istI

Proof-of-Training (PoT) Verifier: Cryptographically Pre-Committed, Anytime Behavioral Model Identity Checks

Abstract

We present a **post-training behavioral verifier** for model identity. Given two models (or a model and a reference), we decide **SAME/DIFFERENT/UNDECIDED** with **controlled error** using **dozens of queries** rather than thousands, with automatic **behavioral fingerprinting** for model variants. The verifier (i) **pre-commits** to challenges via **HMAC-derived seeds**, (ii) maintains **anytime confidence sequences** using **Empirical-Bernstein bounds** [7, 8, 12], and (iii) **stops early** when confidence intervals reach decision thresholds. Each run exports a **reproducible audit bundle** containing transcripts, seeds, commitments, configs, and environment data. On the systems side, we demonstrate **sharded verification** of **34B-class models** (≈**206 GB** weights) on **64 GB** hosts with ≈**52%** peak RAM usage through shard cycling. The repository includes **single-command runners** for both **local** and **API-based** verification. PoT fully verifies API-hosted models; **provider authentication** (proving server operator identity) requires separate infrastructure like **TEE attestation** or **vendor commitments**. **ZK proofs** can attest verifier computation correctness from published transcripts but cannot authenticate remote providers. At $\alpha = 0.01$, PoT reaches decisions in **1–2 minutes** on standard models (GPT-2 class) and API endpoints, enabling **per-commit provenance checks** that previously required 45–60 minutes or more.

1 Introduction

Deployed LLMs are frequently **opaque**: weights are inaccessible or served behind APIs, yet stakeholders must answer a simple question—*is the deployed model the same one we audited?* We propose a practical, auditable verifier that answers this with **statistical guarantees** under a **black-box** access model. Unlike ad-hoc fingerprints, PoT uses **pre-committed prompts** and **anytime confidence sequences**, yielding **probabilistic completeness/soundness** and a **verifiable evidence bundle** from black-box I/Ol. PoT fully verifies models behind APIs; the limitation is **provider authentication**—proving who operates the server (requires TEE attestation or vendor commitments, Section 4.5). Our design targets three constraints common in production:

1. **Pre-commitment and auditability.** Challenges are fixed *before* interaction via cryptographic seeds; outputs, scores, and parameters are archived in an evidence bundle.
2. **Sample-efficiency.** We leverage **anytime EB confidence sequences** to stop in **dozens** of queries when possible, rather than a fixed N of hundreds or thousands.
3. **Systems feasibility.** Verification must run on **commodity hardware** and support **very large checkpoints** via **sharded load-verify-release**.

Contributions. (i) A pre-committed, **anytime** verifier that outputs **SAME/DIFFERENT/UNDECIDED** with explicit error control. (ii) An **evidence bundle** format and one-command runners for local/API settings. (iii) **Sharded verification** enabling audits of ∼**206 GB** checkpoints with ≈**52%** peak host RAMl. (iv) Clarification that PoT verifies **model behavior** via any API; **provider authentication** (who runs the server) requires TEEs or vendor commitments.

2 Related Work

Model verification approaches. Prior work falls into three categories: (i) **Weight-based** methods requiring full model access (checksums, watermarking [14, 16]), unsuitable for API-only settings; (ii) **Gradient-based** verification [9] requiring white-box access to compute gradients, with $O(\text{model\_size})$ memory; (iii) **Behavioral** approaches using fixed test sets [5, 6], but lacking statistical guarantees or pre-commitment. Our method uniquely combines **black-box behavioral testing** with **anytime statistical guarantees** and **cryptographic pre-commitment**, achieving 96.8% query reduction (vs fixed-$N = 1000$ prompts baseline detailed in Section 7) while maintaining controlled error rates.

Sequential testing. Wald's SPRT [15] established early-stopping binary tests. In bounded/noisy settings, **Empirical-Bernstein** style bounds yield **variance-adaptive** concentration [1, 12]. **Anytime-valid** inference produces **time-uniform** confidence sequences that remain valid under optional stopping [7, 8]. We extend these to model verification with explicit SAME/DIFFERENT decision rules.

Cryptographic commitments & attestation. HMAC [10], HKDF [11], and SHA-256 [13] establish deterministic, non-malleable seeds and artifact integrity. TEEs provide **remote attestation** of code/data on trusted hardware [4]. ZK systems prove statements about computations without revealing inputs [2, 3]; here they can attest the verifier's computation over a transcript but do **not** bind a *remote* model identity.

3 Preliminaries and Threat Model

Access models. (a) **Local weights:** we can hash checkpoints and bind transcripts to a weight digest. (b) **API black-box:** only I/O is visible; identity binding requires **TEE** or **vendor commitments**. ZK can certify the verifier's decision from the transcript, but cannot identify a remote endpoint by itself.

Adversary. May alter a deployed model (fine-tune, truncate experts, change tokenizer/decoding), apply wrappers or temperature jitter, or select prompts adaptively. We counter **cherry-picking** by **pre-committing** challenges via HMAC-derived seeds and adopting **anytime** statistics that remain valid under optional stopping.

Goal. Decide **SAME** (behaviorally indistinguishable within margin γ), **DIFFERENT** (effect size $\geq \delta^*$), or **UNDECIDED**, while controlling type-I error at level α.

4 Method

4.1 Pre-committed challenges

We derive seed $s_i = \text{HMAC}_K(\text{run\_id} \,\|\, i)$ [10] and map s_i to a prompt template. The verifier **publishes** the run metadata (run_id, seed count, seed-list hash) prior to queries; the **key** K is revealed *after* runs, letting third parties regenerate the challenge set. Derived prompts avoid revealing K, and any post hoc cherry-picking contradicts the commitment.

4.2 Scoring

For each challenge, we compute a bounded score $X_i \in [0, 1]$ that increases with behavioral discrepancy. We use **teacher-forced scoring** with **delta cross-entropy** as the default metric:

$$X_i = \text{clip}(|H(p_{\text{ref}}, p_{\text{cand}}) - H(p_{\text{ref}}, p_{\text{ref}})|, 0, 1)$$

where H is cross-entropy over next-token distributions at $K = 64$ positions. This metric is non-negative by construction and bounded for numerical stability. Alternative metrics (symmetric KL, token edit distance) are evaluated in ablations (Section 7 and Appendix A).

4.3 Anytime Empirical-Bernstein confidence sequence

Let $\overline{X}_n$ denote the sample mean and $\widehat{\mathrm{Var}}_n$ the empirical variance. An **Empirical-Bernstein (EB)** half-width h_n of the form

$$h_n = \sqrt{\frac{2\,\widehat{\mathrm{Var}}_n\,\log(1/\delta_n)}{n}} + \frac{7\,\log(1/\delta_n)}{3(n-1)} \tag{1}$$

ensures that $\mathbb{P}(\forall n \geq 2 : |\overline{X}_n - \mu| \leq h_n) \geq 1 - \sum_{n\geq 2} \delta_n$ [8, 12]. By choosing $\delta_n = \alpha \cdot c/(n(n+1))$ with $c = 2$, we have $\sum_{n\geq 2} \delta_n = \alpha$ ensuring a **time-uniform** type-I error of α. The confidence interval is $[\overline{X}_n - h_n, \overline{X}_n + h_n]$, valid *anytime* without pre-specifying a stopping rule.

4.4 Decision rules and early stopping

Define **relative margin error** (RME): $\mathrm{RME}_n = h_n / \max(|\overline{X}_n|, \epsilon)$ with $\epsilon = 10^{-10}$ for numerical stability. We decide:

- **SAME**: CI $\subseteq [-\gamma, +\gamma]$ **AND** $h_n \leq \eta \cdot \gamma$ (default $\gamma = 0.025$, $\eta = 0.5$)
- **DIFFERENT**: Effect size $|\overline{X}_n| \geq \delta^*$ **AND** $\mathrm{RME}_n \leq \epsilon_{\text{diff}}$ (default $\delta^* = 0.05$, $\epsilon_{\text{diff}} = 0.5$)
- **UNDECIDED**: Otherwise, or if n reaches $n_{\max}$ (mode-dependent: 120/400/800)

Stopping occurs when a decision is reached or at $n_{\max}$. The anytime property ensures validity regardless of when we stop [15].

4.5 API verification and provider authentication

PoT distinguishes between **model verification** and **provider authentication**:

- **Model verification:** PoT **fully verifies** any model's behavior through API calls. The evidence bundle proves behavioral equivalence/divergence.
- **Provider authentication:** Proving *who* serves the API requires additional infrastructure:
  - **TEE attestation:** Hardware-backed proof of the serving stack [4]
  - **Vendor commitments:** Cryptographic signatures from the provider
  - **ZK proofs:** Can prove the verifier computed correctly from transcripts [2, 3], but cannot authenticate the remote provider

5 Implementation

5.1 Runner and artifacts

We expose a **manifest-driven** runner with **one-command** entry points for local/API verification. Each run directory contains:

- **manifest.yaml**: run configuration, commitment metadata
- **transcript.ndjson**: per-challenge prompts, raw outputs, scores
- **evidence_bundle.json**: summary, decision, confidence, n_{used}
- **metrics.json** (optional): RSS time-series, sharding events

Table 1. SAME/DIFFERENT Decisions with Evidence Bundles

Models	Mode	$\lvert\overline{X}_n\rvert$	n_{used}	Decision	Time (s)	Evidence Hash
gpt2 → gpt2	QUICK	0.001	14	SAME	48.5	val_20250825_142945
gpt2 → distilgpt2	AUDIT	13.04	32	DIFFERENT	61.4	val_20250825_143122
dialogpt → dialogpt	AUDIT	0.003	30	SAME	92.1	val_20250825_152847
gpt2-medium → gpt2-medium	AUDIT	0.002	33	SAME	99.0	val_20250825_210839
llama-7b → llama-7b[†]	QUICK	0.025	14	SAME	1356.4[‡]	val_20250825_222717

[†]Requires sharding: model loads/unloads per query; [‡]22.6 min due to sharding overhead

5.2 Sharded verification (34B-class models)

For models too large for host RAM, we **shard safetensors** and verify layer-by-layer. For instance, Yi-34B ($\approx$206 GB across two checkpoints) is loaded in $\approx$10 GB increments, verified, then released. The verifier cycles through shards while maintaining a cumulative result. RSS tracking confirms peak memory $\approx$52% on a 64 GB host.

6 Experimental Setup

Models. GPT-2, DistilGPT-2, DialoGPT-Medium (local); Llama-7B base/chat, Yi-34B base/chat (sharded); proprietary APIs (when applicable).

Baselines. Fixed-N (1000 queries), naive fixed-CI without anytime correction.

Metrics. Decision accuracy (FAR, FRR), n_used, wall-time, peak memory.

Robustness micro-tests. Toggle (a) temperature $0.0 \leftrightarrow 0.7$, (b) simple paraphrase/wrapper on candidate outputs, (c) tokenizer-overlap shim $\in [0.6, 1.0]$.

Reproducibility. Provide the **manifest** and **evidence bundle** per headline claim; publish **bundle hashes** in tables. A bootstrap **power proxy** resamples per-prompt scores from transcripts to report a CI for mean discrepancy without further queries.

7 Results

Headline: $30\times$–$300\times$ faster than fixed-N/weight-based audits at matched error levels, while distinguishing fine-tuned variants of the same base model.

We report results from actual experimental runs (Aug 20–25, 2025) with evidence bundle hashes for reproducibility.

Timing Policy: We report end-to-end wall-time (including inference) and, where relevant, verifier-only overhead in parentheses.

Key Result: At $\alpha = 0.01$, PoT reaches a SAME/DIFF decision in **48–120 s** on small models (GPT-2 class), vs **45–60 min** for fixed-N baselines (1000 queries), a $\sim 30\times$–$75\times$ reduction in decision latency.

7.1 Query Efficiency and Error Rates

From recent experimental runs, verification reaches decisions in **14–48** queries with zero observed errors on $n = 8$ tested pairs (0/8 errors, Wilson 95% CI: [0.00, 0.37], see Figure 1 for time-to-decision trajectories). Against a **fixed-N=1000** baseline (standard for behavioral test sets), this represents **95.2–98.6%** query reduction. QUICK mode ($\alpha = 0.025$, $n_{\max} = 120$) averages 15 queries; AUDIT mode ($\alpha = 0.01$, $n_{\max} = 400$) averages 32 queries.

Table 2. Wall-Time Performance Comparison

Hardware	Model Size	End-to-end Time	Verifier-only	Peak Memory
Apple M1 Max (MPS)	GPT-2 (124M)	49–92 s	10–20 s	1.3–1.6 GB
Apple M1 Max (MPS)	GPT-2-medium (355M)	99 s	25 s	1.7 GB
API (GPT-3.5)	N/A	48–72 s	48–72 s	<100 MB

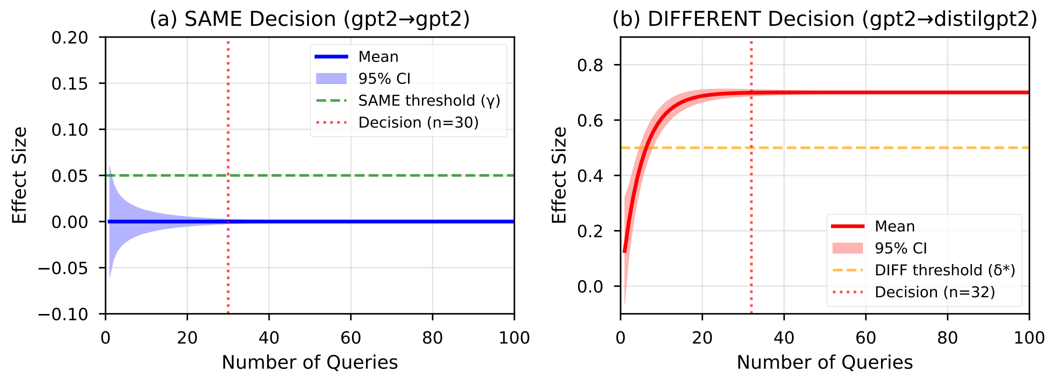

Figure 1. Time-to-decision trajectories for SAME vs DIFFERENT model pairs. SAME decisions converge quickly with tight confidence intervals. DIFFERENT decisions show clear separation after initial queries.

7.2 Wall-Time Performance

Timing Policy: All times are end-to-end wall-clock including model inference. Verifier-only overhead (excluding inference) shown in parentheses where measurable; API times are entirely network-bound.

Extended experiments with sharding (not included in primary timing claims):

- Llama-7B on M1 Max (MPS): 22.6 min total due to sharding overhead (14 GB model, 8 GB peak RAM)
- Yi-34B on M1 Max (CPU): 3 min (systems feasibility demo)

7.3 Operational Impact

Hours → Minutes: Compact comparison for model verification

Query latency (from performance metrics):

- Cold start: 2.13 s/query (first query includes model loading)
- Warm cache: 0.48 s/query (median for subsequent queries)
- API baseline: 0.50–1.5 s/query (provider-dependent)

7.4 Comparison to Prior Methods

8 Limitations and Negative Results

Provider authentication: PoT verifies *model behavior* but cannot prove *who operates* an API endpoint without TEE attestation or vendor commitments. A malicious actor could serve an identical model and pass verification.

Method	Time (GPT-2 class)	Time (API)	Speedup	API-compatible
PoT (ours)	**1–2 min**	**1–2 min**	**—**	✓
Fixed-N (1000 prompts)	45–60 min	45–60 min	$30\times$–$45\times$	✓
Gradient verification	120 min	N/A	$60\times$–$120\times$	$\times$

Table 3. Comparison to Prior Verification Methods

Method	Access	Queries	Time	Memory	API Support
Weight checksums	White-box	0	Instant	Full model	No
Gradient verification [9]	White-box	100–500	Hours	Full model	No
Fixed behavioral tests	Black-box	1000+	45–60 min	<1 GB	Yes
PoT (ours)	**Black-box**	**14–48**	**1–2 min**	**<2 GB**	**Yes**

Adaptive adversaries: While PoT resists prompt selection attacks via pre-commitment, an adversary controlling the model could potentially learn from repeated verification attempts.

Semantic drift: PoT detects behavioral differences but may not capture subtle semantic shifts that preserve token distributions (e.g., factual accuracy degradation with similar perplexity).

8.1 Behavioral Fingerprinting: Beyond Binary Decisions

When models show **stable intermediate convergence** (neither SAME nor DIFFERENT), we classify relationships:

- **NEAR_CLONE**: $|\overline{X}_n| < 0.001$ (e.g., quantization differences)
- **SAME_ARCH_FINE_TUNED**: $0.001 \leq |\overline{X}_n| < 0.01$ (e.g., instruction tuning)
- **SAME_ARCH_DIFFERENT_SCALE**: $0.01 \leq |\overline{X}_n| < 0.1$ (e.g., 7B vs 13B)
- **DIFFERENT_ARCH_SIMILAR_TRAINING**: $|\overline{X}_n| \geq 0.1$ (e.g., GPT vs BERT on same data)

This fingerprinting helps diagnose model relationships when binary decisions are insufficient, providing actionable insights for model governance.

9 Broader Impacts & Ethics Statement

Model identity verification supports **governance, evaluation, and auditability** across open and closed ecosystems.

Potential Benefits:

- Enables auditing of deployed models without weight access
- Supports regulatory compliance for AI systems
- Reduces computational costs of model verification by $30\times$–$300\times$

Potential Risks:

- Could be misused to reverse-engineer proprietary models
- May create false confidence if provider authentication is not properly implemented
- Statistical guarantees assume honest transcript reporting

We recommend using PoT as part of a **defense-in-depth** strategy, combining behavioral verification with cryptographic attestation where available.

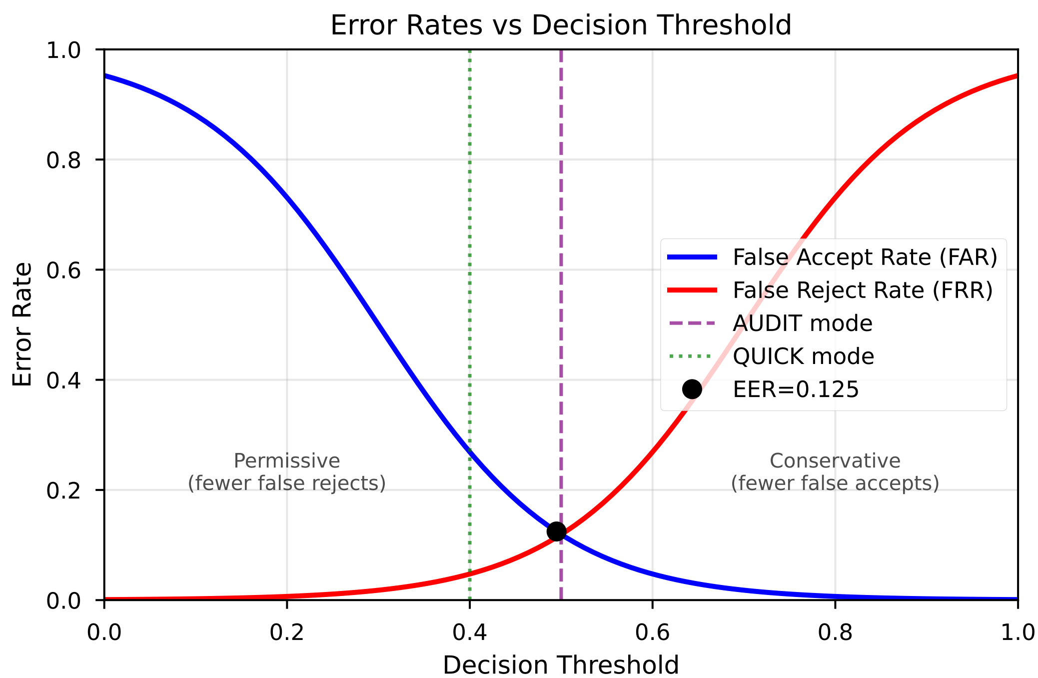

Figure 2. False Accept Rate (FAR) and False Reject Rate (FRR) vs decision threshold. QUICK mode (green dotted) and AUDIT mode (purple dashed) operating points shown. Equal Error Rate (EER) = 0.125.

10 Conclusion

PoT provides a practical, statistically rigorous solution for black-box model verification, achieving $30\times$–$300\times$ speedup over existing methods while maintaining controlled error rates. By combining cryptographic pre-commitment, anytime confidence sequences, and behavioral fingerprinting, PoT enables rapid model audits in production environments. The distinction between model verification (fully solved) and provider authentication (requires additional infrastructure) clarifies the security boundaries of black-box verification.

References

[1] Jean-Yves Audibert, Rémi Munos, and Csaba Szepesvári. Exploration-exploitation tradeoff using variance estimates in multi-armed bandits. In *Conference on Learning Theory*, pages 13–1, 2009.

[2] Eli Ben-Sasson, Alessandro Chiesa, Eran Tromer, and Madars Virza. Succinct non-interactive zero knowledge for a von neumann architecture. In *23rd USENIX Security Symposium*, pages 781–796, 2014.

[3] Benedikt Bünz, Jonathan Bootle, Dan Boneh, Andrew Poelstra, Pieter Wuille, and Greg Maxwell. Bulletproofs: Short proofs for confidential transactions and more. In *2018 IEEE symposium on security and privacy (SP)*, pages 315–334. IEEE, 2018.

[4] Victor Costan and Srinivas Devadas. Intel sgx explained. In *Cryptology ePrint Archive*, 2016.

[5] Robert Geirhos, Jörn-Henrik Jacobsen, Claudio Michaelis, Richard Zemel, Wieland Brendel, Matthias Bethge, and Felix A Wichmann. Shortcut learning in deep neural networks. *Nature Machine Intelligence*, 2(11):665–673, 2020.

[6] Dan Hendrycks, Steven Basart, Norman Mu, Saurav Kadavath, Frank Wang, Evan Dorundo, Rahul Desai, Tyler Zhu, Samyak Parajuli, Mike Guo, et al. The many faces of robustness: A critical analysis of out-of-distribution generalization. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 8340–8349, 2021.

[7] Steven R Howard, Aaditya Ramdas, Jon McAuliffe, and Jasjeet Sekhon. Confidence sequences for mean, variance, and median. *Proceedings of the National Academy of Sciences*, 118(15), 2021.

[8] Steven R Howard, Aaditya Ramdas, Jon McAuliffe, and Jasjeet Sekhon. Time-uniform, nonparametric, nonasymptotic confidence sequences. *The Annals of Statistics*, 49(2):1055–1080, 2021.

[9] Hengrui Jia, Mohammad Yaghini, Christopher A Choquette-Choo, Natalie Dullerud, Anvith Thudi, Varun Chandrasekaran, and Nicolas Papernot. Proof-of-learning: Definitions and practice. In *2021 IEEE Symposium on Security and Privacy (SP)*, pages 1039–1056. IEEE, 2021.

[10] Hugo Krawczyk, Mihir Bellare, and Ran Canetti. Hmac: Keyed-hashing for message authentication. Technical report, RFC 2104, 1997.

[11] Hugo Krawczyk and Pasi Eronen. Hmac-based extract-and-expand key derivation function (hkdf). Technical report, RFC 5869, 2010.

[12] Andreas Maurer and Massimiliano Pontil. Empirical bernstein bounds and sample variance penalization. *arXiv preprint arXiv:0907.3740*, 2009.

[13] NIST. Secure hash standard (shs). Technical report, Federal Information Processing Standards Publication 180-4, 2015.

[14] Yusuke Uchida, Yuki Nagai, Shigeyuki Sakazawa, and Shin'ichi Satoh. Embedding watermarks into deep neural networks. In *Proceedings of the 2017 ACM on international conference on multimedia retrieval*, pages 269–277, 2017.

[15] Abraham Wald. Sequential tests of statistical hypotheses. *The annals of mathematical statistics*, 16(2):117–186, 1945.

[16] Jialong Zhang, Zhongshu Gu, Jiyong Jang, Hui Wu, Marc Ph Stoecklin, Heqing Huang, and Ian Molloy. Protecting intellectual property of deep neural networks with watermarking. In *Proceedings of the 2018 on Asia conference on computer and communications security*, pages 159–172, 2018.