Pre-Training Mitigates Label Corruption Effects in Embodied AI on CALVIN

Assignee Research

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Abstract

This report synthesises findings from 16 peer-reviewed papers addressing the following research question: To what extent does pre-training mitigate performance drops caused by label corruption in embodied AI agents trained on the CALVIN dataset. 11 claims were extracted from source literature; 1 was 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: Mitigating Noisy Supervision Using Synthetic Samples with Soft Labels. Research question: To what extent does pre-training mitigate performance drops caused by label corruption in embodied AI agents trained on the CALVIN dataset?.

2 Methodology

Systematic literature search across multiple databases yielded 16 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

16 papers retrieved. 11 claims extracted; 1 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 model starts by learning to predict the true labels for correctly labeled training samples, achieving high test accu	×	0.04
With increasing training epochs, the model begins making incorrect predictions as it memorizes the mislabeled samples.	×	0.04
The highest training accuracy is achieved during the early learning stage before the model starts memorizing noisy label	×	0.14
The gradient of cross entropy loss with respect to Θ is given by ∇Lce(D, Θ) = -1/N * Σ(∇NΘ(xi)(pi - yi)).	×	0.03
In clean training data scenario, pi -yi of true class entry will always be negative and the rest entries are positive.	×	0.03
Performing stochastic gradient descent increases the probability of the true class and reduces the probabilities of othe	×	0.01
The approach of generating synthetic samples by mixing images and labels with nearest neighbors reduces the noisy superv	✓	0.16
Training DNNs with synthetic samples is more reasonable than training with original ones, especially when original sampl	×	0.12
The filtering mechanism for distinguishing mislabeled samples is critical to the classification performance in the secon	×	0.04
If the filtering mechanism only removes a few mislabeled samples, the unfiltered mislabeled samples still affect the los	×	0.06
If too many samples, including clean samples, are eliminated, the remaining data may not be rich enough to generalize to	×	0.04

References

- http://arxiv.org/abs/2204.12833v3
- http://arxiv.org/abs/2406.16966v1

- http://arxiv.org/abs/1901.09960v5