

CLAM Latent Space Robustness Across Out-of-Distribution Camera Viewpoints in RT-1

Assignee Research

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Abstract

This report synthesises findings from 11 peer-reviewed papers addressing the following research question: How does the robustness of CLAM’s latent space generalize to out-of-distribution camera viewpoints in RT-1 compared to standard token-based imitation learning policies. 12 claims were extracted from source literature; 1 was independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 4.7/10. 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: How does the robustness of CLAM’s latent space generalize to out-of-distribution camera viewpoints in RT-1 compared to standard token-based imitation learning policies?.

2 Methodology

Systematic literature search across multiple databases yielded 11 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 4.7/10.

3 Results

11 papers retrieved. 12 claims extracted; 1 independently verified. Quality review score: 4.7/10.

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 a	×	0.12
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 [11].	×	0.05
CLAM outperforms state-of-the-art methods in the problem setting where only play data is available as action-labeled dat	✓	0.16
CLAM enables scalable learning from easy-to-collect, cheap play data [21] avoiding the need for expensive task-specific	×	0.05
BC-AL using action-labeled data does not perform well due to imitating suboptimal demonstrations.	×	0.09
CLAM scales with Dunlabeled while supervised IDMs only scale with Dlabeled .	×	0.02
The data regime of CLAM enables learning from easy-to-collect, cheap play data [21] avoiding the need for expensive task	×	0.05
CLAM is evaluated on DMControl, Meta-World, and CALVIN without modification.	×	0.02
All domains used for evaluation are continuous control environments with a fixed episode length and no termination condi	×	0.06
For DMControl tasks, normalized return is reported following [22].	×	0.02

References

- <http://arxiv.org/abs/2002.00819v4>
- <http://arxiv.org/abs/2505.04999v1>
- <http://arxiv.org/abs/2209.11233v2>