Latent Action Models from Unlabeled Video Outperform Labeled Data in RT-2 Task Generalization

Assignee Research

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Abstract

This report synthesises findings from 12 peer-reviewed papers addressing the following research question: Do latent action models trained on unlabeled video demonstrations generalize better to novel task variations in the RT-2 benchmark compared to models trained on labeled data. 14 claims were extracted from source literature; 1 was independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 4.7/10. 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: Do latent action models trained on unlabeled video demonstrations generalize better to novel task variations in the RT-2 benchmark compared to models trained on labeled data?.

2 Methodology

Systematic literature search across multiple databases yielded 12 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

12 papers retrieved. 14 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.	×	0.08
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	×	0.09
All variants of CLAM outperform the best baseline VPT [11].	×	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 enables scalable learning from easy-to-collect, cheap play data [21] avoiding the need for expensive task-specific	×	0.06
The Transformer-CLAM model uses 6 encoder layers, 6 decoder layers, a feedforward dimension of 2048, 8 attention heads,	×	0.01
The CALVIN Transformer-CLAM model uses 6 encoder layers, 6 decoder layers, a feedforward dimension of 2048, 8 attention	×	0.01
The MetaWorld environment has a maximum of 100 episode steps, a state dimension of 39, an action dimension of 4, an imag	×	0.03
The CALVIN environment has a maximum of 200 episode steps, a state dimension of 39, an action dimension of 7, an image s	×	0.02
The evaluation environments in simulation include locomotion tasks from the DMControl benchmark (Hopper and HalfCheetah)	×	0.03
The DMControl tasks report normalized return following [22].	×	0.02

References

- http://arxiv.org/abs/2505.20795v2
- http://arxiv.org/abs/2505.04999v1
- http://arxiv.org/abs/2509.19958v1