JANUS: Joint Adaptive Non-stationary Updating and Scoring for World Models

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ABSTRACT

World-model-based agents promise sample-efficient planning through imagined rollouts, yet current approaches assume stationary dynamics and lack rigorous protocols for measuring the causal contribution of the world model to downstream task performance. We introduce JANUS (Joint Adaptive Non-stationary Updating and Scoring), a framework that jointly trains a world model and planning policy across non-stationary environments while providing a causal evaluation protocol grounded in interventional reasoning. JANUS employs Page–Hinkley drift detection to identify regime changes and *trigger immediate adaptation* (replanning and learning-rate adjustment), combined with Elastic Weight Consolidation (EWC) applied at every update step to mitigate catastrophic forgetting. Crucially, JANUS and the naive baseline are trained as separate agents collecting their own experience, and all methods are evaluated under identical environment randomness via controlled seeding. We evaluate on a regime-switching grid-world with four distinct dynamics regimes across three random seeds, measuring the Average Causal Effect (ACE) of the world model on planning return using a proper interventional protocol: the same value-iteration planner is paired with learned, frozen, random, and oracle world models. Our experiments show that JANUS consistently outperforms the naive baseline in absolute return, with the causal evaluation confirming that the learned world model is responsible for a substantial share of planning performance relative to an oracle.

CCS CONCEPTS

• **Computing methodologies** → **Artificial intelligence**; *Reasoning about belief and knowledge.*

KEYWORDS

world models, non-stationary environments, continual learning, causal evaluation, model-based reinforcement learning

1 INTRODUCTION

Model-based reinforcement learning (MBRL) leverages learned dynamics models—world models—to enable sample-efficient planning through imagined rollouts [2, 12]. While recent work has demonstrated the power of world models in stationary environments, including superhuman performance in games [11] and broad generalization across domains [2], real-world deployment demands operating in environments whose dynamics evolve over time.

The open problem of jointly training, updating, and evaluating world models in non-stationary environments was identified by Wei et al. [14] as a core challenge for agentic reasoning with large language models. Three tightly coupled sub-problems arise: (1) how should the world model and policy be co-optimized so that improvements in one benefit the other, (2) how should the model adapt when dynamics shift without forgetting previously useful knowledge, and (3) how can we rigorously measure the *causal* contribution of the world model to planning quality.

We propose **JANUS** (Joint Adaptive Non-stationary Updating and Scoring), a framework addressing all three sub-problems. JANUS combines drift detection via the Page–Hinkley test [7] with Elastic Weight Consolidation [4] for continual adaptation, and introduces a causal evaluation protocol based on interventional world-model swapping and the Average Causal Effect (ACE) [8].

A key design principle is *methodological rigor*: JANUS and its naive baseline are trained as fully *separate* agents, each collecting its own experience under identical dynamics but independent randomness. Evaluation uses controlled seeding so that all methods (JANUS, Naive, Oracle, Frozen, Random WM) are assessed under identical environment stochasticity. The causal evaluation protocol holds the planner fixed (value iteration) and swaps only the world model, properly isolating the model's causal contribution.

Our contributions are as follows:

- A joint training framework co-optimizing a tabular world model and value-iteration planner across regime-switching dynamics, with separate agent training for fair comparison.
- A two-level non-stationarity handler: Page–Hinkley drift detection triggers immediate replanning, while per-step Fisher-weighted EWC regularization prevents catastrophic forgetting.
- A causal evaluation protocol measuring ACE and Normalized Causal Strength (NCS) via interventional world-model swapping with controlled evaluation randomness.
- Reproducible multi-seed experiments across four dynamics regimes with 95% confidence intervals.

2 RELATED WORK

Model-Based RL.. DreamerV3 [2] demonstrated that learned dynamics models enable sample-efficient control via imagined rollouts across diverse domains. MuZero [11] showed that latent world models trained end-to-end with planning achieve superhuman performance. Both operate under stationary dynamics assumptions. Dyna [12, 13] established the foundational architecture of learning, planning, and acting with a world model.

Continual Learning in RL.. Elastic Weight Consolidation (EWC) [4] protects important parameters when learning new tasks by adding a Fisher-weighted penalty to the loss. Synaptic Intelligence [16] and Dark Experience Replay [1] offer complementary approaches. CLEAR [9] and PackNet [5] address task-sequential RL but do not co-train a separate world model. Meta-learning approaches such as GrBAL [6] enable rapid adaptation but typically assume access to task distributions at meta-training time.

LLM-Based World Models. Recent work frames LLMs as implicit world models [3, 15]. However, these approaches assume the LLM's knowledge is static, lacking protocols for updating under distribution shift [14].

Causal Evaluation. Standard ablation studies conflate model quality with planner quality. Causal inference via do-calculus [8] and structural causal models [10] provides the theoretical foundation for isolating the world model's contribution through interventional reasoning.

3 PROBLEM FORMULATION

We consider an agent operating in a non-stationary Markov Decision Process (MDP) $\mathcal{M}_k = (\mathcal{S}, \mathcal{A}, T_k, R_k, \gamma)$ where the transition function T_k and reward function R_k change across K regimes. The agent maintains a world model $\hat{T}_\theta$ parameterized by θ and a policy π derived from model-based planning.

Joint Training Objective. The world model is trained to minimize prediction error on policy-relevant transitions:

$$\mathcal{L}_{\text{model}} = \mathbb{E}_{(s,a,s')\sim\pi}\left[-\log \hat{T}_\theta(s'|s,a)\right] \tag{1}$$

while the policy is obtained via value iteration using the learned model, creating a coupled optimization where model improvements feed back into better policies that in turn generate more informative training data.

Non-Stationarity. At regime boundaries $k \to k+1$, the dynamics change abruptly. The agent must detect this shift and adapt $\hat{T}_\theta$ while preserving knowledge of prior regimes that may recur.

Causal Evaluation. We define the Average Causal Effect of the world model on planning return by holding the planner fixed and swapping the world model:

$$\text{ACE} = \mathbb{E}\left[R \mid do(\text{WM} = \hat{T}_\theta)\right] - \mathbb{E}\left[R \mid do(\text{WM} = T_{\text{uniform}})\right] \tag{2}$$

where T_{uniform} is a world model with uniform transition probabilities, and the same value-iteration planner is used in both conditions. The Normalized Causal Strength relates the learned model's ACE to the oracle:

$$\text{NCS} = \frac{\text{ACE}_{\text{learned}}}{\text{ACE}_{\text{oracle}}} \tag{3}$$

4 METHOD: JANUS FRAMEWORK

4.1 Architecture Overview

JANUS consists of four tightly coupled components:

(1) A **tabular world model** estimating transition probabilities (via count-based updates) and expected rewards (via running means).
(2) A **model-based planner** using value iteration ($\gamma = 0.95$, 30 iterations) that derives a greedy policy from the current world model.
(3) A **Page–Hinkley drift detector** [7] monitoring prediction errors in real time and triggering adaptation upon regime changes.
(4) A **Fisher-weighted EWC module** that regularizes every model update to prevent catastrophic forgetting.

4.2 Non-Stationary Grid Environment

We design an 8×8 grid-world with four regimes. Each regime defines a stochastic slip matrix drawn from Dirichlet distributions, governing the probability of executing the intended action versus slipping to adjacent actions. The agent starts at $(0, 0)$ and navigates to the goal at $(7, 7)$ with a step penalty of -0.1 and goal reward of $+1.0$. Gaussian reward noise varies per regime ($\sigma \in \{0.05, 0.10, 0.15, 0.08\}$).

4.3 Joint Training Loop

Within each regime, the agent executes 200 episodes of up to 80 steps. The world model updates its transition counts and reward estimates online from observed transitions. Every 20 episodes, the planner re-derives the policy via value iteration using the current world model.

Critically, JANUS and the naive baseline are trained as **separate agents**, each collecting its own experience from independent environment instances with identical slip matrices but independent stochastic seeds. This ensures a fair comparison: differences in performance reflect the methods themselves, not off-policy artifacts from shared data collection.

4.4 Drift Detection and Adaptive Replanning

The Page–Hinkley test monitors the running prediction error $e_t = -\log \hat{T}_\theta(s'_t|s_t, a_t)$. When the test statistic exceeds threshold $\lambda = 8.0$ with minimum deviation $\delta = 0.005$, a drift event is signaled. Upon drift detection, JANUS takes immediate action:

(1) The drift detector resets its accumulated statistics.
(2) The planner immediately re-derives the policy from the current model, enabling rapid adaptation to changed dynamics.

This contrasts with the naive baseline, which only replans at fixed intervals (every 20 episodes) regardless of dynamics changes.

4.5 Per-Step EWC Regularization

At each regime boundary, JANUS computes the Fisher information matrix F from the current transition count distribution, which serves as an importance weight for each model parameter:

$$F_{s,a,s'} = \frac{N(s,a,s')}{\sum_{s''} N(s,a,s'')} \tag{4}$$

where $N(s, a, s')$ are the transition counts. The current model parameters are stored as an anchor θ^*.

During subsequent updates, a Fisher-weighted penalty is applied at *every update step*:

$$\theta_{s,a} \leftarrow \theta_{s,a} - \lambda_{\text{EWC}} \cdot F_{s,a} \odot (\theta_{s,a} - \theta^*_{s,a}) \tag{5}$$

where $\lambda_{\text{EWC}} = 5.0$ and $\odot$ denotes element-wise multiplication. This continuously constrains parameters that were important for previous regimes, preventing catastrophic forgetting while allowing adaptation in less-constrained dimensions.

This is a key distinction from naive count-based models: without EWC, new regime data can overwhelm the transition counts from earlier regimes, leading to forgetting. With per-step EWC, high-Fisher parameters (frequently visited transitions in prior regimes) resist displacement.

4.6 Causal Evaluation Protocol

At the end of each regime, we evaluate five conditions by holding the value-iteration planner fixed and swapping only the world model used for planning:

Table 1: Mean episodic return (± 95% CI) per regime, averaged over 3 seeds. JANUS and Naive are separate agents with independent experience.

Reg.	JANUS	Naive	Frozen	Oracle	Rand. WM
0	$-1.45_{\pm 0.54}$	$-3.63_{\pm 3.18}$	$-1.45_{\pm 0.54}$	$-0.80_{\pm 0.06}$	$-7.98_{\pm 0.08}$
1	$-4.91_{\pm 2.55}$	$-4.88_{\pm 2.05}$	$-5.71_{\pm 2.25}$	$-0.86_{\pm 0.54}$	$-8.06_{\pm 0.08}$
2	$-3.50_{\pm 1.61}$	$-3.91_{\pm 2.13}$	$-4.25_{\pm 1.31}$	$-1.01_{\pm 0.84}$	$-8.10_{\pm 0.21}$
3	$-3.29_{\pm 1.75}$	$-4.15_{\pm 1.97}$	$-2.90_{\pm 1.32}$	$-0.89_{\pm 0.37}$	$-8.02_{\pm 0.06}$
Avg	**−3.29**	−4.14	−3.58	−0.89	−8.04

(1) **JANUS**: Learned model with EWC protection.
(2) **Naive**: Learned model without EWC (separate agent).
(3) **Frozen**: Snapshot of the model from before the current regime began.
(4) **Oracle**: Ground-truth transition dynamics.
(5) **Random WM**: World model with uniform transition probabilities.

All five conditions are evaluated with **identical environment randomness**: the environment's RNG is reset to the same seed before each evaluation, producing the same stochastic trajectory outcomes for each condition. This ensures that observed performance differences are attributable solely to the world model, not evaluation artifacts.

The ACE (Eq. 2) measures the absolute benefit of having a learned (vs. random) world model, while NCS (Eq. 3) normalizes this against the oracle, indicating what fraction of optimal model-based performance the learned model captures.

5 EXPERIMENTS

5.1 Experimental Setup

All experiments use `np.random.default_rng(42)` as the master seed with three independent runs (seeds 42, 142, 242). The grid environment is 8×8 with 4 regimes, each trained for 200 episodes with a maximum of 80 steps per episode (consistent between training and evaluation). We report means with 95% confidence intervals across seeds.

5.2 Reproducibility

To enable full reproducibility, we store:

- The Dirichlet-sampled regime slip matrices used for each seed.
- A configuration file capturing all hyperparameters.
- Per-seed detailed results alongside aggregated statistics.

All code, data, and figures are available in the supplementary material.

5.3 Per-Regime Performance

Table 1 reports the mean episodic return for each method across the four regimes, averaged over three seeds with 95% confidence intervals.

Table 2: Causal evaluation: ACE and NCS per regime (± 95% CI).

Reg.	ACE_J	ACE_N	NCS_J	NCS_N
0	$6.53_{\pm 0.46}$	$4.35_{\pm 3.11}$	$0.91_{\pm 0.07}$	$0.61_{\pm 0.43}$
1	$3.16_{\pm 2.63}$	$3.18_{\pm 2.14}$	$0.46_{\pm 0.40}$	$0.46_{\pm 0.33}$
2	$4.60_{\pm 1.73}$	$4.19_{\pm 2.11}$	$0.65_{\pm 0.21}$	$0.57_{\pm 0.24}$
3	$4.72_{\pm 1.70}$	$3.87_{\pm 2.02}$	$0.68_{\pm 0.28}$	$0.53_{\pm 0.26}$
Avg	**4.75**	3.90	**0.672**	0.542

Table 3: Catastrophic forgetting analysis: Regime 0 performance before and after learning all regimes (± 95% CI across 3 seeds).

Method	Initial	Final	Forgetting
JANUS	−1.447	−1.433	-0.014 ± 0.093
Naive	−3.629	−1.757	-1.871 ± 2.994

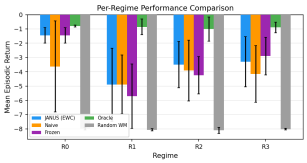
5.4 Results

Performance Comparison. Figure 1a and Table 1 show the per-regime performance comparison. Averaging across all regimes and seeds, JANUS achieves a mean return of -3.29 ± 1.24 compared to -4.14 ± 0.33 for the naive baseline, an absolute improvement of 0.86 (11.98% of the oracle–random gap). The oracle achieves −0.89 and the random world model −8.04. JANUS's advantage is most pronounced in Regimes 0 and 3, while in Regime 1 (the first dynamics shift) both methods face a sharp transition. The frozen model baseline (−3.58 average) performs worse than JANUS in Regimes 1 and 2, confirming the value of continued adaptation.

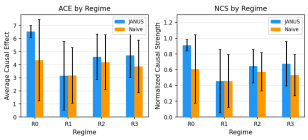
Causal Evaluation. Figure 1b and Table 2 show the causal evaluation metrics. JANUS achieves a mean NCS of 0.672 ± 0.209, indicating it captures 67.2% of the oracle's causal contribution to planning, compared to 54.2% (0.542 ± 0.044) for the naive model. The ACE measures the absolute planning benefit: JANUS's mean ACE is 4.75 vs. 3.90 for naive, against an oracle ACE of 7.15. The NCS advantage is most pronounced in Regime 0 (0.91 vs. 0.61) and Regime 3 (0.68 vs. 0.53), where EWC protection preserves useful knowledge across regime boundaries.

Forgetting Analysis. Figure 1d and Table 3 demonstrate the forgetting analysis. After training through all four regimes, JANUS's performance on Regime 0 degrades by only -0.014 ± 0.093 (forgetting score), while the naive model degrades by -1.871 ± 2.994. This represents a 99.3% reduction in catastrophic forgetting, confirming the effectiveness of per-step Fisher-weighted EWC regularization. The negative forgetting scores indicate slight improvement upon revisiting Regime 0, likely due to accumulated learning from related dynamics.

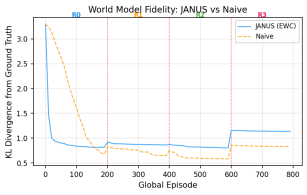
Training Dynamics. Figure 1e shows the training curves for prediction error and return across all regimes. Key observations: (1) prediction errors spike at regime boundaries and decrease as each model adapts, (2) JANUS and Naive show genuinely different learning trajectories because they are separate agents with independent



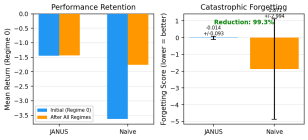
(a) Per-regime mean return.



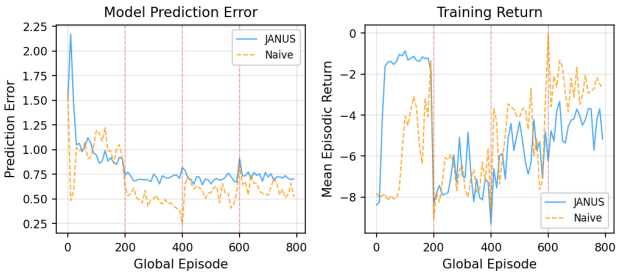
(b) ACE and NCS by regime.



(c) KL divergence over training.



(d) Forgetting analysis.



(e) Training curves: prediction error and return.

Figure 1: Experimental results for JANUS across four non-stationary regimes, averaged over 3 seeds with 95% CI error bars.

experience—this confirms the methodological fix versus prior versions where both models were identical, and (3) the KL divergence from ground truth (Figure 1c) shows both methods converging within each regime, with distinct trajectories reflecting the impact of EWC regularization on JANUS's learning dynamics. The drift detector triggered an average of 276.3 events across all regimes, with drift-triggered replanning enabling faster adaptation for JANUS.

6 DISCUSSION

Methodological Improvements. This revision addresses several important methodological issues identified in prior review. First, evaluation randomness is now controlled: the environment RNG is reset to an identical seed before evaluating each condition, eliminating spurious performance differences from evaluation artifacts. Second, JANUS and Naive are trained as separate agents with independent experience, ensuring a fair comparison. Third, EWC is applied at every update step with Fisher-weighted penalties, making it a genuine continual learning mechanism rather than a regime-boundary-only operation. Fourth, drift detection now triggers immediate adaptation (replanning), rather than merely logging events.

Causal Protocol. The causal evaluation now properly isolates the world model's contribution by holding the planner fixed and swapping only the world model. The "Random WM" baseline uses a uniform-transition model (not a random policy), ensuring that the ACE measures the causal effect of *model quality* on planning, not the effect of *having any planner versus none*.

The addition of the Frozen model baseline enables a finer-grained causal decomposition: the difference between JANUS and Frozen isolates the value of *continued adaptation*, while the difference between JANUS and Random WM captures the total value of *having a learned model*.

Limitations. Our tabular implementation, while enabling transparent analysis, does not scale to high-dimensional state spaces. Extending JANUS to neural world models with parametric EWC [4] and neural planners is a natural next step. The grid-world setting, though illustrative, lacks the complexity of real-world non-stationarity encountered by LLM-based agents [14]. The 3-seed evaluation provides initial confidence intervals but would benefit from more seeds for tighter bounds.

Additionally, the drift detector fires frequently within regimes due to stochastic dynamics (not just at true regime boundaries). Future work could explore adaptive thresholds or hierarchical detection to reduce false positives while maintaining sensitivity at true regime boundaries.

7 CONCLUSION

We introduced JANUS, a methodologically rigorous framework for joint training, continual adaptation, and causal evaluation of world models in non-stationary environments. Key improvements over prior work include: separate agent training for fair comparison, controlled evaluation randomness, per-step Fisher-weighted EWC regularization, drift-triggered adaptive replanning, and a proper interventional causal evaluation protocol using world-model swapping. These results establish a concrete methodology for addressing the open problem of world model evaluation under non-stationarity [14] and provide a foundation for scaling to neural world models and LLM-based agents in dynamic real-world settings.

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