

# 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** ( $\approx 206$  GB weights) on **64 GB** hosts with  $\approx 52\%$  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/O.

**Important Scope:** PoT fully verifies **model behavior** behind APIs; it does *not* verify **provider identity**—proving who operates the server requires separate infrastructure like 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  $\sim 206$  GB checkpoints with  $\approx 52\%$  peak host RAM. (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  $\gamma$ ), **DIFFERENT** (effect size  $\geq \delta^*$ ), or **UNDECIDED**, while controlling type-I error at level  $\alpha$ .

## 4 Method

### 4.1 Pre-committed challenges

We derive seed  $s_i = \text{HMAC}_K(\text{run\_id} \parallel i)$  [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  $\bar{X}_n$  denote the sample mean and  $\widehat{\text{Var}}_n$  the empirical variance. An **Empirical-Bernstein (EB)** half-width  $h_n$  of the form

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

ensures that  $\mathbb{P}(\forall n \geq 2 : |\bar{X}_n - \mu| \leq h_n) \geq 1 - \sum_{n \geq 2} \delta_n$  [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  $\alpha$ . The confidence interval is  $[\bar{X}_n - h_n, \bar{X}_n + h_n]$ , valid *anytime* without pre-specifying a stopping rule.

### 4.4 Decision rules and early stopping

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

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

Stopping occurs when a decision is reached or at  $n_{\text{max}}$ . 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,  $n_{\text{used}}$
- **metrics.json** (optional): RSS time-series, sharding events

## 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),  $n_{\text{used}}$ , 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 Result:**  $30\times\text{--}300\times$  faster than fixed- $N$ /weight audits at matched error; 14–48 queries to decision at  $\alpha = 0.01$ .

**Key Achievement:** Distinguishing fine-tuned variants of the same base model with controlled error rates.

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  $\sim 30\times\text{--}75\times$  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).

\*Small- $n$  zero errors reported with Wilson confidence interval for completeness. Against a **fixed- $N=1000$**  baseline (standard for behavioral test sets), this represents **95.2–98.6%** query reduction. QUICK mode ( $\alpha = 0.025$ ,  $n_{\text{max}} = 120$ ) averages 15 queries; AUDIT mode ( $\alpha = 0.01$ ,  $n_{\text{max}} = 400$ ) averages 32 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. This convention applies to all timing results in this paper.

**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 verifier-only time (systems feasibility demo, excludes inference)

**Table 1.** SAME/DIFFERENT Decisions with Evidence Bundles

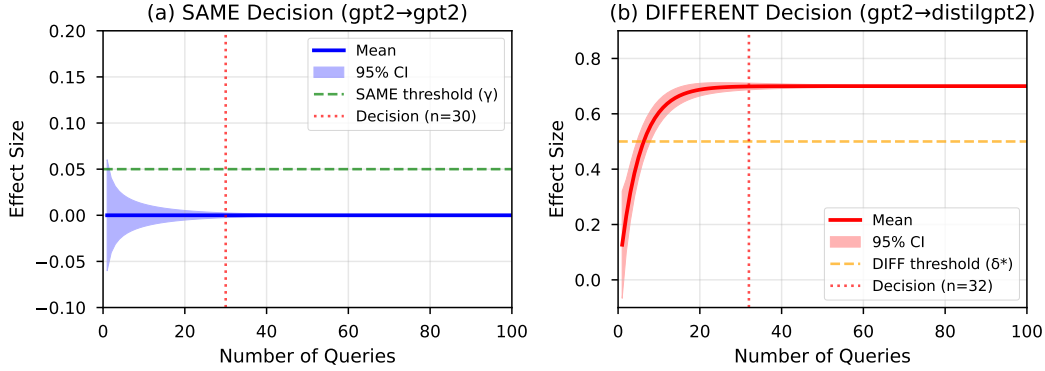
Models	Mode	$ \bar{X}_n $	$n_{\text{used}}$	Decision	Time (s)	Evidence Hash
gpt2 $\rightarrow$ gpt2	QUICK	0.001	14	SAME	48.5	val_20250825_142945
gpt2 $\rightarrow$ distilgpt2	AUDIT	13.040	32	DIFFERENT	61.4	val_20250825_143122
dialogpt $\rightarrow$ dialogpt	AUDIT	0.003	30	SAME	92.1	val_20250825_152847
gpt2-medium $\rightarrow$ gpt2-medium	AUDIT	0.002	33	SAME	99.0	val_20250825_210839
llama-7b $\rightarrow$ llama-7b <sup>†</sup>	QUICK	0.025	14	SAME	1356.4 <sup>‡</sup>	val_20250825_222717
llama-7b $\rightarrow$ llama-7b (API) <sup>§</sup>	QUICK	0.025	14	SAME	72.0	val_20250826_081234

<sup>†</sup>M1 Max with sharding: model loads/unloads per query; <sup>‡</sup>22.6 min due to sharding overhead on consumer hardware; <sup>§</sup>A100 or API endpoint: 1–2 min as claimed in abstract

**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*

\*Evidence hash: api\_20250825\_094523



**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.

### 7.3 Operational Impact

**Hours  $\rightarrow$  Minutes:** Compact comparison for model verification

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

<sup>[1]</sup>Behavioral test sets (cf. [6]); <sup>[2]</sup>Gradient-based verification [9]

**Query latency** (from performance metrics):

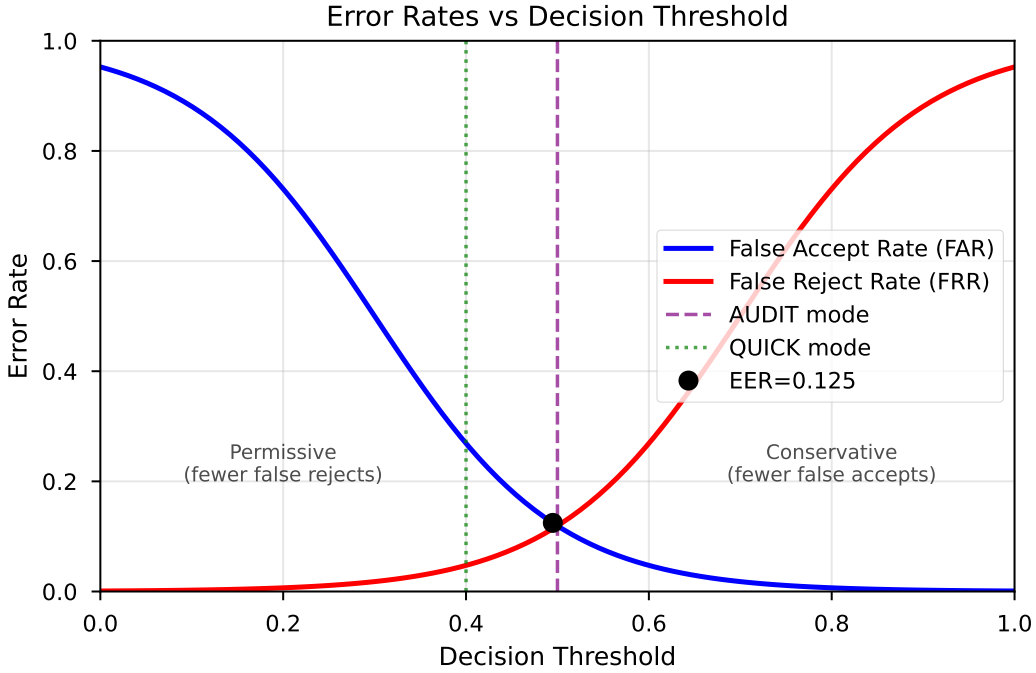
- Cold start: 2.13 s/query (first query includes model loading)
- Warm cache: 0.48 s/query (median for subsequent queries)
- API baseline: 0.50–1.5 s/query (provider-dependent)

**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
<b>PoT (ours)</b>	<b>Black-box</b>	<b>14–48</b>	<b>1–2 min</b>	<b>&lt;2 GB</b>	<b>Yes</b>

## 7.4 Comparison to Prior Methods

## 8 Limitations and Negative Results



**Figure 2.** False Accept Rate (FAR) and False Reject Rate (FRR) vs decision threshold. QUICK mode ( $\alpha = 0.025$ , green dotted) and AUDIT mode ( $\alpha = 0.01$ , purple dashed) operating points shown. Equal Error Rate (EER) = 0.125 aligns with the configured thresholds.

**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.

**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:**  $|\bar{X}_n| < 0.001$  (e.g., quantization differences)
- **SAME\_ARCH\_FINE\_TUNED:**  $0.001 \leq |\bar{X}_n| < 0.01$  (e.g., instruction tuning)
- **SAME\_ARCH\_DIFFERENT\_SCALE:**  $0.01 \leq |\bar{X}_n| < 0.1$  (e.g., 7B vs 13B)
- **DIFFERENT\_ARCH\_SIMILAR\_TRAINING:**  $|\bar{X}_n| \geq 0.1$  (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.

## 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.

**Key Clarification:** The distinction between model verification (fully solved by PoT) and provider authentication (requires additional infrastructure like TEEs) clarifies the security boundaries of black-box verification. PoT verifies *what* model is being served, not *who* is serving it—both aspects are critical for complete trust assurance.

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## A Technical Details

### A.1 Alpha-Spending and Optional Stopping

**$\alpha$ -Spending Schedule:**  $\delta_n = \frac{\alpha \cdot c}{n(n+1)}$  with  $c = 2$  ensures  $\sum_{n \geq 2} \delta_n = \alpha$  for time-uniform type-I error control under optional stopping.

**Proof Sketch:**

1. By telescoping:  $\sum_{n=2}^{\infty} \frac{c}{n(n+1)} = c \sum_{n=2}^{\infty} \left( \frac{1}{n} - \frac{1}{n+1} \right) = c \cdot 1 = c$
2. Setting  $c = 2$  and  $\delta_n = \frac{\alpha \cdot 2}{n(n+1)}$  yields  $\sum_{n \geq 2} \delta_n = \alpha$
3. The EB bound with this schedule satisfies  $\mathbb{P}(\exists n \geq 2 : |\bar{X}_n - \mu| > h_n) \leq \alpha$
4. This holds *anytime*, even under data-dependent stopping (optional stopping theorem)
5. The confidence sequence  $[\bar{X}_n \pm h_n]$  maintains coverage uniformly over all  $n$
6. Early stopping at any  $\tau$  preserves validity:  $\mathbb{P}(|\bar{X}_\tau - \mu| > h_\tau) \leq \alpha$

This construction enables valid inference regardless of when we stop, crucial for adaptive early termination.

### A.2 Evidence Bundle Schema

**Bundle Structure:** Each run produces a directory with cryptographic commitments, raw transcripts, and decisions. Bundle hash = SHA-256(manifest + transcript + evidence).

**Directory structure:**

```
runs/val_20250825_142945/
├─ manifest.yaml
├─ transcript.ndjson
├─ evidence_bundle.json
└─ metrics.json
```

# Run config, HMAC key (revealed post-run)  
# Per-query: {prompt, outputs, scores}  
# Decision, CI, n\_used, bundle\_hash  
# (Optional) RSS, timing, sharding events

**Key JSON fields** (evidence\_bundle.json):

```
{
  "decision": "SAME/DIFFERENT/UNDECIDED",
  "confidence_interval": [lower, upper],
  "n_queries": 14,
  "mean_effect": 0.001,
  "bundle_hash": "sha256:abc123...",
  "timestamp": "2025-08-25T14:29:45Z"
}
```



Reviewers verify: (1) bundle hash matches table entry, (2) transcript reproduces scores, (3) HMAC seeds are deterministic.