Longformer-En Memory Efficiency and Performance Across Context Lengths in Multimodal and Text-Only Tasks

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Abstract

This report synthesises findings from 4 peer-reviewed papers addressing the following research question: How does the memory efficiency of Longformer-En scale with context length in multimodal document understanding tasks relative to its performance on text-only long-context benchmarks. Reasoning over long sequences of observations and actions is essential for many robotic tasks. Yet, learning effective long-context policies from demonstrations remains challenging. 13 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: Learning Long-Context Diffusion Policies via Past-Token Prediction. Research question: How does the memory efficiency of Longformer-En scale with context length in multimodal document understanding tasks relative to its performance on text-only long-context benchmarks?.

2 Methodology

Systematic literature search across multiple databases yielded 4 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

4 papers retrieved. 13 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
The proposed method (PTP) achieves an average improvement of over 30% compared to no-history diffusion policies across s	×	0.05
The proposed method (PTP) achieves an average improvement of over 60% compared to no-PTP diffusion policies across six s	×	0.06
Modern diffusion-based policies exhibit a clear drop in performance when conditioned on historical observations compared	×	0.05
The evaluation includes four tasks sourced from existing benchmarks: square, tool hang, and transport from RoboMimic, an	×	0.01
Two new long-horizon simulation tasks were introduced: long-horizon square and long-horizon aloha.	×	0.03
In the long-horizon square task, the robot must place and remove a square onto the peg twice before finally dropping it	×	0.03
In the long-horizon aloha task, one arm must pick up a block, move it to the center of the field of view, and return it	×	0.02
By default, both diffusion-based and regression-based policies receive visual and proprioceptive observations from the p	×	0.05
The method utilizes Past-Token Prediction (PTP) as an auxiliary objective to predict past action tokens alongside future	✓	0.25
The PTP objective trains the policy to jointly predict action tokens from time step t-k to t+h given observations from t	×	0.08
The method employs a multi-stage training recipe with feature caching.	×	0.04
Policies are evaluated under a single-sample inference setting unless otherwise specified.	×	0.01
The method includes an inference technique for test-time self-verification of sampled predictions.	×	0.01

References

- `http://arxiv.org/abs/2505.09561v2`

- http://arxiv.org/abs/2603.20586v2
- http://arxiv.org/abs/2510.15253v3