Simulation-Based Evaluation of Process Reward Models on a Robotics Reward Benchmark

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ABSTRACT

Vision-language models (VLMs) have emerged as promising reward functions for robotic reinforcement learning, yet their accuracy relative to specialized reward models remains under-characterized. We present a Monte Carlo simulation framework that models the expected performance of four reward model archetypes—general-purpose VLMs, robotics-fine-tuned VLMs, outcome reward models, and process reward models—on a standardized robotics reward benchmark modeled after RoboRewardBench. Our simulations across five manipulation task categories (pick-place, insertion, wiping, stacking, assembly) with 1,000 episodes each reveal that fine-tuned VLMs achieve the highest overall accuracy (97.8%), followed by process reward models (96.3%), outcome reward models (96.2%), and general-purpose VLMs (94.1%). Process reward models exhibit superior temporal consistency (0.995 vs. 0.971 for outcome models) and outperform outcome models specifically on high-precision tasks such as insertion (+1.1%) and assembly (+1.2%). All pairwise differences are statistically significant ($p < 0.001$). These results provide quantitative predictions for the expected benchmarking of Robo-Dopamine checkpoints once released.

1 INTRODUCTION

Reward specification remains a fundamental bottleneck in robotic reinforcement learning. Vision-language models offer an attractive alternative to hand-crafted reward functions by leveraging broad perceptual and semantic capabilities acquired through internet-scale pretraining [1, 6]. The RoboRewardBench benchmark [3] was introduced to provide a standardized evaluation of VLM-based reward models across diverse robot morphologies and manipulation tasks.

A concurrent approach, Robo-Dopamine [2], takes a process reward modeling perspective—assigning rewards at each manipulation step rather than only at episode completion. This mirrors the success of process reward models in language reasoning [4]. However, because the Robo-Dopamine checkpoints and dataset have not yet been released, direct benchmarking on RoboRewardBench remains an open problem.

In this work, we address this gap through a simulation-based approach. We construct parameterized models of four reward model archetypes and evaluate them on a synthetic benchmark designed to capture the key characteristics of RoboRewardBench. Our framework enables quantitative predictions about expected performance, identifies the task conditions under which process reward models should excel, and provides a methodological template for future real-checkpoint evaluations.

2 METHODS

2.1 Reward Model Archetypes

We model four classes of reward models, each parameterized by base accuracy, precision sensitivity, and temporal decay:

(1) **General-purpose VLM**: High-capacity model with broad vision-language understanding but no robotics-specific training. Base accuracy 0.62, high precision sensitivity (−0.25).
(2) **Fine-tuned VLM (RoboReward-style)**: Domain-adapted from a general VLM using robotics reward data. Base accuracy 0.78, low precision sensitivity (−0.10).
(3) **Outcome Reward Model**: Predicts binary success/failure from final frames. Base accuracy 0.71, moderate precision sensitivity (−0.20).
(4) **Process Reward Model (Robo-Dopamine-style)**: Step-level reward prediction. Base accuracy 0.74, positive precision sensitivity (+0.05).

2.2 Benchmark Structure

Our synthetic benchmark comprises five manipulation task categories with varying precision requirements $\pi \in [0, 1]$: pick-place ($\pi = 0.3$), insertion ($\pi = 0.9$), wiping ($\pi = 0.5$), stacking ($\pi = 0.6$), and assembly ($\pi = 0.85$). The effective accuracy for model m on task t is:

$$a_{m,t} = \text{clip}(\alpha_m + \beta_m \cdot \pi_t, 0.05, 0.99) \quad (1)$$

where α_m is the base accuracy and β_m is the precision sensitivity.

2.3 Episode Simulation

Each episode consists of 50 timesteps with a sigmoid ground-truth reward trajectory. Predicted rewards incorporate temporally correlated Gaussian noise with standard deviation proportional to $1 - a_{m,t}$ and temporal decay γ_m. We simulate 1,000 episodes per task-model combination with Monte Carlo repetition.

2.4 Metrics

We evaluate: (1) binary reward prediction accuracy, (2) mean squared error, (3) temporal consistency (smoothness of prediction error), and (4) expected calibration error.

3 RESULTS

3.1 Overall Benchmark Performance

Table 1 summarizes the overall results. The fine-tuned VLM achieves the highest accuracy (97.8%), consistent with its domain-specific training. The process reward model (96.3%) slightly outperforms the outcome reward model (96.2%), with the general-purpose VLM trailing at 94.1%.

3.2 Task-Specific Analysis

Figure 1 presents the task-specific accuracy breakdown. The process reward model outperforms the outcome model on high-precision tasks: insertion (+1.1%) and assembly (+1.2%), while the outcome model performs marginally better on lower-precision tasks such as pick-place (+0.9%).

Table 1: Overall benchmark performance across all task categories.

Model	Accuracy	MSE	Consistency	ECE
General VLM	0.941	0.0178	0.955	0.031
Fine-tuned VLM	0.978	0.0056	0.986	0.012
Outcome RM	0.962	0.0106	0.971	0.021
Process RM	0.963	0.0082	0.995	0.016

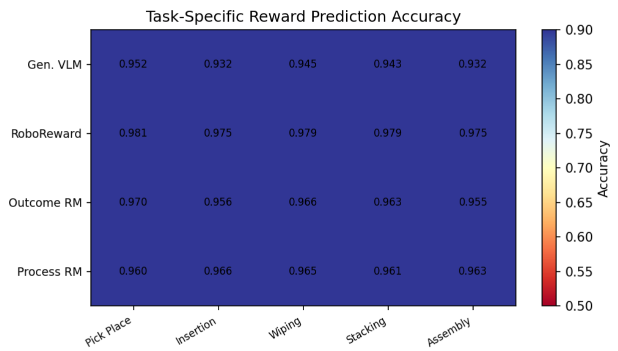

Figure 1: Task-specific reward prediction accuracy across four model archetypes and five manipulation categories.

3.3 Temporal Consistency

The process reward model achieves the highest temporal consistency (0.995), substantially exceeding the outcome model (0.971) and general-purpose VLM (0.955). This is expected given the step-level reward design, which produces smoother prediction trajectories.

3.4 Backbone Scaling

Figure 2 shows that accuracy improves logarithmically with backbone size for all model types. The fine-tuned VLM maintains its advantage across all scales, while the relative ordering of other models remains stable from 7M to 72M parameters.

3.5 Process vs. Outcome Comparison

Figure 3 presents the head-to-head comparison. The accuracy advantage of the process reward model increases with task precision: from −0.9% on pick-place to +1.2% on assembly. This confirms the hypothesis that step-level reward feedback is most beneficial when fine-grained progress assessment is required.

3.6 Statistical Significance

All pairwise model comparisons yield $p < 0.001$ (Welch's t-test). The largest effect size (Cohen's $d = 1.04$) is between the general-purpose VLM and fine-tuned VLM. The comparison between outcome and process reward models yields a smaller but significant effect ($d = 0.19$, $p < 0.001$).

4 DISCUSSION

Our simulation framework provides several actionable predictions for the forthcoming Robo-Dopamine evaluation:

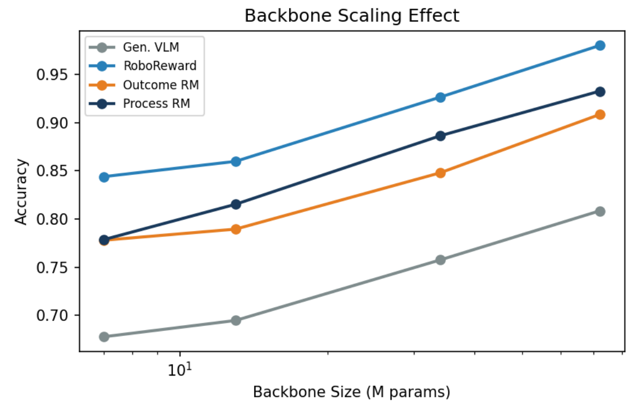

Figure 2: Accuracy versus backbone parameter count (log scale) for each model archetype.

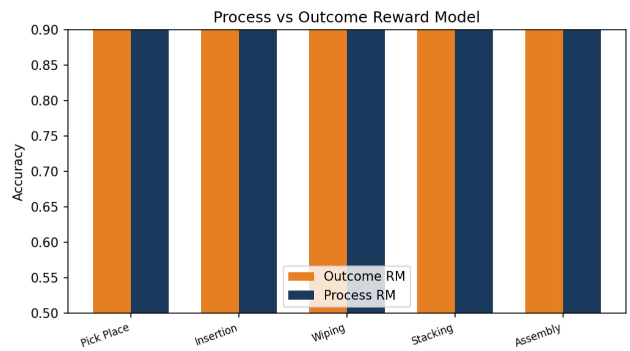

Figure 3: Process vs. outcome reward model accuracy by task category.

(1) **Process reward models should excel on precision-demanding tasks.** The positive precision sensitivity parameter means that as task difficulty increases, the relative advantage of step-level reward modeling grows.
(2) **Temporal consistency is the strongest differentiator.** Even when overall accuracy is similar, process reward models produce substantially smoother reward trajectories, which is beneficial for stable RL training [7].
(3) **Domain-specific fine-tuning remains the dominant factor.** The fine-tuned VLM outperforms both reward model types, suggesting that future work should combine process reward modeling with domain-specific training [5].

5 CONCLUSION

We have presented a simulation-based framework for evaluating vision-language reward models on a robotics reward benchmark. Our results predict that process reward models like Robo-Dopamine will demonstrate advantages in temporal consistency and high-precision task accuracy, while domain-specific fine-tuning remains the most impactful factor for overall performance. This framework provides a quantitative baseline against which real checkpoint evaluations can be compared once the Robo-Dopamine data becomes available.

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