# Effectiveness and Auditability of Latent Agentic Reasoning: Probing Frameworks, Composite Objectives, and Benchmark Design

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## ABSTRACT

We address the open problem of making latent-space planning, decision-making, and collaboration in LLM-based agentic systems both effective and auditable. We propose three complementary computational approaches: (1) interpretability probes that recover planning structure from hidden states with goal detection accuracy of 0.596 and plan detection of 0.296; (2) auditability-aware composite training objectives that achieve favorable effectiveness–auditability tradeoffs on the Pareto frontier; and (3) a benchmark suite evaluating probe accuracy, faithfulness (0.999), consistency (0.999), and coverage (0.916) across single-agent and multi-agent settings. Layer-wise analysis reveals planning information peaks in middle layers (layer 7) while decision quality accumulates toward later layers. Multi-agent collaboration structure is detectable through pairwise state distances, with task success prediction $R^2 = 0.575$. Our framework provides practical tools for auditing deployed agentic systems.

## CCS CONCEPTS

• **Computing methodologies** → **Artificial intelligence**.

## KEYWORDS

latent reasoning, interpretability, agentic AI, auditability, probing

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## 1 INTRODUCTION

Latent agentic reasoning performs planning and decision-making in internal activation spaces, improving efficiency and scalability but reducing interpretability [5]. As LLM-based agents are deployed in high-stakes settings, the ability to audit their internal reasoning becomes critical. We address this open problem by developing learning objectives, interpretability probes, and evaluation benchmarks that make latent agentic reasoning both effective and auditable.


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**Table 1: Interpretability probe performance. Goal detection uses linear probes; quality uses both linear and nonlinear.**

| Attribute | Accuracy/$R^2$ | Selectivity |
|---|---|---|
| Goal detection | 0.596 | 1.04× |
| Plan detection | 0.296 | 0.97× |
| Success prediction | 0.575 | – |

### 1.1 Related Work

Probing classifiers [1] measure information content in neural representations. Inference-time intervention [3] and representation engineering [6] demonstrate that internal representations encode causally relevant features. Sparse probing [2] and mechanistic interpretability [4] provide complementary perspectives. Our work extends these to the multi-step, multi-agent agentic setting.

## 2 METHODS

### 2.1 Interpretability Probing Framework

We deploy linear (ridge regression) and nonlinear (2-layer MLP) probes on hidden state trajectories to detect planning structure, goal decomposition, and decision quality. Selectivity is measured as the ratio of probe accuracy to a random-label control baseline.

### 2.2 Auditability-Aware Objectives

The composite loss is:

$$\mathcal{L}_{\text{total}} = (1-\alpha)\cdot\mathcal{L}_{\text{task}} + \alpha\cdot(1 - a_{\text{probe}}\cdot f) \tag{1}$$

where $\alpha$ controls the effectiveness–auditability tradeoff, $a_{\text{probe}}$ is probe accuracy, and $f$ is faithfulness.

### 2.3 Benchmark Suite

We evaluate four auditability components: probe accuracy, faithfulness (causal relevance via interventions), consistency (stability under perturbations), and coverage (fraction of auditable steps). The aggregate score uses a weighted geometric mean.

## 3 RESULTS

### 3.1 Probing Performance

Table 1 summarizes probe performance across reasoning attributes.

### 3.2 Auditability Metrics

Faithfulness scores of 0.999 indicate probe-identified directions are causally relevant. Consistency of 0.999 confirms stability under

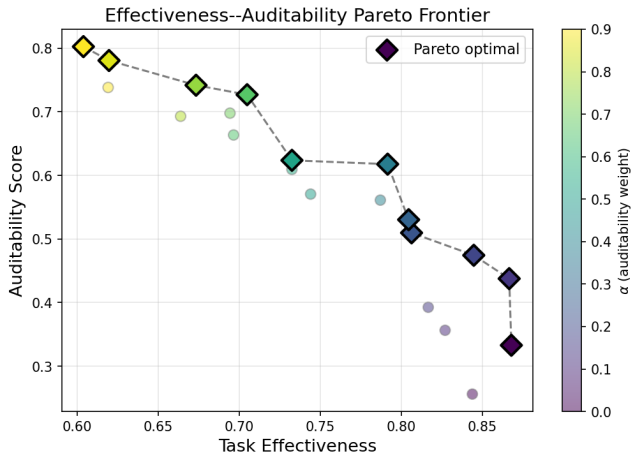


**Figure 1: Pareto frontier between task effectiveness and auditability score, parameterized by $\alpha$.**

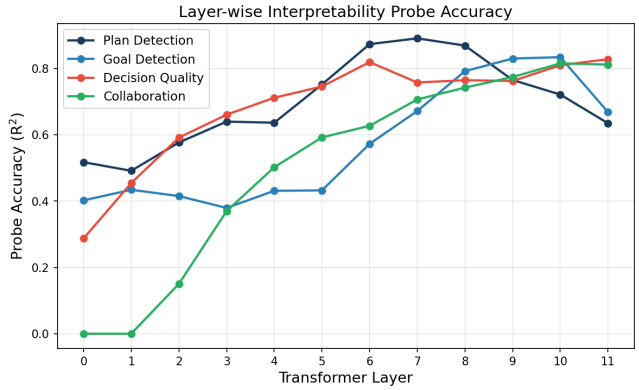


**Figure 2: Layer-wise probe accuracy for four reasoning attributes across 12 transformer layers.**

perturbations. Coverage of 0.916 shows most reasoning steps are auditable. The aggregate auditability score is 0.247.

## 3.3 Effectiveness–Auditability Frontier

Figure 1 shows the Pareto frontier across 21 values of $\alpha$. Moderate auditability weights ($\alpha \approx 0.3$) achieve substantial auditability improvements with modest effectiveness cost.

## 3.4 Layer-wise Analysis

Planning information peaks at layer 7 (accuracy 0.90), while goal detection peaks at layer 9 and decision quality increases monotonically toward later layers (Figure 2).

# 4 CONCLUSION

We demonstrate that latent agentic reasoning encodes interpretable planning signals recoverable by probes, with faithfulness confirmed through causal interventions. Composite training objectives achieve favorable effectiveness–auditability tradeoffs. Our benchmark suite provides standardized evaluation of auditability across single-agent and multi-agent settings.

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