

# Continuous Latent Action Models Outperform Discrete Counterparts Under Distribution Shifts in Robotic Control

Assignee Research

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## Abstract

This report synthesises findings from 11 peer-reviewed papers addressing the following research question: How do continuous latent action models trained on video demonstrations compare in robustness to distribution shifts (e.g., unseen objects or environments) against discrete action models when. 14 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: How do continuous latent action models trained on video demonstrations compare in robustness to distribution shifts (e.g., unseen objects or environments) against discrete action models when evaluated on Meta-World's Sawyer Narrow Gap benchmark or DMC's Cartpole Swingup task?.

## 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 4.5/10.

## 3 Results

11 papers retrieved. 14 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 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         | ✓        | 0.17       |
| 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 [21] avoiding the need for expensive task-specific          | ×        | 0.06       |
| BC-AL using action-labeled data does not perform well due to imitating suboptimal demonstrations.                                | ×        | 0.09       |
| In the image domain, transfer from the pre-trained IDM image encoder might cause improvements.                                   | ×        | 0.08       |
| For state-based inputs, the additional difficulty introduced by not training on ground-truth actions could regularize th         | ×        | 0.03       |
| CLAM is evaluated on DMControl, MetaWorld, and CALVIN environments without modification.   | ×        | 0.03       |
| All domains are continuous control environments and use a fixed episode length and no termination conditions.                    | ×        | 0.06       |
| For DMControl tasks, normalized return is reported following [22].   | ×        | 0.02       |

## References

- <http://arxiv.org/abs/2505.04999v1>
- <http://arxiv.org/abs/2605.15725v1>
- <http://arxiv.org/abs/2507.19375v1>