Sample Efficiency Comparison of Latent Action Models and Discrete Quantization in Robotic Task Learning

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Abstract

Learning robot policies using imitation learning requires collecting large amounts of costly action-labeled expert demonstrations, which fundamentally limits the scale of training data. A promising approach to address this bottleneck is to harness the abundance of unlabeled observations-e.g., from video demonstrations-to learn latent action labels in an unsupervised way. However, we find that existing methods struggle when applied to complex robot tasks requiring fine-grained motions. We design continuous latent action models (CLAM) which incorporate two key ingredients we find necessary for l

1 Introduction

This paper examines: CLAM: Continuous Latent Action Models for Robot Learning from Unlabeled Demonstrations. Research question: What is the sample efficiency gap between unsupervised continuous latent action models and discrete action quantization methods when trained on limited video demonstrations for complex robotic tasks?.

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 7.4/10.

3 Results

12 papers retrieved. 13 claims extracted; 9 independently verified. Quality review score: 7.4/10.

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	✓	0.28
CLAM improves upon the best baseline VPT by more than 2$\times$ average normalized return on the DMControl (locomotion) tasks.	✓	0.22
CLAM improves upon the best baseline VPT by around 2-3$\times$ success rate on the Meta-World (manipulation) tasks.	✓	0.19
Transformer-CLAM achieves performance close to or even better than that of BC-Expert which uses the same amount of privi	✓	0.24
All variants of CLAM outperform the best baseline VPT.	✓	0.19
CLAM outperforms state-of-the-art methods in the problem setting where only play data is available as action-labeled dat	✓	0.25
CLAM scales with |Dunlabeled| while supervised IDMs only scale with |Dlabeled|.	×	0.13
CLAM can leverage vast, unstructured observation data to learn latent actions in an unsupervised manner.	✓	0.17
CLAM enables scalable learning from easy-to-collect, cheap play data avoiding the need for expensive task-specific data	✓	0.28
CLAM is evaluated on DMControl, MetaWorld, and CALVIN environments.	×	0.06
CLAM is evaluated on locomotion tasks (Hopper and HalfCheetah) and manipulation tasks (Assembly, Bin Picking, Peg Insert	✓	0.24
CLAM is evaluated in CALVIN with the Close Drawer and Slider Left tasks.	×	0.03
For DMControl tasks, normalized return is reported following [22].	×	0.07

References

- http://arxiv.org/abs/2605.15725v1
- http://arxiv.org/abs/2503.00200v3

- http://arxiv.org/abs/2505.04999v1