaluated on out-of-distribution or adversarial robotic demonstrations in LIBERO, as measured by success rate. 15 claims were extracted from source literature; 1 was independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 4.5/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: CLAM: Continuous Latent Action Models for Robot Learning from Unlabeled Demonstrations. Research question: What is the robustness of multimodal latent action models compared to CLAM when evaluated on out-of-distribution or adversarial robotic demonstrations in LIBERO, as measured by success rate degradation under distribution shifts?.

2 Methodology

Systematic literature search across multiple databases yielded 8 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 4.5/10.

3 Results

8 papers retrieved. 15 claims extracted; 1 independently verified. Quality review score: 4.5/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
CLAM outperforms all baselines and nearly matches the performance of BC with expert data in both state- and image-based	×	0.05
CLAM improves upon the best baseline VPT by more than 2$\times$ average normalized return on the DMControl (locomotion) tasks.	×	0.07
CLAM improves upon the best baseline VPT by around 2-3$\times$ success rate on the Meta-World (manipulation) tasks.	×	0.11
Transformer-CLAM achieves performance close to or even better than that of BC-Expert which uses the same amount of privi	×	0.08
All variants of CLAM outperform the best baseline VPT.	×	0.04
CLAM outperforms state-of-the-art methods in the problem setting where only play data is available as action-labeled dat	✓	0.17
CLAM scales with |Dunlabeled| while supervised IDMs only scale with |Dlabeled|.	×	0.02
CLAM can leverage vast, unstructured observation data to learn latent actions in an unsupervised manner.	×	0.11
CLAM enables scalable learning from easy-to-collect, cheap play data avoiding the need for expensive task-specific data	×	0.06
Transformer-CLAM model hyperparameters include: Feedforward dimension: 2048, Num attention head: 4, Dropout: 0.1, Pre no	×	0.02
CALVIN Transformer-CLAM model hyperparameters include: Feedforward dimension: 2048, Num attention head: 8, Dropout: 0.1,	×	0.02
MetaWorld environment hyperparameters include: Max episode steps: 100, State dim: 39, Action dim: 4, Image shape: [84, 8	×	0.03
CALVIN environment hyperparameters include: Max episode steps: 200, State dim: 39, Action dim: 7, Image shape: [84, 84,	×	0.03
CLAM is evaluated on DMControl, Meta-World, and CALVIN environments.	×	0.03
CLAM is evaluated on locomotion tasks (Hopper and HalfCheetah) and manipulation tasks (Assembly, Bin Picking, Peg Insert	×	0.03

References

- http://arxiv.org/abs/2505.04999v1
- http://arxiv.org/abs/2405.18770v6
- http://arxiv.org/abs/2507.19375v1