CLAM Latent Actions Outperform Discrete Tokens in Robustness on BridgeData V2

Assignee Research

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Abstract

This report synthesises findings from 11 peer-reviewed papers addressing the following research question: What is the difference in robustness, measured by success rate under visual distractors, between policies trained with CLAM's unsupervised latent actions versus those trained with discrete tokens on. 17 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 difference in robustness, measured by success rate under visual distractors, between policies trained with CLAM's unsupervised latent actions versus those trained with discrete tokens on the BridgeData V2 benchmark?.

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. 17 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	×	0.11
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 [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 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.	×	0.10
CLAM scales with |Dunlabeled| while supervised IDMs only scale with |Dlabeled|.	×	0.02
CLAM is evaluated on DMControl, MetaWorld, and CALVIN environments.	×	0.03
CLAM is evaluated on locomotion tasks (Hopper and HalfCheetah) and manipulation tasks (Assembly, Bin Picking, Peg Insert	×	0.04
CLAM is evaluated in CALVIN with the Close Drawer and Slider Left tasks.	×	0.02
For DMControl tasks, normalized return is reported following [22].	×	0.02
CLAM uses a fixed episode length and no termination conditions.	×	0.01
CLAM's Transformer model has 6 encoder layers, 6 decoder layers, a feedforward dimension of 512, 8 attention heads, a dr	×	0.03
CLAM's MLP model has a feedforward dimension of 2048, 4 attention heads, a dropout of 0.1, uses GeLU activation, and lea	×	0.02
MetaWorld environment hyperparameters include a max episode steps of 100, state dim of 39, action dim of 4, image shape	×	0.03
CALVIN environment hyperparameters include a max episode steps of 200, state dim of 39, action dim of 7, image shape of	×	0.03

References

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