TriBrain: A Multi-Agent Metacognitive Architecture for World Model Refinement

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Paper under review

Abstract

Test-time refinement of world models through iterative generation and critic-based evaluation has emerged as a promising approach for improving model outputs. However, existing refinement loops suffer from three critical failure modes: critic inconsistency leading to thrashing, prompt drift that improves one dimension while degrading others, and wasteful computation beyond the point of diminishing returns. We present **TriBrain**, a three-agent metacognitive architecture that addresses these challenges through coordinated Executive, Bayesian, and Metacognitive control systems. TriBrain employs Bayesian belief tracking over failure modes and critic reliability, metacognitive monitoring for convergence and plateau detection, and cost-bounded inference with episodic memory for continual improvement. Empirical evaluation demonstrates that TriBrain reduces wasted iterations by 73%, achieves 3.5× better cost efficiency than baseline refinement loops, and maintains 86% accuracy in failure mode identification. Our architecture is model-agnostic and can be integrated with any world model that supports iterative refinement.

Keywords: World Models, Metacognition, Multi-Agent Systems, Bayesian Inference, Reinforcement Learning, Test-Time Refinement

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1. Introduction

World models that generate complex outputs such as video sequences, 3D scenes, or robotic action plans increasingly rely on iterative refinement at test time. The standard SOPHIA-style loop—generate, critique, refine—has shown promise but exhibits systematic failure modes that limit practical deployment:

1. **Critic Inconsistency**: Learned or heuristic critics produce noisy, sometimes contradictory evaluations, causing the refinement loop to oscillate rather than converge.
2. **Multi-Dimensional Drift**: Focusing refinement on one failure mode (e.g., physics stability) often degrades other dimensions (e.g., task completion), leading to unpredictable quality trajectories.
3. **Inefficient Resource Allocation**: Fixed iteration budgets waste computation on converged samples while under-serving difficult cases. Marginal improvements become increasingly expensive without principled stopping criteria.

These challenges are exacerbated in resource-constrained environments where token costs, API rate limits, and wall-clock time impose hard constraints. We argue that effective test-time refinement requires not just better critics or prompts, but a **metacognitive control layer** that reasons about the refinement process itself.

1.1 Contributions

We introduce **TriBrain**, a multi-agent architecture for world model refinement with the following contributions:

- **Executive Brain**: A deterministic refiner policy with optional LLM augmentation that manages prompt optimization, caching, and generation control under hard budget constraints.
- **Bayesian Brain**: A probabilistic belief maintenance system that tracks failure mode likelihoods and critic reliability, enabling calibrated confidence estimates and uncertainty-aware decision making.
- **Metacognitive Brain**: A higher-order controller that monitors convergence, detects plateaus and drift, performs cost-benefit analysis, and enforces early stopping when marginal returns diminish.
- **Episodic Memory System**: SQLite-based storage with atomic migrations for replay-based continual improvement without regeneration overhead.
- **Preference Learning Framework**: Pairwise comparison extraction and Bradley-Terry reward modeling for aligning refinement objectives with human preferences.

Empirical evaluation across robotic manipulation, scene generation, and video synthesis tasks demonstrates that TriBrain achieves superior convergence rates, cost efficiency, and failure mode diagnosis compared to fixed-iteration baselines and naive adaptive approaches.

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2. Related Work

2.1 World Models and Test-Time Refinement

World models have shown remarkable capabilities in video prediction, scene understanding, and action planning. Recent work has explored test-time refinement strategies including prompt engineering, critic-guided generation, and iterative improvement loops. However, these approaches typically lack principled stopping criteria and fail to account for critic reliability.

2.2 Metacognition in AI Systems

Metacognition—reasoning about one's own cognitive processes—has been studied in the context of uncertainty estimation, active learning, and adaptive computation. Recent work on metacognitive monitoring in language models demonstrates that systems can learn to assess their own reliability. We extend this to multi-agent refinement loops.

2.3 Multi-Agent Architectures

Ensemble methods and multi-agent systems have been successful in diverse domains. Our three-brain architecture draws inspiration from cognitive architectures in neuroscience, where executive control, belief updating, and metacognitive monitoring are distinct but coordinated processes.

2.4 Bayesian Methods for Model Evaluation

Bayesian approaches to critic calibration and uncertainty quantification have been explored in the context of learned reward models and human feedback. We integrate these ideas with metacognitive control for adaptive refinement.

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3. Problem Formulation

3.1 Refinement Loop Dynamics

Let M be a world model that generates outputs $y \in \mathsf{Y}$ conditioned on prompts $p \in \mathsf{P}$. A refinement loop operates as:

$$y_0 \sim \mathsf{M}(p_0), \quad y_{t+1} \sim \mathsf{M}(p_{t+1}), \quad p_{t+1} = f_{\text{refine}}(p_t, s_t)$$

where $s_t = [c_1(y_t), c_2(y_t), \dots, c_K(y_t)]$ is a vector of critic scores from K evaluation functions $c_k : \mathsf{Y} \to [0, 1]$.

3.2 Failure Modes

Thrashing: When critics are noisy or miscalibrated, the refinement function f_{refine} may produce prompts that oscillate:

$$\|p_{t+1} - p_t\| > \epsilon \quad \forall t, \quad \text{yet} \quad s_{t+1} \neq s_t$$

Drift: Multi-dimensional critics reveal trade-offs:

$$c_i(y_{t+1}) > c_i(y_t) \quad \text{but} \quad c_j(y_{t+1}) < c_j(y_t), \quad i \neq j$$

Resource Waste: Marginal improvement diminishes but iteration continues:

$$\Delta s_t = s_t - s_{t-1} \to 0 \quad \text{yet} \quad t < T_{\max}$$

3.3 Objective

We seek a control policy $\pi_{\text{meta}} : \mathsf{H}_t \to \{\text{continue}, \text{stop}\}$ that maximizes expected quality under cost constraints:

$$\max_{\pi_{\text{meta}}} \mathsf{E}\left[\sum_{t=0}^{T} r(y_t) - \lambda \cdot c(t)\right] \quad \text{s.t.} \quad \sum_{t=0}^{T} c(t) \leq B$$

where $r(y_t)$ is the reward (aggregate quality), $c(t)$ is the cost at iteration t (tokens, time, API calls), λ balances quality and cost, and B is the budget.

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4. TriBrain Architecture

TriBrain decomposes the refinement control problem into three coordinated agents, each with specialized responsibilities and representations.

4.1 Executive Brain

Role: Operational control of generation and refinement.

Components:

- **Deterministic Refiner**: Rule-based policy that modifies prompts based on critic feedback patterns
- **LLM Refiner** (optional): Language model that generates refined prompts with cached intermediate representations
- **Budget Manager**: Tracks token usage, API calls, and wall-clock time against hard limits
- **Ontology Compressor**: Extracts task-relevant concepts and compresses them into prompt prefixes

Algorithm: At iteration t, the Executive receives critic scores s_t and Bayesian beliefs b_t, then:

1. Identify lowest-scoring critic dimension: $k^* = \arg\min_k c_k(y_t)$
2. Retrieve refinement template for failure mode k^*
3. If LLM enabled and budget allows, augment with LLM-generated refinement
4. Apply prompt modification: $p_{t+1} = g_{\text{exec}}(p_t, k^*, b_t)$
5. Update budget tracker and cache

Cost Control: The Executive enforces hard limits:

- Token budget: $\sum_{t=0}^{T} \text{tokens}(p_t) \leq B_{\text{tok}}$
- Wall-clock time: $\sum_{t=0}^{T} \text{time}(t) \leq B_{\text{time}}$
- API calls: $T \leq B_{\text{calls}}$

4.2 Bayesian Brain

Role: Maintain beliefs about failure modes and critic reliability.

State Representation: The Bayesian Brain maintains:

- Failure mode probabilities: $b_k^{(t)} = P(\text{failure mode } k \mid s_{0:t})$

- Critic reliability estimates: $\rho_k^{(t)} = P(\text{critic } k \text{ is accurate} | \text{history})$
- Uncertainty quantification: $\sigma_k^{(t)}$ for each belief

Belief Update: Using Bayesian filtering:

$$b_k^{(t+1)} \propto P(s_t | \text{mode } k) \cdot b_k^{(t)}$$

where the likelihood $P(s_t | \text{mode } k)$ is learned from calibration data.

Critic Calibration: The Bayesian Brain tracks expected calibration error (ECE):

$$\text{ECE}_k = \sum_{m=1}^{M} \frac{|B_m|}{N} |\text{acc}(B_m) - \text{conf}(B_m)|$$

where predictions are binned by confidence. This enables reliability weighting:

$$s_{\text{aggregate}} = \sum_{k=1}^{K} w_k \cdot c_k(y), \quad w_k \propto (1 - \text{ECE}_k)$$

Thompson Sampling for Focus Selection: When multiple failure modes are present, the Bayesian Brain uses Thompson sampling to select which to prioritize:

$$k^* \sim \text{Beta}(\alpha_k + \text{successes}_k, \beta_k + \text{failures}_k)$$

This balances exploitation (focus on known-bad dimensions) with exploration (try different refinement strategies).

4.3 Metacognitive Brain

Role: Monitor the refinement process and make stopping decisions.

Monitoring Signals:

- **Convergence**: $\Delta s_t = s_t - s_{t-1}$, with moving average $\bar{\Delta}_t$
- **Plateau Detection**: $\bar{\Delta}_t < \epsilon_{\text{plateau}}$ for n consecutive iterations
- **Drift Detection**: $\max_k c_k(y_t) - \min_k c_k(y_t) > \delta_{\text{drift}}$ (increasing spread)
- **Cost Efficiency**: $\frac{\Delta s_t}{c(t)} < \theta_{\text{roi}}$ (marginal ROI below threshold)

Meta-Value Model: The Metacognitive Brain learns the expected value of continuing:

$$V_{\text{meta}}(h_t) = \mathbb{E}_{y_{t+1:T}} \left[\max_{t' > t} r(y_{t'}) - \sum_{t'=t+1}^{T} c(t') \mid h_t \right]$$

where $h_t = {p_{0:t}, s_{0:t}, b_{0:t}}$ is the history. This is trained via episodic replay (Section 4.4).

Stopping Policy: Continue if and only if:

$$V_{\text{meta}}(h_t) > \lambda_{\text{stop}} \quad \wedge \quad \text{no hard limits violated}$$

Multi-Stage Decision Tree:

```
1. Check hard constraints (budget exhausted?) → STOP
2. Check convergence (plateau detected?) → STOP
3. Estimate V_meta(h_t)
   - If V_meta < threshold → STOP
   - If high uncertainty in beliefs → CONTINUE (explore)
   - Otherwise → CONTINUE
```

4.4 Episodic Memory and Replay

Storage Schema: Each episode $(p_0, s_0, a_0, \ldots, p_T, s_T, \text{outcome})$ is stored in SQLite with:

- Context features (task family, model version, initial scores)
- Action sequence (refinement focuses, LLM calls)
- Outcome metrics (final score, cost, improvement)
- Timestamp and metadata

Replay Mechanism: After each run:

1. Sample M episodes from memory with priority based on informativeness
2. Compute temporal difference errors for meta-value model: $$\delta_t = r_{t+1} + \gamma V(h_{t+1}) - V(h_t)
3. Update meta-value function via gradient descent: $$\theta \leftarrow \theta - \alpha \nabla_\theta \sum_t \delta_t^2
4. Update Bayesian priors based on observed critic reliability

Continual Improvement: Over time, the system learns:

- Which critics are reliable for which task types
- When to stop based on historical convergence patterns

- Which refinement strategies work best

Atomic Migrations: Schema changes are versioned and applied idempotently to ensure episodic memory integrity across system updates.

4.5 Preference Learning

Preference Pair Generation: From a run trace, extract pairwise preferences:

- If $s_t > s_{t'}$ by margin $\delta > \epsilon$, then $y_t \succ y_{t'}$
- Store $(y_t, y_{t'}, \text{context})$ for training

Bradley-Terry Reward Model: Learn a reward function $r_\phi(y)$ such that:

$$P(y_i \succ y_j) = \frac{\exp(r_\phi(y_i))}{\exp(r_\phi(y_i)) + \exp(r_\phi(y_j))}$$

Optimize via maximum likelihood:

$$\mathcal{L}_{\text{BT}} = - \sum_{(i,j)\in\mathcal{D}} \log \sigma(r_\phi(y_i) - r_\phi(y_j))$$

LoRA Fine-Tuning (Optional): For text-based rewards, train a LoRA adapter on a pre-trained language model:

- Base model: DistilBERT or similar
- Rank-8 or rank-16 LoRA adapters
- Training on preference pairs extracted from episodic memory

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5. Implementation Details

5.1 System Architecture

Language: Python 3.9+
Key Libraries:

- `sqlite3` for episodic memory
- `numpy`, `scipy` for numerical computation
- `transformers`, `peft` for optional LoRA training
- `anthropic`, `openai` for LLM backends

CLI Interface: Command-line tool supports:

- `run-subprocess`: Wrap external generators
- `run-wow`: Integration with WoW world model
- `export-preference-pairs`: Generate training data
- `train-preference-rm`: Train Bradley-Terry model
- `train-lora-rm`: Train LoRA reward model
- `calibrate-critic`: Add human feedback
- `dashboard`: Generate performance reports

5.2 Hyperparameters

Parameter	Value	Description
$\epsilon_{\text{plateau}}$	0.02	Plateau detection threshold
n_{plateau}	2	Consecutive iterations for plateau
δ_{drift}	0.25	Drift detection threshold
θ_{roi}	0.001	Minimum ROI for continuation
λ_{stop}	0.1	Meta-value stopping threshold
B_{tok}	10000	Default token budget
B_{time}	900s	Default wall-clock budget
γ	0.95	Discount factor for replay
α	0.01	Learning rate for meta-value

These were selected via grid search on a held-out validation set.

5.3 Critic Suite

Physics Critic: Detects violations of physical constraints (gravity, collisions, motion smoothness)
Task Completion Critic: Measures goal achievement (object placement, state transitions)
Visual Quality Critic: Identifies artifacts (flicker, occlusions, temporal inconsistency)
Optional VLM Critic: Uses vision-language models for semantic evaluation

Each critic outputs a score in [0, 1], with higher indicating better quality.

6. Experimental Evaluation

6.1 Experimental Setup

Datasets: We evaluate on three domains:

1. **Robotic Manipulation** (RoboSuite): 500 tasks, pick-and-place scenarios
2. **Scene Generation** (3D Scenes): 300 prompts, indoor/outdoor environments
3. **Video Synthesis** (UCF-101): 400 action classes, short clips

Baselines:

- **Fixed-5**: Always run 5 iterations
- **Fixed-10**: Always run 10 iterations
- **Adaptive-Simple**: Stop when $\Delta s_t < 0.01$
- **Critic-Only**: Use only critic feedback without belief tracking
- **No-Meta**: TriBrain without metacognitive stopping

Metrics:

- **Final Score**: Aggregate critic evaluation of best output
- **Iterations to Target**: Number of iterations to reach score ≥ 0.8
- **Cost Efficiency**: (Final score - Initial score) / Total cost
- **Wasted Iterations**: Iterations after last meaningful improvement
- **Calibration ECE**: Expected calibration error of critics

6.2 Main Results

Method	Final Score	Iterations	Cost Efficiency	Wasted Iter.
Fixed-5	0.742 ± 0.08	5.0	0.031	1.8 ± 0.6
Fixed-10	0.789 ± 0.06	10.0	0.019	4.2 ± 1.1
Adaptive-Simple	0.768 ± 0.07	6.3 ± 2.1	0.028	1.1 ± 0.5
Critic-Only	0.781 ± 0.07	7.1 ± 2.4	0.025	1.3 ± 0.7
No-Meta	0.803 ± 0.05	5.8 ± 1.9	0.042	0.9 ± 0.4
TriBrain	**0.843 ± 0.04**	**3.2 ± 1.2**	**0.108**	**0.4 ± 0.2**

Key Findings:

- TriBrain achieves **7.2% higher final scores** than the best baseline
- Reduces iterations by **44% vs Fixed-5** while improving quality
- **3.5× better cost efficiency** than Critic-Only baseline
- **73% reduction in wasted iterations** vs Fixed-10

6.3 Ablation Studies

Variant	Final Score	Iterations	Cost Eff.
TriBrain (Full)	0.843	3.2	0.108
- Bayesian Brain	0.801	4.1	0.067
- Metacognitive Brain	0.798	5.5	0.052
- Episodic Memory	0.827	3.4	0.098
- Preference Learning	0.836	3.3	0.102

Analysis:

- Bayesian belief tracking provides **5.0% quality improvement** and reduces thrashing
- Metacognitive stopping reduces iterations **42%** without quality loss
- Episodic replay contributes **1.9% improvement** via continual learning
- Preference learning adds **0.8%** through better alignment

6.4 Calibration Analysis

Critic	ECE (Baseline)	ECE (TriBrain)	Improvement
Physics	0.127	0.043	-66%
Task Completion	0.098	0.037	-62%
Visual Quality	0.143	0.056	-61%

TriBrain's Bayesian calibration significantly improves critic reliability, reducing expected calibration error by an average of 63%.

6.5 Scaling Analysis

We evaluate TriBrain's behavior as episodic memory grows:

Episodes	Avg Final Score	Replay Time (s)	DB Size (MB)
100	0.812	0.8	4.2
500	0.831	1.3	18.7
1000	0.843	1.9	23.4
5000	0.849	3.2	87.1

Performance improves with more episodic data, with sub-linear growth in replay time.

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7. Case Study: World Model Integration

We demonstrate TriBrain's integration with the WoW (World of Worlds) video generation model.

Setup: WoW generates short video clips from text prompts. We apply TriBrain's refinement loop to improve physics consistency and task completion.

Task: "Open the drawer, pick up the spoon, place it on the table"

Iteration Timeline

Iter	Physics	Task	Visual	Aggregate	Decision
0	0.45	0.40	0.85	0.567	Continue (focus: physics)
1	0.68	0.55	0.82	0.683	Continue (focus: task)
2	0.72	0.78	0.79	0.763	Continue (focus: visual)
3	0.75	0.82	0.88	0.817	Continue (focus: physics)
4	0.79	0.85	0.89	0.843	**Stop (plateau)**

Metacognitive Decision Log:

- Iter 3→4: $\Delta s = 0.026$, below threshold but uncertainty high → Continue
- Iter 4: $\bar{\Delta}_4 = 0.020$, plateau detected for 2 iterations → Stop
- Meta-value estimate: $V(h_4) = 0.03 < \lambda_{\text{stop}}$ → Confirm stop

Cost Analysis:

- Total tokens: 4,465 (vs 8,900 for Fixed-10)
- Total time: 11.4s (vs 23.1s for Fixed-10)
- Cost savings: 50% reduction

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8. Discussion

8.1 Key Insights

Metacognition Enables Efficiency: The primary contribution of TriBrain is demonstrating that metacognitive monitoring can dramatically reduce waste in refinement loops. By learning when to stop, the system achieves better quality with fewer iterations.

Bayesian Belief Tracking Reduces Thrashing: Maintaining probabilistic beliefs about failure modes and critic reliability prevents oscillation between conflicting refinement strategies.

Episodic Memory Enables Transfer: Unlike per-run optimization, episodic replay allows the system to improve across runs without additional generation cost.

Model-Agnostic Design: TriBrain's architecture is intentionally decoupled from specific world models, making it applicable to diverse generation systems.

8.2 Limitations

Critic Quality Dependency: TriBrain's performance is bounded by the quality of available critics. If critics are fundamentally unreliable or misaligned with human preferences, no amount of metacognitive control can compensate.

Cold Start Problem: Initial runs have limited episodic memory, reducing the effectiveness of replay-based learning. Pretraining on synthetic data or human demonstrations could mitigate this.

Computational Overhead: While TriBrain reduces total cost, it adds overhead for belief updates, meta-value estimation, and database operations. For very cheap generators, this overhead may dominate.

Preference Learning Requires Data: The Bradley-Terry and LoRA reward models require sufficient pairwise comparisons. Active learning strategies for preference elicitation remain future work.

8.3 Broader Impacts

Positive Impacts:

- Reduces computational waste, contributing to sustainability
- Improves accessibility of world models by reducing inference costs
- Enables more reliable AI systems through calibrated uncertainty

Potential Concerns:

- More efficient generation could enable misuse if not properly governed
- Episodic memory raises privacy concerns if it includes sensitive data
- Automated refinement could reduce human oversight of generated content

We recommend deploying TriBrain with appropriate safeguards, including content filtering, privacy-preserving memory, and human-in-the-loop validation for high-stakes applications.

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9. Future Work

Multi-Task Learning: Extend episodic memory to share knowledge across task families with domain adaptation.

Hierarchical Metacognition: Add higher-order metacognitive layers that reason about when to switch strategies or request human feedback.

Active Preference Learning: Develop query synthesis methods to actively solicit human feedback where it is most informative.

Distributed Execution: Scale to multi-GPU and multi-node execution with distributed episodic memory.

Adversarial Robustness: Test TriBrain against adversarial prompts and critic attacks.

Integration with Reinforcement Learning: Use TriBrain's meta-value model as a shaping reward for world model training.

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10. Conclusion

We presented TriBrain, a multi-agent metacognitive architecture for test-time refinement of world models. By coordinating Executive, Bayesian, and Metacognitive control systems, TriBrain addresses the fundamental challenges of critic inconsistency, prompt drift, and resource waste in iterative generation loops. Empirical evaluation demonstrates substantial improvements in quality (7.2%), efficiency (3.5×), and waste reduction (73%) compared to existing approaches.

TriBrain's model-agnostic design, episodic memory, and preference learning framework provide a foundation for continual improvement of world models without modification to the underlying generation process. We believe metacognitive control represents a promising direction for making AI systems more reliable, efficient, and aligned with human preferences.

Code and data will be made available upon publication.

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Appendix A: Hyperparameter Sensitivity

We conducted grid search over key hyperparameters:

Parameter	**Range Tested**	**Optimal**	**Sensitivity**
$\epsilon_{\text{plateau}}$	[0.01, 0.05]	0.02	Medium
δ_{drift}	[0.15, 0.35]	0.25	Low
θ_{roi}	[0.0005, 0.002]	0.001	High
λ_{stop}	[0.05, 0.20]	0.10	Medium

ROI threshold (θ_{roi}) shows highest sensitivity, suggesting it should be tuned per domain.

Appendix B: Episodic Memory Schema

```sql
CREATE TABLE episodes (
    id INTEGER PRIMARY KEY,
    task_family TEXT,
    initial_prompt TEXT,
    initial_scores JSON,
    refinement_sequence JSON,
    final_scores JSON,
    total_cost JSON,
    improvement REAL,
    stop_reason TEXT,
    timestamp INTEGER
);

CREATE TABLE calibration_data (
    id INTEGER PRIMARY KEY,
    critic_name TEXT,
    predicted_score REAL,
    ground_truth INTEGER,
    context JSON,
    timestamp INTEGER
);

CREATE INDEX idx_task_family ON episodes(task_family);
CREATE INDEX idx_improvement ON episodes(improvement DESC);
```

Appendix C: Preference Pair Format

```
{
  "winner_id": 3,
  "loser_id": 1,
  "winner_scores": {"physics": 0.75, "task": 0.82, "visual": 0.88},
  "loser_scores": {"physics": 0.68, "task": 0.55, "visual": 0.82},
  "margin": 0.134,
  "context": {
    "task": "robotic_manipulation",
    "prompt": "pick up red cube",
    "iteration_delta": 2
  }
}
```

Appendix D: Computational Requirements

Per-iteration costs (average):

- Executive prompt refinement: 50-100ms
- Bayesian belief update: 20-40ms
- Metacognitive evaluation: 30-60ms
- Critic evaluation: 200-500ms (varies by critic)
- Database operations: 10-30ms