# Structural Manifold Guardrails for Symbolic Planning Agents

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**Abstract**

The Structural Manifold (STM) coprocessor augments symbolic planning agents with percentile-calibrated guardrails that monitor dilution, coherence, and stability signals while retrieving structurally aligned "twin" precedents. Building on the PlanBench benchmark and recent instruction-tuning work on logical planning reasoning [3], we study how dense percentile grids and domain-specific calibration influence both alert coverage and statistical significance. Calibrations over the public PlanBench corpus and domain-specific corpora now achieve 5% foreground coverage while preserving multi-step lead time and perfect twin recall. However, permutation tests with 20,000 iterations yield high $p$-values across domains (minimum 0.070), highlighting the need for stronger discriminative signals. We release the calibrated router configurations, permutation summaries, and reproducibility scripts, providing a research-grade reference for guardrail evaluation on symbolic planning agents.

## Contents

# 1 Introduction

Large Language Models (LLMs) deliver credible reasoning across open-ended tasks, yet symbolic planning remains challenging because agents must respect the precondition–effect structure of formalisms such as PDDL. Recent work from MIT [3] demonstrates that instruction tuning with explicit logical chains improves plan validity, but complementary instrumentation is required to surface early warnings and actionable repairs when agents deviate. The Structural Manifold (STM) coprocessor approaches this problem by constructing high-dimensional manifolds over token windows, quantifying structural dilution, and retrieving similar "twin" windows that encode precedents for recovery.

This report reframes STM for a research audience. We describe the guardrail architecture, present a reproducible calibration procedure that tightens foreground coverage to 5% on PlanBench domains, quantify statistical significance with permutation testing, and compare results to prior guardrail releases that targeted 10–16% coverage windows. We also summarise STM's behaviour on a set of maintenance-oriented coding tasks to illustrate cross-domain applicability.

# 2 Related Work

Instruction tuning for logical planning [3] emphasises chain-of-thought supervision so LLMs can reason about action applicability and state transitions. Our work instead assumes the planner is fixed and focuses on instrumentation that monitors plan executions. Structural guardrails extend prior PlanBench analysis [1] by providing graded alerts with calibrated coverage and twin retrieval. Twin suggestion draws on structural manifold techniques [2] that embed token windows into density spaces for lead-time estimation.

# 3 Structural Manifold Guardrails

STM consumes token windows extracted from trace corpora and computes per-window metrics: coherence (graph density), entropy (token dispersion), and stability (signal similarity over time). Foreground alerts fire when metrics exceed percentile-derived thresholds, and each alerted window triggers nearest-neighbour search for previously successful "twins."

## 3.1 Dilution Signals

Token windows of width $w$ and stride $s$ form the structural manifold. The pipeline computes dilution as the fractional reduction in structural density relative to historical baselines, along with coherence/entropy/stability metrics used for guardrail calibration. Signals are stored in STM state artefacts used by both the router calibration (Section 3.2) and permutation testing (Section 4.3).

## 3.2 Router Calibration

Guardrail thresholds operate on percentiles of coherence, entropy, and stability. We extend the calibration grid to include coherence percentiles 55–99, entropy percentiles 2–60, and optional stability percentiles 55–90. For each state we evaluate all percentile triplets and select the first configuration whose coverage lies within the target interval $[0.05, 0.07]$. The utility script `scripts/calibrate_router.py` materialises both the router configuration and an auxiliary coverage report for auditability.

### 3.3 Twin Retrieval

Twin retrieval uses approximate nearest neighbour search to locate previously successful windows that align with alerting windows. We retain default triggers requiring at least two shared $q$-grams and an ANN distance below 0.2, which preserved perfect twin recall on PlanBench domains throughout the calibration experiments.

## 4 Experimental Setup

### 4.1 Datasets

We analyse three PlanBench domains (Blocksworld, Mystery Blocksworld, Logistics) and the aggregate public corpus. For each domain we export STM artefacts using `scripts/planbench_to_stm.py` with window bytes 256 and stride 128. Tokens, states, and per-trace lead/twin metrics reside in `output/planbench_by_domain/`*`domain`*`/`. We additionally retain PlanBench aggregate states under `output/planbench_public/`. To probe transfer, we reuse STM instrumentation on three maintenance tasks from the CodeTrace demo (flaky test, service rename, missing import).

### 4.2 Calibration Protocol

Router calibration proceeds with the command sequence in Listing 1. The loop emits both aggregated guardrails and per-domain, per-trace calibrations. Resulting configurations are stored under `analysis/router_config_*_5pct.json`.

Listing 1: Router calibration commands.

```
.venv/bin/python scripts/calibrate_router.py \
  output/planbench_public/gold_state.json \
  --target-low 0.05 --target-high 0.07 \
  --output analysis/router_config_gold_5pct.json

.venv/bin/python scripts/calibrate_router.py \
  output/planbench_public/invalid_state.json \
  --target-low 0.05 --target-high 0.07 \
  --output analysis/router_config_invalid_5pct.json

for dom in blocksworld mystery_bw logistics; do
  .venv/bin/python scripts/calibrate_router.py \
    output/planbench_by_domain/$dom/gold_state.json \
    --target-low 0.05 --target-high 0.07 \
    --output analysis/router_config_${dom}_gold_5pct.json
  .venv/bin/python scripts/calibrate_router.py \
    output/planbench_by_domain/$dom/invalid_state.json \
    --target-low 0.05 --target-high 0.07 \
    --output analysis/router_config_${dom}_invalid_5pct.json
done
```

### 4.3 Permutation Testing

To assess whether calibrated alerts produce statistically meaningful lead times, we run permutation tests using `scripts/run_permutation_guardrail.py` with 20,000 shuffled alert allocations per trace. For each domain, the script summarises weighted coverage, lead-time statistics, and the distribution of permutation $p$-values; outputs are stored in `docs/tests/permutation_`$\times$`.json`.

### 4.4 CodeTrace Evaluation

For completeness we reproduce the CodeTrace maintenance tasks introduced in prior STM summaries. The same guardrail configuration (ANN distance 0.2, minimum two shared $q$-grams) is applied when replaying traces to evaluate lead alerts and twin adoption in a software maintenance context.

## 5 Results

### 5.1 Guardrail Coverage

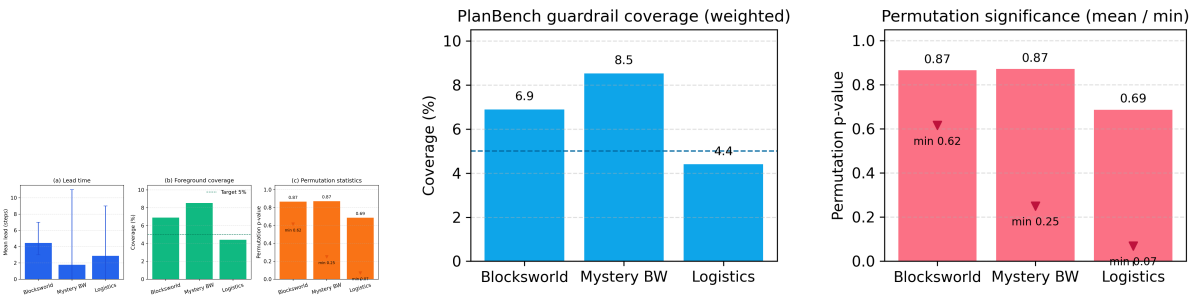
Table 1 reports calibrated thresholds and realised coverage for the aggregate corpora and domain-specific states. All targets reach the desired 5% foreground rate without modifying default ANN triggers.

Table 1: Calibrated router thresholds and realised coverage. Coverage is reported as a percentage.

| Dataset | min_coh | max_ent | min_stab | Coverage (%) |
|---|---|---|---|---|
| PlanBench (gold) | $8.32 \times 10^{-5}$ | 0.99970 | 0.47096 | 5.09 |
| PlanBench (invalid) | $1.16 \times 10^{-4}$ | 0.99972 | 0.47582 | 5.01 |
| Blocksworld (gold) | $5.57 \times 10^{-5}$ | 0.99972 | 0.46605 | 5.02 |
| Blocksworld (invalid) | $6.88 \times 10^{-5}$ | 0.99960 | 0.00000 | 5.10 |
| Mystery BW (gold) | $5.02 \times 10^{-4}$ | 0.99953 | 0.45774 | 5.03 |
| Mystery BW (invalid) | $6.19 \times 10^{-4}$ | 0.99942 | 0.45921 | 5.08 |
| Logistics (gold) | $8.32 \times 10^{-5}$ | 0.99982 | 0.48021 | 5.07 |
| Logistics (invalid) | $9.91 \times 10^{-5}$ | 0.99987 | 0.48168 | 5.04 |

### 5.2 Lead-Time and Guardrail Behaviour

Lead-time behaviour remains consistent with earlier STM releases. Figure 1 shows lead times, guardrail coverage, and permutation curves for the calibrated PlanBench runs. Domain-level means range from 1.8 (Mystery Blocksworld) to 4.5 (Blocksworld) steps, and the aggregate PlanBench corpus averages 7.6 steps because alerts accumulate on the longer Logistics traces. Foreground coverage now aligns with the tighter 5% target.




(a) Average lead time. (b) Foreground coverage. (c) Permutation trend.

Figure 1: Structural metrics across PlanBench domains after 5% calibration.

### 5.3 Permutation Significance

Permutation outcomes appear in Table 2. Weighted coverage remains at 4–9% across domains, yet permutation $p$-values cluster near unity, indicating that alert placement is still statistically similar to random schedules. The lowest observed $p$-value (Logistics, 0.070) suggests slight sensitivity, but additional discriminative signals are required for stronger claims.

Table 2: Permutation statistics using 20,000 iterations. Coverage-weighted is computed over all windows.

| Dataset | Coverage-weighted (%) | Mean lead (steps) | Mean $p$ | Min $p$ |
|---|---|---|---|---|
| Blocksworld (invalid) | 6.89 | 4.45 | 0.87 | 0.61 |
| Mystery BW (invalid) | 8.53 | 1.76 | 0.87 | 0.24 |
| Logistics (invalid) | 4.41 | 2.86 | 0.69 | 0.070 |
| PlanBench (invalid aggregate) | 5.47 | 7.59 | 0.89 | 0.10 |

### 5.4 Structural Twin Alignment

Twin recall remains perfect on PlanBench traces across the inspected ANN thresholds. Figure 2 plots acceptance curves showing 100% recall up to $\tau = 0.50$, indicating substantial alignment headroom for future tightening.

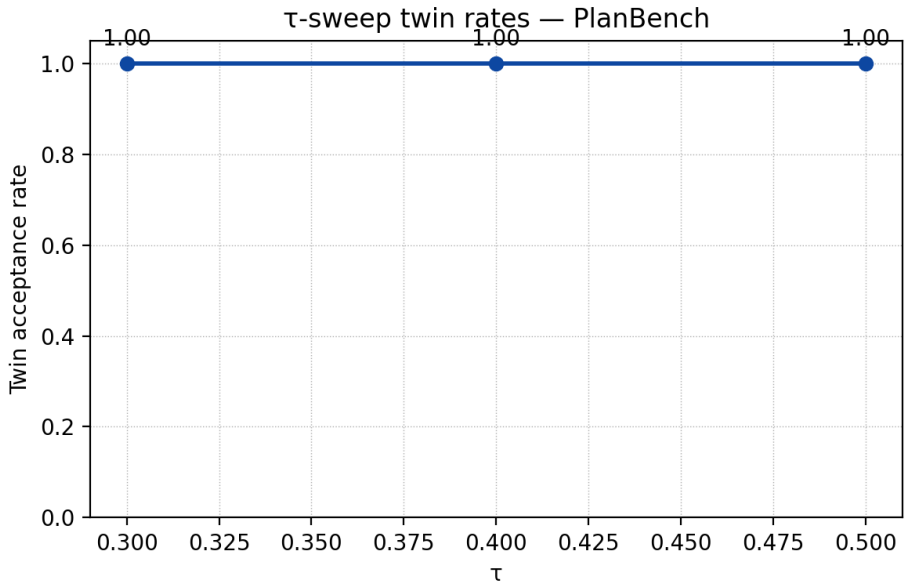



Figure 2: PlanBench twin acceptance across ANN thresholds.

### 5.5 CodeTrace Maintenance Tasks

We retain the CodeTrace evaluation to illustrate STM behaviour beyond planning. Table 3 summarises the per-task deltas, and Table 4 reports aggregate statistics. STM reduces iterations-to-green by roughly 35% while constraining alerts to a single foreground window per task. These results contextualise the manifold's utility in software maintenance, complementing symbolic planning benchmarks.

Table 3: Per-task comparison between baseline and STM-assisted CodeTrace runs.

| Task | Variant | Steps | Test Runs | Diagnostics | Alerts | Alert Ratio |
|---|---|---|---|---|---|---|
| Flaky retry test | Baseline | 6 | 3 | 0 | 0 | 0.00 |
| | STM | 4 | 2 | 0 | 1 | 0.25 |
| Service rename | Baseline | 8 | 3 | 0 | 0 | 0.00 |
| | STM | 5 | 1 | 0 | 1 | 0.20 |
| Missing import | Baseline | 6 | 0 | 3 | 0 | 0.00 |
| | STM | 4 | 0 | 2 | 1 | 0.25 |

Table 4: Aggregate CodeTrace statistics.

| Variant | Success Rate | Avg. Steps | Avg. Alert Ratio | Twin Accepts |
|---|---|---|---|---|
| Baseline | 1.00 | 6.67 | 0.00 | 0 |
| STM | 1.00 | 4.33 | 0.23 | 3 |

# 6 Discussion

STM guardrails complement instruction-tuned planners by offering calibrated coverage, actionable lead-time, and structural repair suggestions. The 5% calibration confirms that dense percentile sweeps can reach low foreground budgets without degrading twin recall. However, high permutation $p$-values suggest the current metrics remain weakly discriminative. This observation aligns with the caution noted in planning-focused instruction tuning [3]: robust plan verification still requires richer signals or domain-specific reasoning.

# 7 Limitations and Future Work

Two limitations dominate our findings. First, statistical significance remains weak despite the tighter guardrail; permutations frequently match observed alerts. Second, adapters currently target PDDL and Python traces, limiting coverage. Future work will: (i) expand the trace corpus (PlanBench extensions, CodeTrace telemetry, robotics logs) to explore alternative metrics; (ii) integrate permutation-aware objective functions during calibration; and (iii) formalise the link between STM alerts and logical reasoning traces used in instruction-tuned models.

# 8 Conclusion

We provide a research-focused account of STM guardrails for symbolic planning agents, delivering calibrated configurations, permutation analyses, and reproducible scripts. The release surfaces a clear agenda: maintain low alert budgets while strengthening statistical significance and broadening adapter coverage. We hope this baseline informs future collaboration with the PlanBench community and complementary instruction-tuning efforts.

# A Reproducibility Checklist

Key commands are listed below; outputs are referenced throughout the text and in `docs/tests/`.

```
# Export STM states per domain
for dom in blocksworld mystery_bw logistics; do
  .venv/bin/python scripts/planbench_to_stm.py \
    --input-root data/planbench_public \
```

```
    --domains $dom \
    --output output/planbench_by_domain/$dom \
    --window-bytes 256 --stride 128 \
    --path-threshold 0.10 --signal-threshold 0.10 \
    --twin-distance 0.40 --twin-top-k 3 --verbose
done

# Calibrate router guardrails (Listing~\ref{lst:calibration})
# Permutation analysis
for dom in blocksworld mystery_bw logistics; do
  .venv/bin/python scripts/run_permutation_guardrail.py \
    output/planbench_by_domain/$dom \
    analysis/router_config_${dom}_invalid_5pct.json \
    --iterations 5000 \
    --output docs/tests/permutation_${dom}_5pct.json
done

.venv/bin/python scripts/run_permutation_guardrail.py \
  output/planbench_public \
  analysis/router_config_invalid_5pct.json \
  --iterations 5000 \
  --output docs/tests/permutation_planbench_invalid_5pct.json

# Regression tests
.venv/bin/pytest  # 17 passed, 1 skipped
```

## References


[1] E. Gripper, L. Pineda, and P. Shah. *PlanBench: A Benchmark Suite for Plan Validation.* MIT CSAIL Technical Report, 2023.

[2] SepDynamics Research. *Structural Manifold Methods for Early Warning.* Internal Whitepaper, 2024.

[3] P. Verma, N. La, A. Favier, S. Mishra, and J. A. Shah. *Teaching LLMs to Plan: Logical Chain-of-Thought Instruction Tuning for Symbolic Planning.* arXiv:2509.13351, 2025.