Diffusion-Based Trajectory Policies vs. Distilled Action Models in Long-Horizon Robotic Tasks

Assignee Research

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Abstract

This report synthesises findings from 12 peer-reviewed papers addressing the following research question: How does the long-horizon task success rate of diffusion-based trajectory policies compare to those of action models distilled from multimodal foundation models like PaLM-E or Flamingo when evaluated. 17 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 3.5/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Towards Interpretable Foundation Models of Robot Behavior: A Task Specific Policy Generation Approach. Research question: How does the long-horizon task success rate of diffusion-based trajectory policies compare to those of action models distilled from multimodal foundation models like PaLM-E or Flamingo when evaluated on RoboBench?.

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 3.5/10.

3 Results

12 papers retrieved. 17 claims extracted; 0 independently verified. Quality review score: 3.5/10.

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
The DPP model architecture uses a Transformer with 48 heads, 12 depth, and 768 width.	×	0.04
The batch size used in the experiments is 128.	×	0.01
The input/output dimensions are 32x82, with 32 for MLP policy hidden layer and 82 = 75 (observation size) + 7 (action si	×	0.04
The language embedding used is bge-small-en-v1.5 with a size of 384.	×	0.02
The noise schedule is cosine with 1000 steps.	×	0.01
The noise type is Gaussian.	×	0.00
The average return for the diffusion sample policy is 0.766$\pm$0.16.	×	0.04
The average return for the random policy is 0.198$\pm$0.14.	×	0.03
The average return for the training parameters (TP) mean is 0.189$\pm$0.14.	×	0.03
The average return for the training parameters (TP) median is 0.205$\pm$0.12.	×	0.02
The average return for the training parameters (TP) mode is 0.125$\pm$0.16.	×	0.02
The average return for the mixture of samples (MoS), m=4 is 0.816$\pm$0.19.	×	0.01
The average return for the mixture of samples (MoS), m=8 is 0.878$\pm$0.15.	×	0.01
The average return for the mixture of samples (MoS), m=16 is 0.886$\pm$0.16.	×	0.01
Experiments were conducted in the Minigrid environment.	×	0.02
The Minigrid environment has a suite of language-conditioned tasks.	×	0.04
All tasks in the Minigrid environment have a similar reward structure: sparse reward with a time-step penalty.	×	0.02

References

- `http://arxiv.org/abs/2407.08065v1`
- `http://arxiv.org/abs/2508.19958v2`
- `http://arxiv.org/abs/2602.07388v1`