

When AI Settles Down: Late-Stage Stability as a Signature of AI-Generated Text Detection

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Abstract

Zero-shot detection methods for AI-generated text typically aggregate token-level statistics across entire sequences, overlooking the temporal dynamics inherent to autoregressive generation. We analyze over 120k text samples and reveal *Late-Stage Volatility Decay*: AI-generated text exhibits rapidly stabilizing log probability fluctuations as generation progresses, while human writing maintains higher variability throughout. This divergence peaks in the second half of sequences, where AI-generated text shows 24–32% lower volatility. Based on this finding, we propose simple features: *Derivative Dispersion* and *Local Volatility*, which are computed exclusively from late-stage statistics. Without perturbation sampling or additional model access, our method achieves state-of-the-art performance on EvoBench and MAGE benchmarks and demonstrates strong complementarity with existing global methods. Our code is available at <https://github.com/skJack/TSD>.

1 Introduction

The widespread adoption of large language models (LLMs) has raised significant concerns about the potential misuse of AI-generated text, making accurate detection of AI-generated content an increasingly important task (Yang et al., 2024c; Wu et al., 2025). Recent zero-shot detection methods, such as DetectGPT (Mitchell et al., 2023), Fast-DetectGPT (Bao et al., 2024), and LLR (Su et al., 2023) have achieved promising results by analyzing the probabilistic characteristics for different AI-generated and human written texts. These approaches typically compute global statistics, such as average model log-probability, rank, curvature, or sampling discrepancy over the entire text sequence.

Despite their effectiveness, these methods share a common implicit assumption: *token-level statistics are treated as stationary and exchangeable*

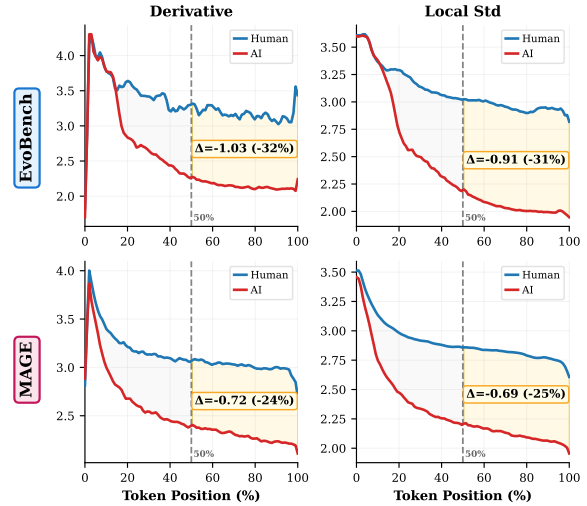


Figure 1: Temporal dynamics of **log probability** features for human vs. AI text on EvoBench (top) and MAGE (bottom). Left: Absolute derivative (change rate); Right: Local standard deviation (volatility). Shaded regions show the human-AI gap, with Δ indicating mean difference (AI – Human) and relative percentage. Yellow regions (50–100%) highlight larger divergence in the second half.

across the sequence. That is, discriminative signals are assumed to be uniformly distributed, so sequence-wide aggregation suffices. This assumption does not fully leverage characters of the autoregressive nature of LLM generation. Text is not produced all at once; instead, it is generated token by token, with each prediction conditioned on an ever-growing context. As a result, the statistical properties of generated tokens may evolve dynamically over time.

Recent empirical studies have observed that detection performance improves with increasing text length, with longer texts generally being easier to detect (Li et al., 2024; Xu et al., 2025; Bao et al., 2024). However, this phenomenon is typically attributed to longer texts simply “containing more information.” What remains largely unex-

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plored is *how discriminative signals are distributed across different stages of the generation process*, and whether later tokens exhibit qualitatively different behavior from earlier ones.

To address this issue, we conduct a large-scale temporal analysis of over 120K human-written and AI-generated texts from the EvoBench (Yu et al., 2025) and MAGE (Li et al., 2024) benchmarks. Using multiple surrogate models, we examine how various token-level statistics including negative log-probability, rank, entropy, and sampling discrepancy – evolve across normalized text positions. Crucially, we go beyond raw values and analyze two second-order temporal dynamics: the *derivative*, which captures how rapidly a statistic changes between consecutive tokens, and the *local standard deviation*, which measures regional volatility within a sliding window.

Our analysis reveals that the temporal dynamics of negative log-probability provide particularly discriminative signals. As illustrated in Figure 1, we observe that both the derivative and local standard deviation of negative log-probability decrease more rapidly for AI-generated text than for human text, with the gap widening noticeably in the second half of the sequence (50%–100% positions). Quantitatively, on EvoBench, the derivative of negative log-probability for AI text is 32% lower than that of human text ($\Delta = -1.03$), and local standard deviation is reduced by 31% ($\Delta = -0.91$); on MAGE, similar reductions of 24% and 25% are observed. In other words, AI-generated tokens in the latter portion of text exhibit smaller and more stable probability fluctuations as the model’s predictions become increasingly consistent as context accumulates. We term this pattern **Late-Stage Volatility Decay**. This pattern is consistent with the autoregressive nature of generation: as more context becomes available, the model’s prediction distribution tends to sharpen, reducing the variability of token-level statistics. Human writing, by contrast, continues to introduce unexpected lexical choices and maintains higher volatility throughout.

Based on this observation, we propose simple yet effective temporal features computed from token negative log-probability to capture this late-stage dynamics: (1) *derivative dispersion*, the standard deviation of the absolute first derivative in the second half, quantifying the intensity of probability fluctuations; and (2) *local volatility*, calculated as the mean of local standard deviation within a sliding window over the second half, this metric mea-

sures local stability, capturing how AI text tends to maintain smoother, more consistent probability transitions as generation progresses.

Since our temporal cues are empirically complementary to prior signals, a simple fusion with Fast-DetectGPT (Bao et al., 2024) yields consistent gains by combining *global distributional* and *local temporal* evidence. Experiments on MAGE (Li et al., 2024) and EvoBench (Yu et al., 2025) show that our approach excels on longer texts while remaining competitive on shorter ones, and that fusion further improves robustness across diverse generators. Our contributions are summarized as follows:

- We systematically reveal the *Late-Stage Volatility Decay* phenomenon in AI-generated text—a distinctive temporal signature associated with the autoregressive generation process.
- We propose a simple yet effective method that operationalizes this phenomenon through second-half temporal features, requiring no additional training or model access beyond a surrogate LLM.
- We achieve state-of-the-art detection performance across multiple benchmarks, demonstrating the value of temporal analysis in machine-generated text detection.

2 Temporal Dynamics of Zero-Shot Detection Metrics

To understand whether discriminative signals vary across text positions, we empirically analyze how these statistics evolve over generation to identify which temporal patterns best distinguish human and AI-generated text.

2.1 Analysis Setup

Datasets and Models. We analyze over 120k text samples from two established benchmarks: EvoBench (Yu et al., 2025) and MAGE (Li et al., 2024). Both datasets contain parallel human-written and AI-generated texts across diverse domains and generation settings. We use Llama-3-8B-Instruct (Grattafiori et al., 2024) as the primary surrogate model for computing token-level statistics. Results with alternative surrogate models GPT-J-6B (Wang and Komatsuzaki, 2021) and Falcon-7B (Almazrouei et al., 2023) are provided in Appendix N. Additional experiments on frontier

models including reasoning-enhanced systems are presented in Appendix O.

Zero-Shot Detection Metrics. We examine six token-level statistics commonly used in zero-shot detection: (1) *log probability* $\log P(x_t|x_{<t})$, reflecting model confidence at each position; (2) *Sampling Discrepancy* (Bao et al., 2024), referred to as conditional probability curvature in the original work; (3) *rank* of the actual token among all vocabulary items; (4) *entropy* of the predicted distribution; (5) *token probability* $P(x_t|x_{<t})$ the raw conditional probability without log transformation; and (6) *top- k concentration*, the cumulative probability of the top-10 tokens.

Temporal Features. To capture the dynamics of these metrics, we compute two second-order features at each position: the *absolute first derivative* $|m_t - m_{t-1}|$, measuring the rate of change between consecutive tokens, and the *local standard deviation* within a sliding window of 20 tokens, quantifying regional volatility. For cross-sample comparison, we normalize token positions to percentiles (0–100%), enabling aggregation across texts of varying lengths.

2.2 Comparative Metric Sensitivity

We first investigate which base metrics exhibit meaningful temporal differences between human and AI-generated text. Figure 2 presents the temporal evolution of all six metrics on EvoBench, showing the raw values (left), absolute derivatives (middle), and local standard deviations (right) across normalized text positions.

Not All Metrics Capture Temporal Dynamics. We first observe that temporal discriminability varies dramatically across metrics. While *log probability* and *sampling discrepancy* show clear separation between human and AI curves, particularly in their derivative and local standard deviation, metrics such as *entropy*, *token probability*, and *top- k concentration* exhibit nearly overlapping trajectories throughout the sequence.

To quantify these differences, we measure the slope ratio: how much steeper AI’s temporal trend is compared to human. As shown in Table 1, log probability exhibits the strongest temporal dynamics, with slope ratios of 2.4 for derivative and 2.6 for local standard deviation on EvoBench, and 2.4 for derivative and 1.8 for local standard deviation on MAGE. Sampling discrepancy shows compara-

Metric	EvoBench		MAGE	
	Deriv.	Local	Deriv.	Local
Log Probability	2.4	2.6	2.4	1.8
Sampling Discrepancy	2.2	2.5	2.3	2.2
Rank	1.2	1.2	1.0	1.1
Entropy	1.4	1.3	1.4	1.2
Token Probability	0.9	–	–	–
Top- k Concentration	1.4	1.3	0.9	1.0

Table 1: Slope ratio across metrics, measuring how many times steeper AI’s temporal trend is compared to human. Higher values indicate stronger temporal dynamics. “–” indicates inconsistent trend directions between human and AI.

ble trends, with ratios of 2.2 (derivative) and 2.5 (local) on EvoBench, and 2.3 (derivative) and 2.2 (local) on MAGE, though it requires additional sampling overhead. In contrast, entropy, token probability, and top- k concentration show slope ratios close to 1.0, indicating minimal temporal differentiation. Based on these findings, we focus subsequent analysis on log probability, which provides the strongest temporal signal without additional computation.

2.3 Late-Stage Volatility Decay

We begin by examining the temporal dynamics of log probability, which emerges as the most informative metric throughout our analysis. Figure 1 visualizes the derivative and local standard deviation of log probability across normalized token positions for human-written and AI-generated text.

Two consistent trends are immediately apparent. First, for both human and AI-generated, volatility decreases as generation progresses, reflecting increasing contextual constraint. Second, and more importantly, AI-generated text stabilizes substantially faster than human text. The decline in both derivative magnitude and local variability is markedly steeper for AI-generated sequences, and the gap between the two curves widens progressively over time.

This divergence becomes most pronounced in the second half of the sequence (50%–100% positions). In this region, AI-generated text exhibits significantly smaller fluctuations in token-level log probability, while human text maintains higher volatility. We refer to this systematic asymmetry as *Late-Stage Volatility Decay*.

Quantitative Characters. Table 2 quantifies the late-stage volatility decay from two complemen-

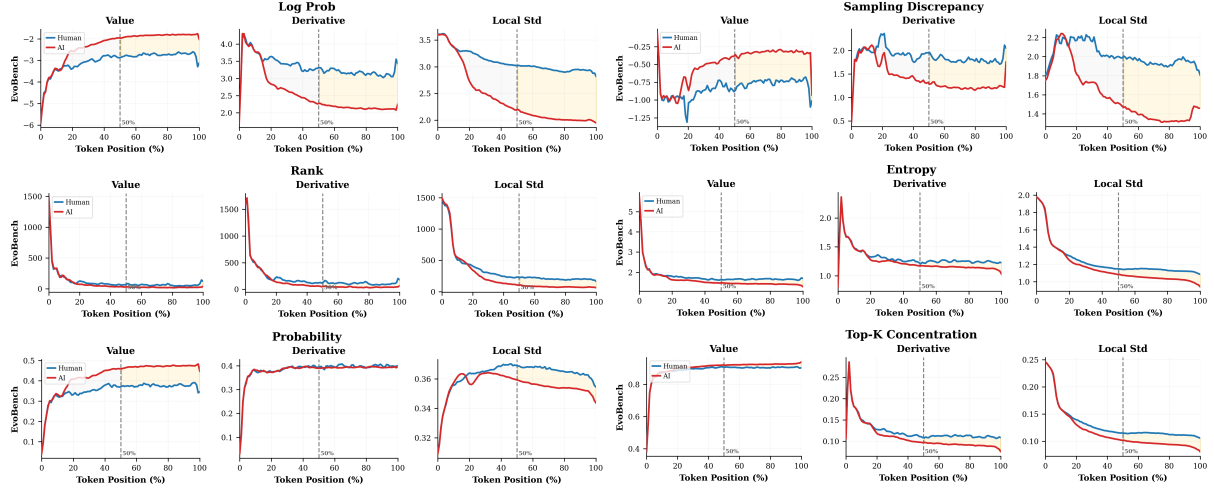


Figure 2: Temporal dynamics of six base metrics on EvoBench. Each row shows a metric’s raw value (left), absolute derivative (middle), and local standard deviation (right) across normalized token positions (0–100%). Log probability and Sampling Discrepancy (alias Conditional Probability Curvature) display clear human-AI separation that widens in the second half, while entropy and top- k concentration show minimal divergence.

Dataset	Feature	H-decay	A-decay	Ratio	Gap%
EvoBench	Derivative	−9.6%	−27.1%	2.4	−32%
	Local Std	−8.9%	−26.5%	2.6	−31%
MAGE	Derivative	−7.5%	−16.7%	1.9	−24%
	Local Std	−7.3%	−16.5%	1.9	−25%

Table 2: Late-stage volatility decay of log probability features. *H-decay/A-decay*: percentage decrease from first to second half for human/AI-generated text. *Ratio*: how many times faster AI decays than human. *Gap%*: relative human-AI difference in the second half. AI-generated text consistently decays 1.9–2.6 faster across datasets.

tary perspectives. The *decay rate* measures how fast each class stabilizes from the first to second half. The *second-half gap* measures the relative difference between human and AI-generated text in later positions, directly reflecting discriminability.

On EvoBench, human text decays by only 9.6% from the first to second half in terms of derivative, while AI-generated text decays by 27.1%, a rate 2.4 times faster. This asymmetric decay widens the human-AI distinction: in the second half, the relative difference reaches 32%. The local standard deviation exhibits the same pattern, where 2.6 times faster AI decay leads to a 31% gap in the second half.

These patterns generalize across datasets. On MAGE, AI-generated text decays approximately 1.9 times faster than human text, resulting in 24–25% second-half gaps for both features. While absolute magnitudes vary between datasets, the

qualitative pattern remains consistent.

Interpretation. We interpret this pattern as a second-order consequence of *uncertainty contraction* in autoregressive generation (Hou et al., 2025). The features DD and LV measure the *volatility* of token surprise $s_t = -\log P(x_t|x_{<t})$ rather than its level, and this volatility is governed by the *varentropy* of the predictive distribution, $V_t = \text{Var}_{x \sim P(\cdot|x_{<t})}[-\log P(x|x_{<t})]$: for text sampled from the model, the local fluctuation amplitude of s_t scales with $\sqrt{V_t}$. As context accumulates, an autoregressive model becomes increasingly committed to topic, entities, and style, so both its predictive entropy and V_t tend to decrease (Basani and Chen, 2025; Hou et al., 2025), and the volatility of surprise contracts accordingly. Human text is not sampled from the surrogate: its surprise reflects a persistent human–model mismatch that writers continually replenish through unexpected lexical and stylistic choices, so its volatility is sustained rather than contracting. Because AI volatility contracts while human volatility persists, the human–AI divergence accumulates over the sequence and is largest in the second half—precisely the decay-ratio and second-half-gap pattern in Table 2.

We stress that this account is a mechanistic *hypothesis* consistent with our observations, not a proof. It is exact for the *generation-time* distribution (a model scoring its own samples), whereas a zero-shot detector measures a *surrogate* scoring a completed text, whose conditionals need not match those of the source generator. Appendix N shows

that the pattern is surrogate-independent across three model families, and Appendix N.4 shows, on an open-source generator, that the decay is present in the generation-time distribution itself and transfers to a different scorer—consistent with this account.

2.4 Summary of Findings

Our empirical analysis demonstrates that AI-generated text exhibits accelerated stabilization in later stages of generation, leading to significantly reduced volatility in token-level surprise. This reveals that discriminative signals are not uniformly distributed across positions, but instead concentrate in the second half of sequences due to this late-stage stabilization. As a result, features computed from the second half capture substantially stronger human–AI divergence than full-sequence averages, which dilute informative late-stage signals with less discriminative early tokens. This insight directly motivates the design of our detection method.

3 Method

Motivated by our empirical analysis in Section 2, we build a simple, training-free method that explicitly exploits this late-stage temporal asymmetry. Rather than aggregating statistics over the entire sequence, we focus on the second half of the text, where the human–AI divergence in token-level dynamics is maximal.

3.1 Late-Stage Stability Metrics

Following Bao et al. (2024), we adopt a surrogate LLM for calculating token-level probabilities. Given a text $x = (t_1, \dots, t_n)$, we query the surrogate model to obtain $p_i = P(t_i \mid t_{<i})$ and define token surprise $s_i = -\log p_i$. Based on the Late-Stage Volatility Decay phenomenon, we focus exclusively on the *second half* of the sequence to characterize late-stage stability. Let $\mathcal{H}_2 = \{i \mid i > \lfloor n/2 \rfloor\}$ denote the set of token positions in the second half. Motivated by the two temporal features examined in Section 2, we define corresponding detection features that directly quantify their dispersion in the second half.

Derivative Dispersion (DD). This feature captures the variability of surprise changes between consecutive tokens.¹ We first compute the absolute

¹Throughout, “derivative” denotes the *discrete first difference* between consecutive tokens; DD may equivalently be read as *First-Difference Dispersion*.

first-order difference of surprise,

$$d_i = |s_i - s_{i-1}|, \quad i = 2, \dots, n, \quad (1)$$

which measures how rapidly surprise fluctuates from one token to the next. We then quantify the dispersion of these change rates in the second half:

$$\text{DD} = \text{Std}(\{d_i\}_{i \in \mathcal{H}_2}). \quad (2)$$

AI-generated text, with its increasingly stable predictions, exhibits lower DD values as the change rates become more uniform in later positions.

Local Volatility (LV). To capture regional stability patterns that may not be reflected in pointwise statistics, we compute a sliding-window standard deviation around each position:

$$\ell_i = \text{Std}(s_{i-w/2}, \dots, s_{i+w/2}), \quad (3)$$

with window size w (default $w=20$). This measures how much surprise varies within a local neighborhood. We then average these local volatility values over the second half:

$$\text{LV} = \text{Mean}(\{\ell_i\}_{i \in \mathcal{H}_2}). \quad (4)$$

This feature is particularly sensitive to the smooth, consistent probability transitions characteristic of AI-generated text in later positions. The same regional-dispersion notion also has a natural coarsest scale: letting the window span the entire late-stage region reduces ℓ_i to the overall dispersion of late-stage surprise,

$$\text{SD} = \text{Std}(\{s_i\}_{i \in \mathcal{H}_2}), \quad (5)$$

which complements the windowed average by capturing region-wide spread that local windows smooth over. We therefore treat SD as the global-scale companion of LV.

3.2 Combined Detection Metric

DD, LV, and SD measure complementary aspects of late-stage volatility—pointwise change rates, windowed regional variation, and region-wide dispersion—and all of them yield lower values for AI-generated text due to late-stage stabilization. We negate their sum to form our Temporal Stability Detection (TSD) score:

$$S_{\text{TSD}} = -(\text{DD} + \text{SD} + \text{LV}). \quad (6)$$

Higher S_{TSD} indicates greater likelihood of AI-generated text. Classification is performed by

thresholding: $\hat{y} = \mathbb{I}[S_{\text{TSD}} > \tau]$, where τ is chosen as the F1-maximizing threshold on a validation split (Youden’s J selects the same operating region). All AUROC comparisons in this paper are threshold-free; Appendix H details the calibration protocol and shows that a single threshold transfers across benchmarks with at most 0.2 F1 loss, together with a sensitivity analysis.

Length-Adaptive Extension. The default $\mathcal{H}_2$ uses the midpoint as the start of the late-stage window. When input length varies substantially across a deployment, this fixed split may be suboptimal: very short inputs leave too few tokens in the second half for stable estimation. We provide a simple training-free router that adjusts the tail ratio based on input length, expanding the analysis window for shorter inputs and retaining the deep tail for longer ones. The router preserves the zero-shot nature of TSD and adds no learned parameters; details and ablations are in Appendix C. All main-paper experiments use the default 50% midpoint.

3.3 Fusion with Global Metrics

Our temporal features capture *when* statistical patterns emerge (late-stage dynamics), which is empirically complementary to existing methods that focus on *what* distributional anomalies exist (sequence-wide aggregation). This complementarity suggests a natural fusion strategy: combining temporal features with global statistical methods to leverage both perspectives.

We demonstrate this with Fast-DetectGPT (Bao et al., 2024), a representative global method that computes sampling discrepancy across the entire sequence. We adopt a simple additive fusion to combine both signals, preserving the zero-shot setting without introducing learned parameters:

$$S_{\text{fusion}} = S_{\text{TSD}} + S_{\text{global}}. \quad (7)$$

The additive form yields gains comparable to multiplicative, max, and weighted alternatives (Appendix I.4), which we interpret as evidence that the two signals are empirically complementary, so the specific combination mechanism matters less than the fact of combining them. Appendix I.5 quantifies this complementarity directly through correlation and error-overlap analyses: the two scores are only moderately correlated within each class, share just 22–30% of their errors, and each corrects a majority of the other’s mistakes.

By explicitly modeling late-stage volatility, our method departs from the common assumption of stationarity in token-level statistics. The resulting features are simple, interpretable, and computationally efficient, yet capture a fundamental temporal signature of machine-generated text.

4 Experiments

4.1 Experimental Setup

Evaluation Benchmarks. We conduct experiments on two complementary benchmarks. **EvoBench** (Yu et al., 2025) specifically targets the evolving nature of LLMs, comprising over 32,000 pairs across seven model families (GPT-4, GPT-4o, Claude, Gemini, LLaMA-2, LLaMA-3, Qwen) with 29 distinct model versions. EvoBench captures both version updates within model families and variations from fine-tuning or quantization, providing a rigorous test for detection robustness as source models evolve. **MAGE** (Li et al., 2024) provides broad coverage with over 30,000 test pairs spanning eight model families (including OpenAI GPT series, LLaMA, OPT, FLAN-T5, and others), representing diverse generation settings across multiple domains.

Baselines. We compare with representative zero-shot detectors from five categories: token-level statistics, including Likelihood (Solaiman et al., 2019), Entropy (Gehrmann et al., 2019), Rank (Gehrmann et al., 2019), and Log-Rank (Mitchell et al., 2023); relative scoring, including LLR (Su et al., 2023); perturbation-based detection, including Fast-Detect (Bao et al., 2024); sequential methods, including Lastde (Xu et al., 2025), FourierGPT (Xu et al., 2024), and Diverge (Basani and Chen, 2025); and UCE (Hou et al., 2025), an uncertainty-contraction estimator originally proposed for model-generated time series that we apply to token-surprisal sequences. All baselines use the same surrogate model for fair comparison.

Implementation Details. We use Llama-3-8B-Instruct as the surrogate model and truncate inputs to 512 tokens. TSD computes DD and LV on the second half of each sequence, with window size $w=20$ for LV. TSD+ denotes additive fusion with Fast-DetectGPT (Bao et al., 2024). Following prior work (Mitchell et al., 2023; Bao et al., 2024), we report AUROC as the primary metric.

Category	Method	EvoBench								MAGE
		LLaMA-3	LLaMA-2	Claude	GPT-4o	Gemini	GPT-4	Qwen	Avg	Avg
Global	Likelihood	88.84	61.68	79.70	77.80	78.89	77.80	77.40	77.44	56.81
	Entropy	28.85	57.58	33.61	35.43	38.34	38.10	30.34	37.46	51.90
	Rank	68.49	58.38	64.50	64.64	64.46	63.43	55.06	62.71	58.99
	Log-Rank	86.47	59.99	77.37	76.80	75.99	74.87	76.10	75.37	55.91
	LLR	66.46	49.61	61.73	60.57	59.12	58.43	63.08	59.86	51.78
	Fast-Detect	<u>94.17</u>	80.27	81.57	74.89	80.48	75.58	71.96	79.85	69.69
Temporal	Lastde	90.80	80.54	76.75	71.34	76.50	71.51	69.20	76.66	70.71
	FourierGPT	63.99	57.23	58.20	55.52	56.69	55.16	64.39	58.74	60.34
	Diveye	84.65	73.46	74.21	73.32	74.06	72.28	68.85	74.40	69.60
	UCE	75.62	61.35	68.72	62.04	61.28	59.38	63.63	64.57	54.17
Ours	DD	91.12	80.77	82.56	80.57	79.86	78.48	71.78	80.73	71.72
	LV	92.57	79.79	82.51	84.88	84.64	83.58	74.55	83.22	71.26
	TSD	92.33	<u>80.91</u>	<u>85.20</u>	84.55	84.06	82.93	73.58	<u>83.36</u>	71.56
	TSD+	94.50	83.42	87.12	85.68	87.40	85.00	74.48	85.37	75.20

Table 3: Detection performance (AUROC %) on EvoBench and MAGE. DD: Derivative Dispersion; LV: Local Volatility; TSD: the combined score in Eq. (6); TSD+: TSD fused with Fast-DetectGPT. Best results are **bolded**, second best are underlined. Full MAGE results in Appendix A.1; bootstrap 95% confidence intervals in Appendix G.

4.2 Main Results

Table 3 reports detection performance on EvoBench and MAGE. We show per-family results for EvoBench and average results for MAGE, with full MAGE results in Appendix A.1.

TSD achieves the best standalone performance, reaching 83.36% AUROC on EvoBench and 71.56% on MAGE, outperforming all baselines including Fast-DetectGPT. This is achieved with only simple second-half dispersion statistics, without perturbation sampling or frequency-domain analysis. The gains are especially clear on recent and capable generators. On GPT-4o and GPT-4, TSD improves over Fast-DetectGPT by 9.66% and 7.35%, respectively, suggesting that late-stage volatility remains discriminative even when global distributional anomalies become less pronounced. Compared with other temporal methods, TSD also performs better than Lastde (76.66%) and Diveye (74.40%) on EvoBench, indicating the benefit of explicitly targeting late-stage stabilization.

Combining TSD with Fast-DetectGPT further improves performance. TSD+ reaches 85.37% on EvoBench and 75.20% on MAGE, showing that temporal stability and global discrepancy provide complementary signals. To make the respective contributions explicit: *standalone* TSD establishes the value of the late-stage signal by itself on EvoBench (83.36 vs. 79.85 for the best baseline), as well as on RAID and M4, where it attains the best average AUROC among all evaluated methods (Appendices D and E). On MAGE—whose gen-

Position	DD		LV		TSD	
	Evo	MAGE	Evo	MAGE	Evo	MAGE
First Half	59.91	66.54	62.37	67.26	63.59	68.02
Full Seq	72.64	70.31	75.82	70.39	77.00	70.49
Second Half	80.73	71.71	83.21	71.25	83.36	71.56

Table 4: Ablation on position selection.

erators are heterogeneous and include many short FLAN-T5 outputs (Appendix A)—standalone TSD (71.56) is on par with the strongest temporal baseline (Lastde, 70.71), and the additional headroom comes from fusion. The gain from fusion is therefore particularly useful on MAGE, where generators are more heterogeneous. In Appendix I.4, we further explore alternative fusion strategies and show that improved fusion can further enhance performance, suggesting that the reported TSD+ results are a simple yet effective instantiation rather than the upper bound of temporal-global integration. Bootstrap-resampled confidence intervals in Appendix G confirm that TSD significantly outperforms Fast-DetectGPT on both benchmarks ($p < 0.01$).

4.3 Ablation Study

Position Selection. To validate the importance of late-stage features, we compare three position selection strategies: using only the first half, the full sequence, and only the second half of text. As shown in Table 4, second-half features substantially outperform alternatives across all metrics and datasets. On EvoBench, TSD computed from the second half

Base Metric	EvoBench	MAGE
Entropy	53.52	55.24
Probability	61.69	55.37
Top-10 Concentration	53.06	55.66
Rank	76.06	62.98
Sampling Discrepancy	77.66	68.97
Log Probability (Ours)	83.36	71.56

Table 5: TSD performance with different base metrics.

achieves 83.36%, compared to 77.00% for the full sequence and only 63.59% for the first half. The performance gap between second-half and first-half features exceeds 20 points on EvoBench, directly confirming that late-stage volatility decay provides the primary discriminative signal. Using the full sequence dilutes this signal with less informative early-stage statistics, resulting in intermediate performance. A finer-grained sweep over seven position ranges (Appendix I.1) shows monotonic improvement from early to mid-late positions and a drop when the window is restricted to the last third or quarter, where too few tokens remain for reliable estimation. Additional experiments in Appendix K further confirm that the relative midpoint (50%) consistently outperforms fixed absolute positions across datasets.

Base Metric Selection. We evaluate the effectiveness of different base metrics for computing temporal features, applying the same TSD computation to each metric.

As shown in Table 5, log probability substantially outperforms all alternatives, achieving 83.36% on EvoBench compared to 77.66% for sampling discrepancy and 76.06% for rank. Entropy, probability, and top-10 concentration yield near-random performance below 62%. This result aligns with our analysis in Section 2: log probability directly measures token surprise, which exhibits the clearest late-stage volatility decay pattern due to the autoregressive generation mechanism. A mechanistic explanation for why these alternative metrics show weaker temporal divergence is provided in Appendix J. Per-base-metric DD and LV breakdowns are in Appendix I.2, and a window-size ablation for LV is in Appendix I.3.

4.4 Robustness Analysis

We further evaluate robustness along three dimensions beyond the standard EvoBench/MAGE setting, with full results reported in the appendix.

Input length stability. Like all zero-shot detectors, our method depends on having enough tokens for reliable estimation, an issue widely observed in this line of work and explicitly acknowledged by commercial systems (e.g., minimum-length requirements of 100–300 words). A length-binned comparison across all methods (Appendix B) shows that this degradation pattern is shared by every zero-shot baseline—Fast-DetectGPT, Lastde, and Diveye all lose 28–35 pp from their best to their worst bin—and that TSD+ in fact achieves the strongest absolute performance in the most challenging short-text regime (68.99% in the 0–80 token bin). A simple length-adaptive variant (Appendix C) further closes the gap on short inputs without learned parameters. We therefore view length as a property of the detection problem itself rather than a specific limitation of our temporal design.

Adversarial robustness. On RAID (Dugan et al., 2024), which includes whitespace, case, synonym, misspelling, and paraphrase attacks, TSD achieves the best average AUROC of 0.792 and ranks first on four of five attacks. It outperforms Fast-DetectGPT by 20.0 points on average, suggesting that second-order temporal statistics are less affected by local surface perturbations than curvature-based global scores. Full results are in Appendix D.

Multilingual generalization. On the multilingual M4 subset (Wang et al., 2024), covering eight languages, TSD achieves the best average AUROC of 0.904, outperforming Fast-DetectGPT at 0.838. Notably, TSD remains strong on Chinese, where Fast-DetectGPT degrades substantially, indicating that late-stage volatility is relatively robust to tokenization and language variation. Full results are in Appendix E.

5 Related Work

We review zero-shot detection for LLM-generated text, broadly grouping prior work into two streams: *global statistical methods* that aggregate distributional cues over the whole text, and *sequential/temporal methods* that exploit how token-level probability signals evolve along the generation trajectory.

Global Statistical Detection Methods. Zero-shot detection leverages surrogate LLMs to extract distributional artifacts without requiring task-specific training data. Early approaches focused on

absolute token statistics, employing metrics such as entropy, perplexity, and rank histograms to identify machine-generated anomalies (Gehrmann et al., 2019; Solaiman et al., 2019; Ippolito et al., 2020). To improve robustness, perturbation-based methods emerged, measuring the local curvature of the log-likelihood landscape around the candidate text, as exemplified by DetectGPT (Mitchell et al., 2023) and its more efficient variant Fast-DetectGPT (Bao et al., 2024) and Glimpse (Bao et al., 2025). Concurrently, relative probability approaches have been developed to normalize scores through cross-model comparisons or likelihood ratios, including DetectLLM (Su et al., 2023), Binoculars (Hans et al., 2024), DNA-GPT (Yang et al., 2024b), and intrinsic dimension estimation (Tulchinskii et al., 2023). Despite their diversity, these methods primarily rely on *global aggregation*, which average statistics over the entire sequence and treat token positions as exchangeable, overlooking the critical temporal dynamics of the generation process.

Sequential and Temporal Analysis. While global statistics provide strong baselines, recent work has shifted toward analyzing the dynamic evolution of probability signals. In the frequency domain, Spectrum (Xu et al., 2024) and MGT-Prism (Liu et al., 2025) reveal that AI-generated text exhibits consistent spectral artifacts in likelihood curves. In the time domain, Lastde (Xu et al., 2025) mines discriminative local subsequences from probability vectors, and DivEye (Basani and Chen, 2025) quantifies the rhythmic diversity of surprisal fluctuations. Theoretical studies have further hypothesized that recursive generation leads to uncertainty contraction over time (Hou et al., 2025), originally in the context of model-generated time series—a view that transfers naturally to token-surprisal sequences. While these methods may implicitly capture some late-stage signals, for instance, low-frequency components could encode long-range patterns, they do not explicitly analyze the temporal dynamics of the second half, nor do they characterize the specific features we identify. Our work provides the first systematic analysis revealing late-stage volatility decay, where AI-generated text exhibits monotonically decreasing variability as context accumulates.

6 Conclusion

We investigated *Late-Stage Volatility Decay*, a temporal signature of autoregressive generation

wherein AI-generated text exhibits progressively stabilizing token-level statistics while human writing maintains higher variability throughout. We propose simple yet effective features: Derivative Dispersion and Local Volatility for AI-generated text detection. Despite their simplicity, these temporal features achieve state-of-the-art performance on standard benchmarks across different model families, and demonstrate strong complementarity with global methods, particularly excelling on longer texts where late-stage dynamics fully manifest. Our findings suggest that exploiting the temporal structure of autoregressive generation offers a promising direction for robust detection as language models continue to evolve.

Limitations

TSD assumes sufficient tokens for late-stage estimation: like all zero-shot detectors, it degrades substantially on inputs under roughly 80 tokens (Appendix B), and although TSD+ remains the strongest method in this regime and the length-adaptive router (Appendix C) recovers part of the gap, detection on very short texts remains unreliable. Our evaluation also targets fully human-versus fully AI-written text; in mixed-authorship settings, surface-level AI polishing of human drafts smooths part of the volatility TSD relies on and raises the false-positive rate from 11.7% to 27.0% (Appendix F)—a failure mode shared by all surrogate-probability detectors and partially mitigated by a decay-consistency extension, though co-written text remains an open challenge. More broadly, unusually formulaic human writing (e.g., non-native or heavily edited prose) may be misclassified as AI-generated, paraphrase and white-box attacks can reduce accuracy (Appendix D), and deploying a binary classifier requires threshold calibration on a representative pooled mix (Appendix H). Because both error types carry real costs, TSD should not be the sole basis for consequential decisions and is best used as one signal among several, with human review. Finally, TSD+ uses simple score addition with Fast-DetectGPT; dynamic or learned fusion is left to future work.

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A MAGE Results

A.1 Detailed Results

Table 6 presents the complete detection performance on the MAGE benchmark across all eight generator families.

The MAGE benchmark reveals complementary strengths across detection approaches, with different methods excelling on specific generator families due to architectural and distributional mismatches with the surrogate model.

Our temporal features achieve the strongest performance on generators that are closer to the Llama-3 surrogate in their decoding behavior. Specifically, LV attains 91.79% on OpenAI, 94.41% on GLM, and 95.45% on LLaMA, outperforming all baselines in these categories. Even the simple DD feature remains competitive (86.75%, 91.94%, and 90.76%), suggesting that derivative-based temporal dispersion captures reliable generation dynamics when the surrogate can effectively characterize token-level uncertainty.

The Human-Paraphrase category is particularly challenging because humans revise AI outputs to evade global distributional detectors. Here, TSD+ reaches 72.03%, outperforming Fast-DetectGPT (61.92%) by over 10 points. A plausible explanation is that human edits can dilute global cues while still leaving residual late-stage temporal irregularities inherited from the original model output; fusing temporal and global signals mitigates this mismatch.

For generator families that diverge substantially from decoder-only Transformers, global baselines can become more reliable. Fast-DetectGPT achieves the best performance on FLAN-T5 (76.29%) and BigScience (72.40%). Importantly, FLAN-T5 samples in MAGE are also typically shorter, which limits the available “late-stage” token budget and makes temporal cues less stable. In such cases, Fast-DetectGPT provides a complementary, less length-sensitive signal that compensates for the reduced temporal evidence, lifting TSD from 35.17% to 55.92% on FLAN-T5.

Overall, while no single method dominates every family, TSD+ achieves the best average AU-ROC (75.20%) by avoiding catastrophic failures and remaining robust across heterogeneous generators. When temporal features are strong (e.g., LLaMA), they substantially improve over global baselines; when temporal evidence is weak (notably for short or architecturally dissimilar gen-

Category	Method	MAGE								
		OpenAI	GLM	Human-Para	FLAN	LLaMA	BigScience	OPT	EleutherAI	Avg
Global	Likelihood	89.12	91.30	60.61	30.98	92.96	37.51	31.00	21.02	56.81
	Entropy	23.08	17.98	62.83	66.65	20.30	<u>66.22</u>	<u>76.39</u>	<u>81.76</u>	51.90
	Rank	73.74	83.12	53.58	34.93	81.74	45.49	52.75	46.63	58.99
	Log-Rank	87.05	90.28	53.81	31.56	91.69	37.38	32.39	23.10	55.91
	LLR	72.90	74.24	36.21	36.17	78.09	39.97	40.17	36.52	51.78
	Fast-Detect	76.40	80.41	61.92	76.29	67.35	72.40	64.61	58.12	69.69
Temporal	Lastde	74.47	83.87	62.96	66.35	72.01	64.63	72.35	69.07	70.71
	FourierGPT	59.31	84.88	68.32	4.72	84.39	39.60	57.55	63.97	60.34
	Diveye	87.89	92.61	62.10	34.65	93.80	52.00	67.60	66.11	69.60
	UCE	18.81	20.02	<u>70.60</u>	<u>67.05</u>	23.48	62.86	82.81	87.73	54.17
Ours	DD	86.75	91.94	61.98	39.60	90.76	55.71	74.84	72.16	<u>71.72</u>
	LV	91.79	94.41	67.21	34.61	95.45	53.38	69.01	64.20	<u>71.26</u>
	TSD	<u>90.84</u>	<u>94.01</u>	65.42	35.17	<u>94.17</u>	53.78	71.79	67.34	71.56
	TSD+	89.13	93.19	72.03	55.92	88.34	64.88	72.74	65.36	75.20

Table 6: Full detection performance (AUROC %) on MAGE benchmark across all generator families. Human-Para refers to human-paraphrased AI text. DD: Derivative Dispersion; LV: Local Volatility; TSD: Temporal Stability Detection; TSD+: TSD fused with Fast-DetectGPT. Best results are **bolded**, second best are underlined.

erations), the Fast-DetectGPT component acts as a safety net. This complementarity supports our hypothesis that temporal dynamics and global distributional discrepancies capture complementary aspects of AI-generated text (quantified directly in Appendix I.5). A per-family length–performance breakdown is reported jointly with the EvoBench view in Appendix B.1.

B Length-Binned Evaluation Across Methods

Section 4 of the main paper notes a positive correlation between sequence length and TSD performance. A natural question is whether this length sensitivity is a TSD-specific weakness, or a property shared by zero-shot AI-text detection in general. To answer this, we partition the combined EvoBench + MAGE evaluation data into five token-length bins (0–80, 80–150, 150–250, 250–350, ≥ 350 tokens) and evaluate every method under identical conditions and using the same surrogate model (LLaMA-3-8B-Instruct).

Table 7 highlights three findings.

(1) Length sensitivity is field-wide, not TSD-specific. Every zero-shot detector exhibits a substantial drop in the 0–80 bin: Fast-DetectGPT loses 28.9 points relative to its ≥ 350 score; Lastde loses 31.4; Diveye loses 33.3. This is consistent with the well-documented fact that human and machine distributions overlap more in short contexts, and with the minimum-length requirements enforced by commercial systems (e.g., Turnitin: 300 words;

GPTZero: ≥ 200 words; Originality.ai: 100 words). A complementary per-family view across both EvoBench and MAGE is reported in Appendix B.1, and shows the same pattern—indicating that the positive length–AUROC correlation is a property of the detection problem itself rather than an artifact of our temporal design.

(2) TSD+ is the best-performing method on short text. In the most challenging 0–80 bin, TSD+ reaches 68.99, outperforming Fast-DetectGPT (65.65, -3.34 pp), Lastde (63.61, -5.38 pp), and Diveye (61.23, -7.76 pp). DD alone (68.59) is already competitive with Fast-DetectGPT despite using no perturbation sampling.

(3) Relative degradation is comparable or smaller for TSD. Going from the ≥ 350 bin to the 0–80 bin, TSD degrades by 29.6% relative to its peak, comparable to Fast-DetectGPT (30.6%) and smaller than Diveye (35.2%) and Lastde (33.0%). The temporal framework is therefore not a uniquely fragile design on short text.

Together with the adaptive variant in Appendix C, these results reframe the short-text question: rather than being a weakness of our method, length sensitivity is a shared limitation that TSD navigates better than existing alternatives.

B.1 Length Sensitivity Across Generator Families

To complement the cross-method length-binned analysis in Appendix B (which pools data into token-length bins and compares all methods), we

Method	0–80	80–150	150–250	250–350	≥ 350
Likelihood	63.59	67.60	79.36	68.18	63.16
Entropy	52.15	52.36	62.79	53.13	51.29
Rank	54.91	61.23	69.88	73.33	70.78
Log-Rank	62.15	66.66	77.75	66.25	61.74
LLR	53.40	56.13	64.25	56.78	52.88
Fast-DetectGPT	65.65	83.93	88.08	91.31	94.53
Lastde	63.61	85.99	88.06	91.95	94.98
UCE	54.44	56.08	79.91	61.62	54.24
FourierGPT	57.04	64.93	69.42	59.89	70.33
Diveye	61.23	81.65	90.18	91.50	94.51
DD (Ours)	<u>68.59</u>	<u>87.03</u>	91.66	93.90	95.48
LV (Ours)	67.71	86.09	92.99	92.78	94.10
TSD (Ours)	67.33	86.88	<u>93.15</u>	<u>94.23</u>	<u>95.70</u>
TSD+ (Ours)	68.99	87.56	91.99	94.66	96.01

Table 7: AUROC (%) by token-length bin on the combined EvoBench + MAGE evaluation data. All methods share the same LLaMA-3-8B-Instruct surrogate. Best per column **bolded**; second-best underlined.

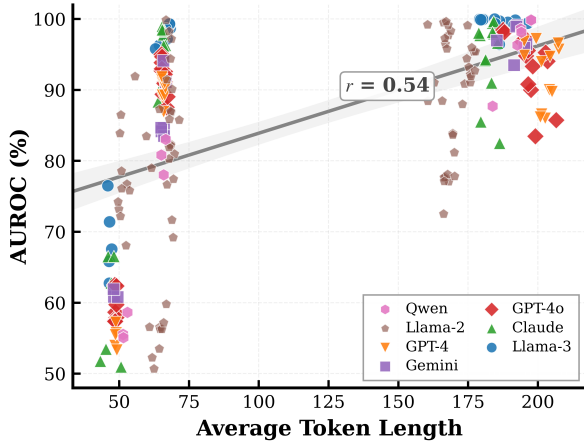


Figure 3: TSD performance (AUROC) versus average token length across seven EvoBench source families. Each point is one family; the dashed line is a linear regression fit (Pearson $r = 0.54$).

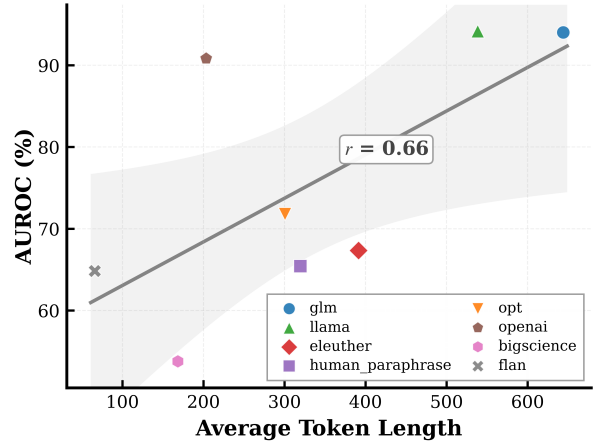


Figure 4: TSD performance (AUROC) versus average token length across eight MAGE generator families. Each point is one family; the dashed line is a linear regression fit (Pearson $r = 0.66$).

now report a per-family view: how TSD performance varies across the natural length distribution of each source. Figure 3 plots TSD AUROC against the average token length of every family in EvoBench, and Figure 4 shows the corresponding view on MAGE.

The two benchmarks show a consistent picture. On EvoBench, we observe a moderate positive correlation between average length and AUROC (Pearson $r = 0.54$): TSD reliably exceeds 82% on families whose outputs exceed 150 tokens on average, while the cases below 70% all correspond to families whose average length falls under 100 tokens. On MAGE, the same trend is even more pronounced ($r = 0.66$): families with shorter outputs (notably FLAN-T5) exhibit weaker temporal separability, which partially explains why TSD under-

performs on FLAN-T5 in Table 6, while LLaMA, OpenAI, and GLM families—whose outputs are long enough to fully expose the late-stage decay—reach the highest TSD scores.

We emphasize that this per-family trend should be read jointly with the cross-method length-binned comparison in Table 7 rather than in isolation. That comparison shows that *every* zero-shot baseline degrades substantially on short inputs—Fast-DetectGPT, Lastde, and Diveye lose between 28.9 and 33.3 points from their best to their worst bin—which is consistent with the well-documented fact that human and machine distributions overlap more in short contexts. Concretely, in the most challenging 0–80 token bin, TSD+ still achieves the highest absolute AUROC (68.99%) among all evaluated methods, and TSD’s relative degradation across

bins is smaller than that of Diveye and Lastde. Taken together with Figures 3 and 4, length should therefore be viewed as a property of the zero-shot detection problem itself, not as a TSD-specific limitation. This length sensitivity also motivates our fusion strategy: Fast-DetectGPT contributes a complementary global discrepancy signal that remains effective even when the available temporal evidence is limited, improving robustness across length-diverse generators. As shown in Appendix C, a simple training-free length-adaptive router further narrows the remaining gap on short inputs.

C Length-Adaptive Segmentation

The standard TSD computes statistics over the second half of the input ($r = 0.5$, where r denotes the *tail ratio*: the fraction of the sequence used as the late-stage window). On very short inputs, the second half contains too few tokens for reliable estimation. Motivated by this observation, we explore a training-free length-aware router that adjusts the tail ratio as a function of input length:

$$r(n) = \begin{cases} 0.7, & n < 80, \\ 0.6, & 80 \leq n \leq 250, \\ 0.5, & n > 250, \end{cases} \quad (8)$$

where n is the number of tokens. The intuition is that shorter texts have fewer tokens in their second half, so expanding the analysis window captures more of the available temporal pattern; longer texts focus on the deep tail where the volatility-decay signal is strongest. The router is deterministic and adds no learned parameters, preserving the zero-shot nature of TSD.

Table 8 shows that the adaptive router yields consistent improvements across all bins, with the largest gain on the shortest texts (+2.79 pp on 0–80). Two implications follow. First, the temporal framework is not inherently bounded by the 50% midpoint: a simple length-aware rule already recovers meaningful headroom on short text. Second, this leaves space for more sophisticated future extensions such as learned or continuous-position weightings.

C.1 Data-Driven Justification of the Router

The boundaries (80/250 tokens) and tail ratios (0.7/0.6/0.5) are derived from the data rather than hand-picked. Sweeping the tail ratio r per length bin on the saved per-sample scores of our main

configuration (LLaMA-3-8B-Instruct surrogate, EvoBench + MAGE), the empirically best ratio *decreases monotonically with length*, as shown in Table 9: the 0–80 bin is best served by a large tail ratio ($r = 0.7$, i.e., using most of the text), whereas the longest bins favor a deep tail ($r = 0.1$). This monotone trend holds for 9 out of 9 scoring configurations (TSD, DD, LV, Fast-DetectGPT, and all fusion variants) and on *both* benchmarks individually, which also answers the transfer question: the same routing rule captures the empirical trend on either benchmark. The router $r(n) = 0.7/0.6/0.5$ is a conservative monotone approximation of this empirical optimum, and the 80/250 boundaries mark where the best ratio transitions.

Table 10 reports the per-bin sensitivity around the optimum, together with sample counts and 95% confidence intervals (Hanley–McNeil). Three observations follow. (i) The router recovers the per-bin oracle within ≤ 0.03 AUROC in every bin. (ii) AUROC is stable near the optimum (e.g., in the 0–80 bin, moving r from 0.3 to 0.7 spans only 65.5–66.9), and large drops occur only when a long-text ratio is applied to short texts or vice versa (e.g., $r = 0.9$ on the 80–150 bin loses 13.7 points); this is precisely the mismatch the router avoids, indicating that the router captures real structure rather than fitting noise. (iii) Per-bin sample sizes of 2.5k–30k per class yield tight confidence intervals.

D Adversarial Robustness on RAID

We evaluate adversarial robustness on the RAID benchmark (Dugan et al., 2024), which contains parallel human / AI examples perturbed by a set of attacks targeting different surface levels. We use five attack types: whitespace manipulation, upper/lower case perturbation, synonym substitution, perplexity-based misspelling, and paraphrase. Each split contains 3,547 labeled pairs. All methods use the same surrogate model (LLaMA-3-8B-Instruct) and inference configuration.

Observations. Table 11 summarizes the results. TSD attains the best average AUROC (0.792), outperforming every baseline. On four of the five attacks (whitespace, upper/lower, synonym, misspelling), TSD is the top performer. On paraphrase—where global distributional properties are most heavily altered—TSD (0.713) remains close to the best baseline (LLR, 0.739), while perturbation-based Fast-DetectGPT drops to 0.628.

Several patterns are worth highlighting.

Method	0–80	80–150	150–250	250–350	≥350
TSD (standard)	67.33	86.88	93.15	94.23	95.70
TSD Adaptive	70.12	88.86	94.92	95.32	97.18
Δ	+2.79	+1.98	+1.77	+1.09	+1.48

Table 8: AUROC (%) of standard TSD vs. the length-adaptive variant on the combined EvoBench + MAGE data. The adaptive variant improves performance in every bin, with the largest gain on the shortest texts.

Benchmark	0–80	80–150	150–250	250–350	≥350
EvoBench	0.7	0.3	0.3	–	–
MAGE	0.3	0.3	0.3	0.1	0.1
Merged	0.7	0.3	0.3	0.1	0.1

Table 9: Empirically best tail ratio r per length bin (TSD). “–” indicates bins with too few samples in that benchmark. The best ratio decreases monotonically with length on both benchmarks, matching the monotone structure of the router.

Curvature-style methods (Fast-DetectGPT, Lastde, Diveye) lose substantial ground under surface-level perturbations because their signals operate on absolute log-probability values, which are easily disturbed by local edits. In contrast, TSD’s second-order temporal features (derivative dispersion and local volatility) measure how surprise *fluctuates* in a region; isolated token-level edits do not easily disrupt the aggregate volatility pattern across the second half.

White-box attacks targeting the second half.

An informed adversary could in principle attempt to mask LSVD by injecting high-variability tokens specifically in the second half of the sequence. We note three points. First, this requires white-box knowledge of the detector. Second, injecting artificial variability while maintaining fluency is non-trivial and may introduce its own detectable artifacts. Third, most zero-shot detectors share comparable white-box vulnerabilities under matched threat models. We leave a systematic study of targeted attacks on temporal features to future work; the limitation is acknowledged explicitly in the main paper’s Limitations.

E Multilingual Generalization on M4

We further evaluate whether late-stage volatility decay generalizes beyond English. We use a multilingual subset of the M4 benchmark (Wang et al., 2024) covering eight typologically diverse languages: Arabic (AR), Bulgarian (BG), Chinese (ZH), English (EN), German (DE), Indonesian (ID),

Russian (RU), and Urdu (UR). Each language contains 120 human and 120 machine samples (1,920 total pairs). All methods use the same LLaMA-3-8B-Instruct surrogate.

Observations. Table 12 reports per-language results. TSD achieves the best overall average (0.904), outperforming Fast-DetectGPT (0.838), Lastde (0.831), and all baselines except being marginally above Diveye (0.887) on average. Crucially, TSD is robust across typologically distant language families: Semitic (Arabic 0.928), Slavic (Bulgarian 0.910), Sino-Tibetan (Chinese 0.925), Germanic (English 0.977, German 0.827), Austronesian (Indonesian 0.989), and Indo-Aryan (Urdu 0.993). This supports the view that late-stage volatility decay is a language-agnostic regularity consistent with autoregressive generation rather than an English-specific artifact.

Chinese. A particularly notable observation is that Fast-DetectGPT collapses on Chinese (0.526), while TSD remains strong (0.925). One plausible explanation is that perturbation-based methods are more sensitive to tokenization properties of non-Latin scripts (e.g., BPE behavior on CJK characters), while temporal volatility features operate on the relative dynamics of the generation trajectory and are less affected.

Russian. Russian is the most challenging language for nearly every method (most below 0.70). This is likely a consequence of limited Cyrillic data in the LLaMA-3 pretraining mix, which weakens the surrogate’s calibration for both human and machine Russian text. TSD’s score (0.686) is the best among all evaluated methods on this language. We expect further improvement with a more language-appropriate surrogate.

F Impact of AI-Polished Human Text

Our main evaluation targets fully human-written versus fully AI-generated text (including MAGE’s Human-Paraphrase split, where humans revise

Bin	n (human/AI)	$r=0.1$	$r=0.3$	$r=0.7$	$r=0.9$	Router	Bin-oracle	Router 95% CI
0–80	30,083 / 29,987	63.37	65.48	66.86	64.67	66.86	66.89	[66.43, 67.29]
80–150	14,146 / 13,112	85.86	87.70	83.49	74.05	87.70	87.70	[87.28, 88.13]
150–250	12,024 / 11,895	93.98	94.48	89.42	80.56	94.48	94.48	[94.18, 94.78]
250–350	2,485 / 2,836	95.32	95.31	90.03	81.55	95.31	95.32	[94.74, 95.88]
≥ 350	5,119 / 6,028	97.18	96.80	93.67	85.59	97.18	97.18	[96.87, 97.48]

Table 10: Tail-ratio sensitivity per length bin (TSD AUROC %, EvoBench + MAGE merged), with per-bin sample counts, the routed and per-bin-oracle results, and Hanley–McNeil 95% confidence intervals for the routed result. This analysis re-derives per-bin scores from the saved per-sample outputs of the main configuration; minor differences from Table 8 reflect pooling details, and the relative structure is the object of interest here.

Method	Whitespace	Upper/Lower	Synonym	Misspelling	Paraphrase	Avg
Likelihood	0.727	0.735	0.825	0.727	0.643	0.731
Entropy	0.739	0.723	0.789	0.715	0.687	0.731
Rank	0.747	0.729	0.791	0.717	0.683	0.733
Log-Rank	0.752	0.757	0.843	0.747	0.684	0.757
LLR	0.765	0.766	0.839	0.749	0.739	<u>0.772</u>
Fast-DetectGPT	0.582	0.570	0.663	0.519	0.628	0.592
Lastde	0.626	0.634	0.720	0.586	0.667	0.647
FourierGPT	0.615	0.617	0.548	0.596	0.654	0.606
Diveye	0.626	0.617	0.634	0.653	0.554	0.617
UCE	0.752	0.753	0.813	0.745	<u>0.719</u>	0.756
TSD (Ours)	0.786	0.795	0.855	0.810	0.713	0.792

Table 11: AUROC under five adversarial attacks on RAID. Best per column **bolded**; second-best underlined.

AI outputs). Here we study the *inverse* mixed-authorship scenario: a human-written draft that undergoes surface-level AI refinement. Since we attribute sustained human volatility to unexpected lexical and stylistic choices, a machine polisher might smooth out these signals and inadvertently make human text mimic the AI pattern, producing false positives.

Setup. We take 300 human news paragraphs from CNN/DailyMail (Hermann et al., 2015) and have Qwen2.5-7B-Instruct (Yang et al., 2024a) *lightly polish* each one (improving fluency, grammar, and word choice while preserving meaning and length). We then score the *original-human*, *polished-human*, and a matched set of *real AI* texts (MAGE machine samples) with TSD under the paper’s LLaMA-3-8B-Instruct surrogate, and report the mean TSD score, the human-vs-AI AUROC before and after polishing, and the false-positive rate (FPR) at a fixed operating threshold ($\tau = \text{F1-max}$ on original-human vs. AI).

Polishing does smooth human volatility. Table 13 confirms the concern. Surface AI polishing shifts human text toward the AI side: the mean TSD score rises from -5.67 to -5.36 (closing roughly 27% of the human–AI gap), human-vs-AI separability drops by 6.3 AUROC points (81.66

$\rightarrow 75.32$), and the FPR at a fixed threshold more than doubles ($11.7\% \rightarrow 27.0\%$). We note two qualifications. First, this failure mode is *not specific to TSD*: polishing rewrites human text to be more model-like, which erodes the human–model mismatch that every surrogate-probability zero-shot detector depends on (likelihood-, curvature-, and temporal-based alike). Second, the degradation is partial—after polishing, 73% of human texts are still classified correctly and the AUROC remains well above chance. We nonetheless list mixed-authorship text as an explicit limitation.

A training-free decay-consistency mitigation.

The temporal framework itself offers a mitigation. Genuine AI generation produces a characteristic late-stage *decay* of volatility (high early $\rightarrow$ low late), whereas a uniform surface polisher merely suppresses volatility without reproducing that decay trajectory: the mean relative late-stage decay is 0.149 for real AI text versus 0.085 for polished-human and 0.064 for original-human text. We therefore augment TSD with a *decay-consistency* term that calls a text AI only if its late-stage volatility is low *and* it exhibits an AI-like decay pattern. Table 14 evaluates all detectors at a matched operating point (10% FPR on genuine human text).

The decay-consistency variant Pareto-dominates

Method	AR	BG	ZH	EN	DE	ID	RU	UR	Avg
Likelihood	0.870	0.919	0.948	0.964	0.735	0.967	0.627	0.998	0.879
Entropy	0.600	0.846	0.941	0.888	0.556	0.827	0.556	0.950	0.770
Log-Rank	0.864	0.912	<u>0.952</u>	0.966	0.719	0.964	0.628	0.998	0.875
LLR	0.796	0.823	<u>0.955</u>	0.948	0.597	0.862	0.608	0.933	0.815
Fast-DetectGPT	0.914	0.909	<u>0.526</u>	0.969	0.835	0.957	0.598	0.998	0.838
Lastde	0.956	0.847	0.594	0.949	0.837	0.941	0.546	0.974	0.831
FourierGPT	0.576	0.732	0.627	0.652	0.634	0.556	0.560	0.868	0.651
Diveye	0.916	0.880	0.917	0.972	0.838	0.971	0.684	0.920	<u>0.887</u>
UCE	0.649	0.759	0.937	0.852	0.614	0.834	0.536	0.891	0.759
TSD (Ours)	<u>0.928</u>	<u>0.910</u>	0.925	0.977	0.827	0.989	0.686	0.993	0.904

Table 12: AUROC across 8 languages on the M4 subset. Best per column **bolded**; second-best underlined.

Quantity	Orig. human	Polished	AI
Mean TSD score	-5.671	-5.363	-4.512
AUROC vs. AI	81.66	75.32	-
FPR at fixed τ	0.117	0.270	-

Table 13: Effect of surface-level AI polishing on human text ($n = 300$; higher TSD = more AI-like). Polishing moves human text toward the AI side: separability drops by 6.3 AUROC and the false-positive rate more than doubles.

Method	EvoBench	MAGE
Fast-DetectGPT	79.85 ± 0.48	69.69 ± 0.61
Lastde	76.66 ± 0.55	70.71 ± 0.64
Diveye	74.40 ± 0.52	69.60 ± 0.59
TSD (Ours)	83.36 ± 0.41	71.56 ± 0.56
TSD+ (Ours)	85.37 ± 0.38	75.20 ± 0.52

Table 15: Bootstrap 95% confidence intervals (AUROC %) over 1,000 resamples.

Detector	AI recall	Polished FPR	AUROC*
TSD (baseline)	65.2%	25.7%	72.68
TSD+ (default fusion)	83.6%	33.0%	84.70
TSD+ w/ decay-consistency	70.3%	22.7%	78.45
TSD w/ strong decay weight	48.1%	17.7%	-

Table 14: Decay-consistency mitigation at a matched 10% FPR on genuine human text. *AUROC of polished-human vs. AI. The decay-consistency variant Pareto-dominates baseline TSD (higher AI recall *and* lower polished-human FPR), and the decay weight acts as a tunable robustness knob for high-stakes settings.

baseline TSD—simultaneously higher AI recall (70.3% vs. 65.2%) and fewer false positives on polished human text (22.7% vs. 25.7%)—and increasing the decay weight drives the polished-human FPR down to 17.7% when conservatism is preferred, at the cost of AI recall. This turns the identified weakness into a controllable operating choice built purely on the existing temporal features, with no training involved.

G Statistical Significance

To quantify the reliability of the main results, we perform bootstrap resampling with 1,000 iterations and report 95% confidence intervals (Table 15). TSD’s improvement over Fast-DetectGPT is statistically significant on both benchmarks: the 95% CIs are non-overlapping on EvoBench, and a paired

bootstrap test yields $p < 0.01$ on both EvoBench and MAGE.

H Threshold Selection, Transfer, and Sensitivity

All main-paper comparisons use AUROC, which is threshold-free; a threshold τ is needed only to deploy TSD as a binary classifier. This appendix specifies the calibration protocol and quantifies how well a calibrated threshold transfers across distributions.

Protocol. Scores are the per-sample TSD values of the main configuration (second-half features, $w=20$, LLaMA-3-8B-Instruct surrogate); a text is predicted AI iff its score exceeds τ . We select τ as the F1-maximizing threshold on a validation split; Youden’s J statistic selects the same operating region. Unless stated otherwise, one τ is used per benchmark (not per generator family or length bin).²

In-domain stability. A threshold chosen on a random 50% validation split transfers to the held-out test half with negligible loss: $\Delta F1 = -0.14$ on EvoBench (78.40 transferred vs. 78.54 oracle) and -0.01 on MAGE (69.23 vs. 69.24).

²Pooled-score AUROC in this appendix (83.58 EvoBench / 72.30 MAGE) differs slightly from the main-table averages (83.36 / 71.56), which average per-family AUROCs; both views use identical per-sample scores.

Transfer	Transferred F1	Oracle F1	Δ
Evo val $\rightarrow$ Evo test	78.40	78.54	-0.14
MAGE val $\rightarrow$ MAGE test	69.23	69.24	-0.01
EvoBench $\rightarrow$ MAGE	69.37	69.46	-0.09
MAGE $\rightarrow$ EvoBench	78.18	78.36	-0.18

Table 16: Threshold transfer. In-domain: τ from a 50% validation split applied to the held-out half. Cross-benchmark: a single τ calibrated on one benchmark applied to the *other*. In all cases the transferred F1 is within 0.2 of the oracle (test-optimal) threshold. A parameter-free robust-z recalibration of the scores gives essentially identical results (69.40 / 78.12).

Cross-benchmark transfer. More stringently, a *single* threshold calibrated on one benchmark classifies the other benchmark within 0.2 F1 of that benchmark’s oracle threshold (Table 16): Evo $\rightarrow$ MAGE loses 0.09 F1 and MAGE $\rightarrow$ Evo loses 0.18 F1, despite the two benchmarks differing in domains, generators, and length distributions.

Cross-generator calibration. As an adversarially narrow setting, we calibrate τ on a *single* EvoBench generator family (LLaMA-3, the family with the highest oracle F1) and apply it to every other family. The transferred F1 is nearly lossless on similar families (Qwen: -0.2; Claude: -2.7) but drifts by up to ~ 10 F1 on the most dissimilar ones (GPT-4: -9.7; LLaMA-2: -10.5). This is an operating-point shift, not a separability loss—per-family AUROC is unchanged—and it argues for calibrating on a representative pooled mix rather than a single narrow source, which is exactly the setting of the near-lossless cross-benchmark transfer above.

Sensitivity. Finally, F1 is flat around the optimum: it stays within 1 point of its maximum over a threshold band spanning roughly 26% (EvoBench) and 35% (MAGE) of the score interquartile range (Figure 5). The detector is therefore not hypersensitive to threshold misspecification.

I Extended Ablations

I.1 Finer-grained Position Selection

Table 17 extends the position-selection ablation in the main paper to seven position ranges, providing a finer view of where the late-stage discriminative signal lies.

Two observations emerge. First, performance increases monotonically as the window shifts toward the late stage, peaking at the second half (50–

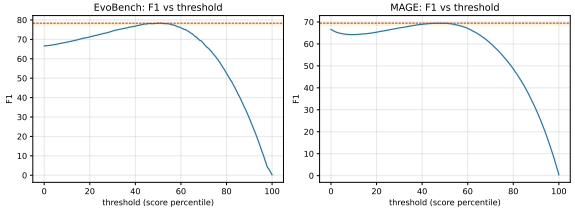


Figure 5: F1 as a function of the decision threshold (expressed as a score percentile) on EvoBench (left) and MAGE (right). The dashed line marks the maximum F1. The curve is flat around the optimum: F1 remains within 1 point of the maximum over a band covering roughly 26–35% of the score IQR.

100%). Second, going beyond the midpoint (e.g., last third or last quarter) hurts performance because too few tokens remain to estimate the volatility features reliably. The 50% midpoint is therefore a sweet spot between signal strength (concentrating on the most discriminative late-stage region) and estimation stability (retaining sufficient tokens).

I.2 DD and LV per Base Metric

Table 18 reports DD, LV, and their combination (TSD) computed on top of each candidate base metric.

Three patterns are notable. (i) Log probability dominates across all configurations. (ii) LV consistently outperforms DD on top base metrics, suggesting that regional volatility carries slightly more discriminative information than pointwise derivative changes. (iii) DD and LV are complementary: the combined TSD score improves over either alone for every base metric.

I.3 Window Size

The Local Volatility (LV) feature depends on the sliding-window size w . Table 19 reports performance as w varies from 5 to 50, with $w = 20$ used as the default in all main-paper experiments.

Performance is stable across a wide range ($w \in [10, 30]$), peaking at $w = 20$. Too small a window yields noisy estimates of local volatility; too large a window over-smooths the temporal signal. The method is therefore not overly sensitive to this hyperparameter.

I.4 Fusion Strategy

The default fusion in TSD+ is a simple score addition with Fast-DetectGPT. Table 20 compares several alternative fusion strategies, including a

Position Range	DD		LV		TSD	
	Evo	MAGE	Evo	MAGE	Evo	MAGE
First 25% (0–25%)	55.82	63.19	57.45	64.08	57.90	64.51
First Half (0–50%)	59.91	66.54	62.37	67.26	63.59	68.02
Middle (25–75%)	71.25	69.13	73.88	69.47	74.62	69.70
Full Sequence	72.64	70.31	75.82	70.39	77.00	70.49
Second Half (50–100%)	80.73	71.71	83.21	71.25	83.36	71.56
Last Third (67–100%)	79.85	71.02	82.47	70.64	82.08	70.83
Last Quarter (75–100%)	77.12	69.84	79.53	69.26	78.86	69.55

Table 17: Finer-grained position-selection ablation (AUROC %). Performance increases monotonically from early to mid-late positions and peaks at the second half. Restricting to the last third or quarter hurts because too few tokens remain for reliable estimation.

Base Metric	DD		LV		TSD	
	Evo	MAGE	Evo	MAGE	Evo	MAGE
Log Probability	80.73	71.72	83.21	71.26	83.36	71.56
Sampling Discrep.	74.48	66.53	76.19	67.82	77.66	68.97
Rank	72.95	60.47	74.76	62.05	76.06	62.98
Entropy	51.48	53.51	52.96	54.77	53.52	55.24
Probability	59.52	53.82	60.89	54.48	61.69	55.37
Top-10 Concentration	50.94	54.05	52.41	55.02	53.06	55.66

Table 18: AUROC (%) of DD, LV, and TSD over each candidate base metric. Log probability dominates on both DD and LV. LV is consistently slightly stronger than DD, suggesting that regional volatility is more discriminative than pointwise derivative changes. Their combination (TSD) further improves over either alone, confirming complementarity.

Window Size w	EvoBench	MAGE
5	80.51	69.78
10	82.14	70.93
20 (<i>default</i>)	83.36	71.56
30	82.97	71.18
50	81.82	70.45

Table 19: TSD performance under varying window size w . Performance is stable in the $w \in [10, 30]$ range and peaks at $w = 20$.

length-adaptive variant that uses the adaptive TSD base from Appendix C.

Two findings are notable. First, standard fusion strategies (addition, multiplication, max, weighted) yield similar improvements with no single approach clearly dominating. This insensitivity is consistent with empirical complementarity: when two signals are largely complementary, the specific combination mechanism matters less than the fact of combining them. We chose score addition as the default because it is the simplest and preserves the zero-shot setting (no learned weights). Second, the length-adaptive variant achieves the best

Fusion Strategy	EvoBench	MAGE
TSD only	83.36	71.56
Score Addition (default TSD+)	85.37	75.20
Score Multiplication	84.18	74.08
Max Fusion	83.76	73.52
Weighted ($\alpha = 0.5$)	85.42	75.15
Weighted (val-tuned α)	85.92	75.83
Length-Adaptive TSD + Fast-Detect	86.45	76.38

Table 20: Comparison of fusion strategies (AUROC %). All standard fusion approaches yield comparable gains, supporting the empirical complementarity of TSD and Fast-DetectGPT signals. The length-adaptive variant achieves the best results overall.

overall results, confirming that a more principled, length-aware fusion can improve over naive combination. This is because adaptive segmentation provides a stronger temporal base signal, particularly on shorter texts where the standard 50% midpoint is suboptimal.

Is there evidence of negative interference? A potential concern is whether fusing TSD with Fast-DetectGPT could cause negative interference if the

	EvoBench	M
AUROC: TSD / Fast / fused	83.58 / 80.15 / 86.20	72.30 / 7
Pearson (overall)	0.636	0
Pearson (within human)	0.534	0
Pearson (within AI)	0.610	0
Jaccard of error sets	0.218	0
P(Fast correct TSD wrong)	0.573	0
P(TSD correct Fast wrong)	0.693	0
Acc.: TSD / Fast / oracle-OR	78.4 / 70.0 / 90.8	68.6 / 1

Table 21: Dependence between TSD and Fast-DetectGPT on identical samples (pooled per-sample scores; “fused” is a z-normalized score sum). The scores are only moderately correlated within class, share just 22–30% of their errors, and each corrects a majority of the other’s mistakes; the either-correct oracle far exceeds both single methods.

two signals are partially redundant. The length-binned results in Table 7 provide a direct empirical test: TSD+ improves over both individual components in every length bin, including the 0–80 bin where the temporal signal is weakest. If partial redundancy were causing negative interference, we would expect degradation in at least one regime. The consistency across all bins provides direct evidence that the two signals are largely complementary: Fast-DetectGPT captures global distributional anomalies (*what* patterns exist), while TSD captures temporal dynamics (*when* patterns emerge). A direct correlation and error-overlap analysis is provided in Appendix I.5.

I.5 Correlation and Error Overlap between TSD and Fast-DetectGPT

Comparable gains from additive, multiplicative, max, and weighted fusion (Table 20) are consistent with complementary signals, but correlated signals can also produce such improvements. Here we measure the dependence between the two scores directly. On the same per-sample scores used throughout (paper configuration, pooled per benchmark), we compute (i) Pearson correlation between the TSD and Fast-DetectGPT scores, both overall and *within each class*—the honest redundancy measure, since it removes the trivial correlation induced by the shared label; (ii) the overlap between the two methods’ error sets at each method’s F1-optimal operating point; and (iii) the accuracy of an either-correct oracle.

Table 21 (and Figure 6) shows that the within-class correlation is moderate at most (0.53–0.61 on EvoBench, 0.26–0.32 on MAGE)—clearly above

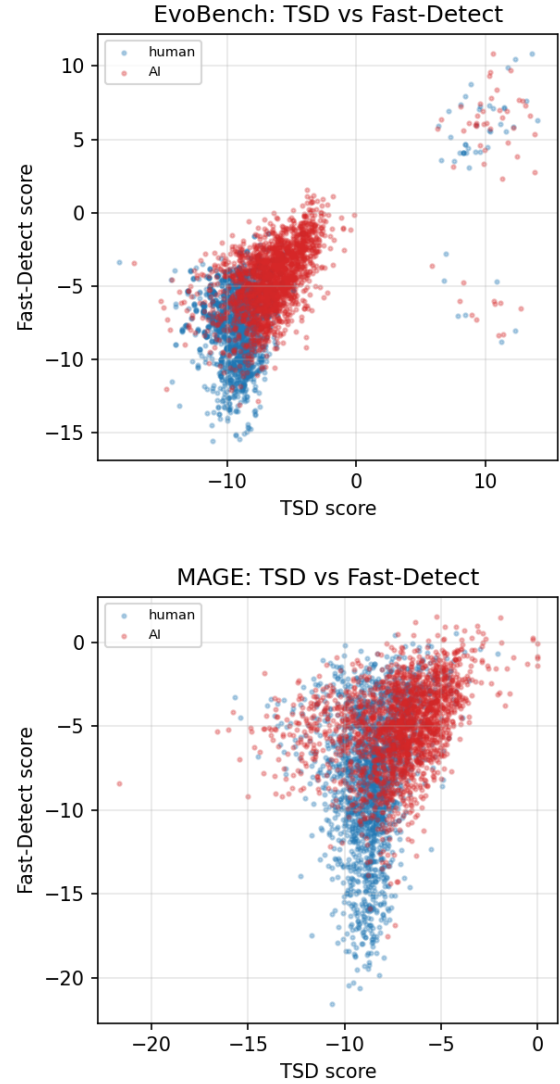


Figure 6: Per-sample TSD score (x-axis) vs. Fast-DetectGPT score (y-axis) on EvoBench (top) and MAGE (bottom), colored by class. The clouds are elongated but far from collinear, visualizing the moderate within-class correlation reported in Table 21.

zero, so the two signals are *not* orthogonal in the strict sense, yet far below redundancy. More directly, the two methods share only 22–30% of their errors (Jaccard), each recovers a majority of the other’s mistakes (52–69%), and the either-correct oracle (90.8% / 84.8% accuracy) sits far above the best single method (78.4% / 68.6%). The fusion gain therefore reflects genuine independent discriminative information. This analysis is why we describe the two signals as *empirically complementary* rather than orthogonal throughout the paper.

J Why Alternative Metrics Show Weaker Temporal Divergence

Section 2 reports that the strength of late-stage temporal divergence varies dramatically across base metrics. Here we provide a mechanistic explanation for each metric in our Section 2 comparison.

Log probability (slope ratio 2.4/2.6 on EvoBench). Token surprise $s_t = -\log P(x_t | x_{<t})$ directly measures how well the surrogate predicts the actually observed token. During autoregressive generation, the model’s predictions for AI-generated text become increasingly aligned with the actual next token as context accumulates. This alignment strengthens monotonically, causing surprise to stabilize. Human text does not follow this optimization trajectory, so its surprise remains volatile. Log probability is the most direct measure of this prediction–observation alignment, which is why it exhibits the strongest temporal dynamics.

Sampling discrepancy (slope ratio 2.2/2.5). This metric measures the curvature of the conditional probability by comparing the observed token against a re-sampled distribution (Bao et al., 2024). It captures a related signal—as AI text stabilizes, the discrepancy between the observed and the expected token also stabilizes—yielding comparable dynamics but requiring additional sampling overhead and access to the surrogate’s logits twice per position.

Rank (slope ratio 1.2/1.0). Rank undergoes a lossy discretization: many tokens with very different probabilities may share similar ranks, especially in the long tail. This compression discards fine-grained probability differences in precisely the region where human–AI temporal divergence is most pronounced, resulting in near-identical temporal trends (ratio ≈ 1.0 on MAGE).

Entropy (slope ratio 1.4/1.3). Entropy measures the spread of the entire predicted distribution, not the match between prediction and the specific observed token. Crucially, entropy can remain high even when the model correctly predicts the next token, as long as other vocabulary items retain non-negligible probability. Because both human and AI contexts lead the surrogate to produce qualitatively similar distributional shapes, entropy trajectories largely overlap.

Token probability and top- k concentration (slope ratio ≈ 1.0). These operate in probabil-

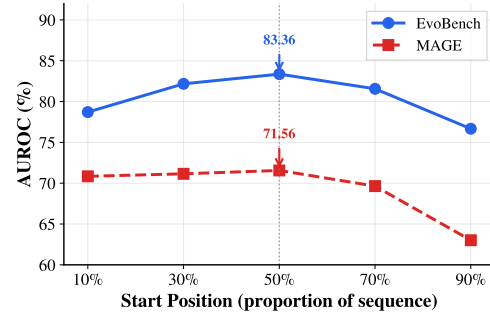


Figure 7: TSD performance versus relative start position. The midpoint (50%) achieves optimal performance on both benchmarks.

ity space rather than log-probability space. The log transformation amplifies differences in low-probability regions—precisely where human text tends to place unexpected tokens. In linear probability space, these tail differences are compressed, making temporal divergence nearly invisible. Top- k concentration further discards all information outside the top-10 tokens, losing the very tail behavior that most distinguishes human from AI generation dynamics.

Summary. The strength of temporal divergence depends on how directly a metric reflects the prediction–observation alignment that tightens during autoregressive generation. Log probability captures this most faithfully. Other metrics either measure a different quantity (entropy, top- k), undergo lossy transformations (rank), or compress the informative signal (probability, top- k). This analysis explains the Section 2 ranking and suggests that, when designing new temporal features, base metrics should be evaluated on their ability to track this alignment process.

K Impact of Start Position

While Section 3 uses the midpoint (50%) as the default start position for computing temporal features, we investigate whether alternative positions yield better performance. We conduct experiments using both relative positions (proportion of sequence) and absolute positions (fixed number of tokens).

Relative Position. Figure 7 shows TSD performance as a function of relative start position, ranging from 10% to 90% of the sequence. The results reveal an inverted-U pattern on both datasets. Starting too early (10%–30%) includes tokens where the late-stage volatility decay has not yet fully manifested, diluting the discriminative signal. Starting

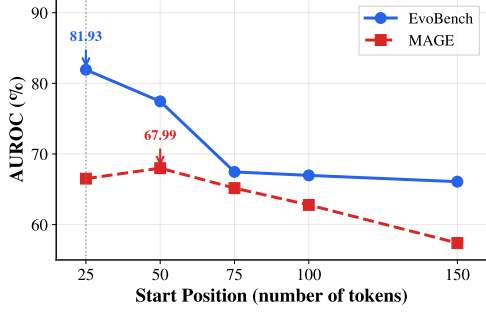


Figure 8: TSD performance versus absolute start position (number of tokens). Performance varies inconsistently across datasets, with EvoBench favoring earlier positions while MAGE shows less sensitivity.

too late (70%–90%) excludes too many tokens, reducing statistical reliability—particularly evident on MAGE where performance drops sharply from 71.56% at 50% to 63.01% at 90%. The midpoint achieves optimal performance on both benchmarks: 83.36% on EvoBench and 71.56% on MAGE.

Absolute Position. We also evaluate using fixed token counts as start positions, shown in Figure 8. While starting at 25 tokens yields high performance on EvoBench (81.93%), this approach shows inconsistent behavior across datasets—MAGE peaks at 50 tokens (67.99%) rather than 25 tokens (66.51%). Moreover, absolute positions fail to adapt to varying sequence lengths: short sequences may have insufficient tokens beyond the start position, while long sequences underutilize available context. In contrast, the relative 50% position consistently achieves strong performance across both datasets regardless of sequence length distribution.

Based on these findings, we adopt the relative midpoint (50%) as the default start position, which provides robust performance across diverse datasets without requiring length-specific tuning.

L Positional-Confound Controls: Permutation and Random-Span Analyses

The stronger signal in later positions could in principle partly reflect confounds rather than generation dynamics: discourse structure (e.g., conclusions being more formulaic), repetition, truncation conventions, or systematic prompt and length differences between human and generated texts. Two design properties already control part of this—EvoBench and MAGE consist of *parallel* human–AI pairs matched in domain and prompt, and

Treatment	AUROC	95% CI
first_half	77.73	[76.06, 79.35]
full	87.27	[86.07, 88.46]
random_span	87.61	[86.38, 88.70]
second_half (method)	88.21	[87.12, 89.30]
permuted_2nd	85.64	[84.40, 86.84]

Table 22: Positional-confound controls on a balanced MAGE sample (LLaMA-3-8B surrogate; equal-length windows; bootstrap 95% CIs). AUROC values exceed the MAGE main-table average because this analysis pools a balanced subsample restricted to ≥ 80 tokens.

our comparisons use both classes under identical preprocessing—but we additionally run direct causal probes.

Setup. We score a balanced MAGE sample ($n=3,369$ texts with ≥ 80 tokens) with the paper’s LLaMA-3-8B-Instruct surrogate, extract per-token surprise, and compute the TSD score on different sub-sequences of each text. All treatments use *equal-length windows*, so window length is controlled by construction: *first_half* and *second_half* are the two contiguous halves; *random_span* is a random contiguous 50% window (position-agnostic); *permuted_2nd* shuffles the token order before taking the second half, destroying temporal ordering while preserving the multiset of surprise values; *full* uses the whole sequence.

Findings. Table 22 yields two conclusions. First, *the signal is genuinely late-positioned*: the second half is the best contiguous window and exceeds the first half by 10.5 AUROC points (88.21 vs. 77.73), reproducing the position ablation of Table 4 on a fresh sample under explicit length control. Second, *the signal depends on temporal ordering, not on the marginal distribution of surprise values*: randomly permuting token order before computing the features drops AUROC from 88.21 to 85.64, with essentially disjoint confidence intervals. A discourse-structure, repetition, or vocabulary confound would be a bag-of-values property, invariant to token order; because permutation measurably hurts, the discriminative content resides in the temporal *ordering* of surprise—consistent with late-stage stabilization rather than a positional artifact. A replication with a Qwen2.5-7B surrogate shows the same directional pattern (second half $>$ first half; permuted $<$ second half) with smaller margins, consistent with MAGE’s weaker position effect relative to EvoBench.

Surrogate	Feature	EvoBench		MAGE	
		Gap%	Decay	Gap%	Decay
Llama-3-8B	Derivative	−32	2.4	−24	1.9
	Local Std	−31	2.6	−25	1.9
GPT-J-6B	Derivative	−22	1.8	−20	1.8
	Local Std	−22	2.0	−21	1.9
Falcon-7B	Derivative	−22	1.9	−19	1.8
	Local Std	−23	2.1	−20	1.8

Table 23: Temporal dynamics of log probability features across different surrogate models. *Gap%*: relative human-AI difference in the second half. *Decay*: ratio of AI to human decay rate. All surrogate models exhibit consistent late-stage volatility decay patterns.

M Complete Temporal Dynamics Visualization

Figure 9 presents the complete temporal dynamics visualization on the MAGE benchmark, complementing the EvoBench results in the main paper. The patterns are consistent across datasets: AI-generated text exhibits steeper decay in both derivative and local standard deviation of log probability, with the gap between human and AI text widening substantially in the second half of sequences.

N Surrogate Model Independence

A natural question arises: does the late-stage volatility decay phenomenon depend on the specific choice of surrogate model? To investigate this, we replicate our analysis using two additional surrogate models from different architectural families: GPT-J-6B (Wang and Komatsuzaki, 2021) and Falcon-7B (Almazrouei et al., 2023). These models differ substantially from Llama-3-8B-Instruct in training data, architecture details, and model scale, providing a rigorous test of generalization.

N.1 Temporal Dynamics Across Surrogate Models

Table 23 presents the temporal dynamics of log probability features extracted using each surrogate model on EvoBench. The late-stage volatility decay phenomenon persists across all three surrogate models with remarkably consistent patterns.

All three surrogate models show: (1) substantial negative gaps in the second half, ranging from −19% to −32%; (2) AI text decaying 1.8–2.6 times faster than human text. While Llama-3-8B produces the strongest signal (likely due to its closer architectural alignment with recent genera-

Surrogate	Feature	H-decay	A-decay	Ratio	Gap%
		EvoBench			
Llama-3-8B	Derivative	−9.6%	−27.1%	2.4	−32%
	Local Std	−8.9%	−26.5%	2.6	−31%
GPT-J-6B	Derivative	−9.8%	−20.1%	1.8	−22%
	Local Std	−9.1%	−20.3%	2.0	−22%
Falcon-7B	Derivative	−10.0%	−21.1%	1.9	−22%
	Local Std	−9.3%	−21.9%	2.1	−23%
		MAGE			
		H-decay	A-decay	Ratio	Gap%
Llama-3-8B	Derivative	−7.5%	−16.7%	1.9	−24%
	Local Std	−7.3%	−16.5%	1.9	−25%
GPT-J-6B	Derivative	−5.0%	−10.9%	1.8	−20%
	Local Std	−4.9%	−10.9%	1.9	−21%
Falcon-7B	Derivative	−5.6%	−11.4%	1.8	−19%
	Local Std	−5.3%	−11.0%	1.8	−20%

Table 24: Late-stage volatility decay details across surrogate models. *H-decay/A-decay*: percentage decrease from first to second half for human/AI text. The decay ratio remains consistently above 1.8 regardless of surrogate model choice.

tors), GPT-J-6B and Falcon-7B still capture meaningful temporal patterns. This consistency suggests that late-stage volatility decay is a robust, surrogate-independent regularity consistent with autoregressive generation rather than an artifact of specific surrogate-generator pairings.

N.2 Late-Stage Volatility Decay Details

Table 24 provides detailed late-stage statistics for each surrogate model, showing the percentage decay from first to second half for both human and AI text.

Across all configurations, AI text exhibits substantially faster decay than human text. The decay ratios range from 1.8 to 2.6, with human text showing modest decay (5–10%) while AI text decays more dramatically (11–27%). This asymmetry is precisely what enables our detection method: the autoregressive generation process causes AI text to stabilize toward the end of sequences, while human text maintains more consistent variability throughout.

N.3 Visualization Across Surrogate Models

Figures 10 and 11 visualize the temporal dynamics using GPT-J-6B and Falcon-7B as surrogate models, respectively. Both figures exhibit the same qualitative patterns observed with Llama-3-8B: log probability shows clear separation in derivative and local standard deviation features, with the gap

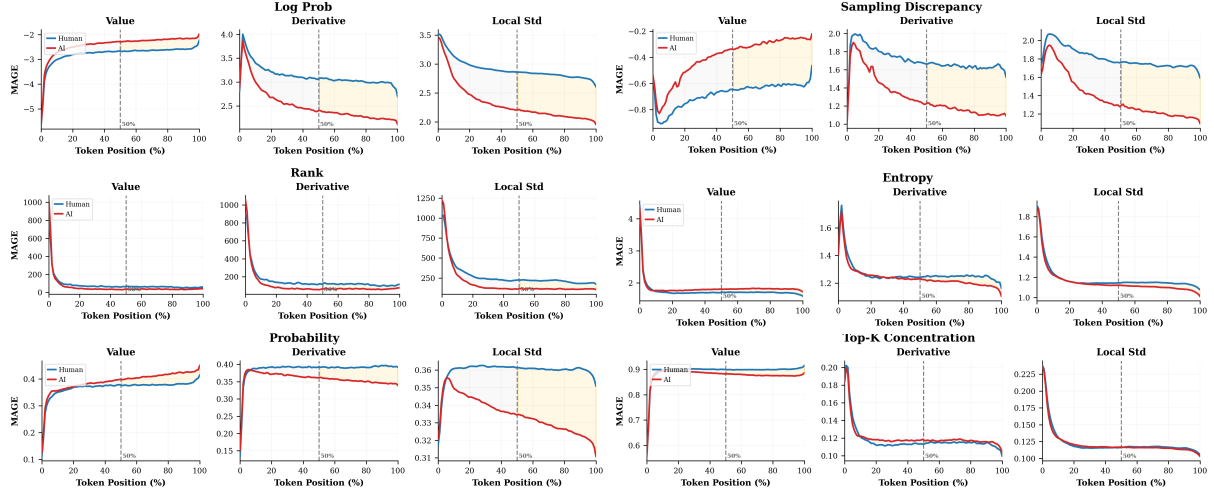


Figure 9: Temporal dynamics of seven token-level metrics on MAGE benchmark. Each metric shows three views: raw value trajectory, derivative (rate of change), and local standard deviation (volatility). The second half of sequences (highlighted in yellow) consistently exhibits larger human-AI gaps in derivative and local standard deviation features, particularly for log probability and sampling discrepancy.

widening in the second half. Sampling discrepancy similarly maintains strong discriminative power across surrogate models.

The consistency across three diverse surrogate models—spanning different architectures (GPT-style, Llama-style, Falcon-style), scales (6B to 8B parameters), and training procedures—provides strong empirical evidence that late-stage volatility decay is a robust, surrogate-independent regularity consistent with autoregressive uncertainty contraction. This surrogate-independence has practical implications: our detection method can leverage whichever surrogate model is most convenient or computationally efficient, without sacrificing the fundamental discriminative signal.

N.4 Generation-Time vs. Surrogate Scoring

The cross-surrogate results above show that late-stage volatility decay is a stable empirical regularity, but they leave open a subtler question: a zero-shot detector measures a *surrogate* model’s scores on a *completed* text, which need not equal the *source generator’s own predictive distribution at generation time*. To test whether the decay originates in the generation process itself—rather than being manufactured by surrogate scoring—we run a controlled probe on an open-source generator, where the generation-time distribution is directly observable.

Setup. From 300 human news prefixes (48 tokens each, CNN/DailyMail; [Hermann et al., 2015](#)) we (a) sample a 160-token continuation with Qwen2.5-

Scorer	AI (%)		Human (%)	
	Deriv.	Local	Deriv.	Local
Gen.-time (Qwen2.5-7B)	−23.6	−18.0	—	—
Self-score (Qwen2.5-7B)	−22.5	−16.5	−0.7	−0.2
Cross-model (Qwen3-14B)	−14.6	−8.5	−1.9	−1.7
Cross-family (LLaMA-3-8B)	−7.8	+1.0*	−1.3	−0.9

Table 25: Late-stage decay of surprise volatility ($N=300$ paired continuations) under generation-time logging and three scorers. *Under the cross-family scorer the local-std decay itself attenuates, but the second-half human-AI gap remains clearly negative: -22.3% (derivative) and -15.3% (local std)—AI volatility stays below human volatility.

7B-Instruct ([Yang et al., 2024a](#)), logging the *true generation-time surprise* of each realized token as it is sampled, and (b) keep the real human continuation of the same prefix. We then re-score both continuations with the same model (self-scoring), with Qwen3-14B ([Yang et al., 2025](#)) (a different model in the same family), and with LLaMA-3-8B-Instruct (a different model family—the paper’s main surrogate). Table 25 reports the late-stage decay (percentage change from the first to the second half) of both volatility features.

Findings. Four observations follow. (i) The decay is present in the *generation-time distribution itself* (-23.6% / -18.0%), so it is not manufactured by post-hoc scoring. (ii) Self-scoring reproduces it almost exactly ($-22.5\% \approx -23.6\%$): for a matched surrogate, scoring-time surprise is the generation-time conditional, so there is

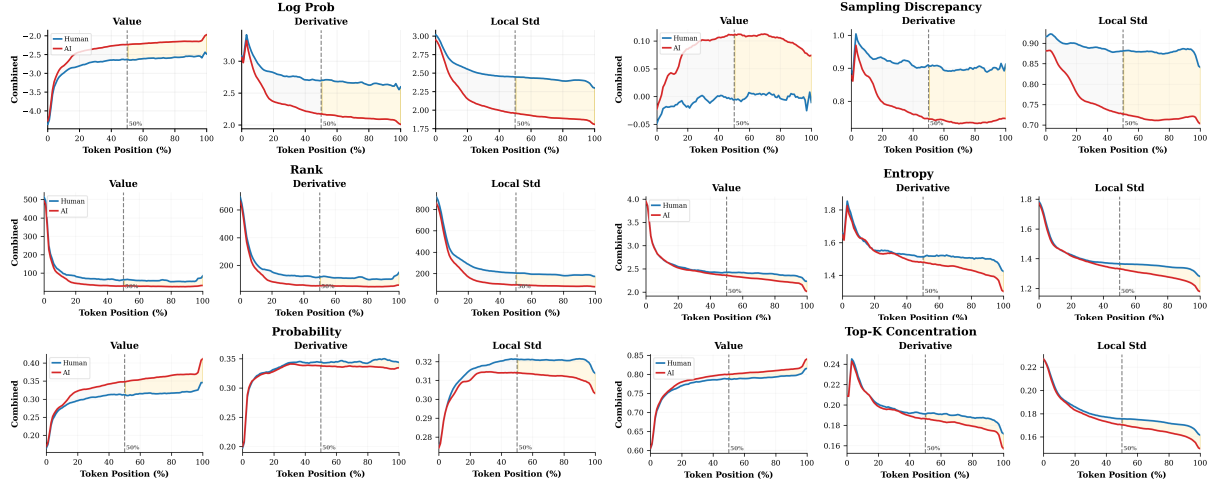


Figure 10: Temporal dynamics on EvoBench using GPT-J-6B as surrogate model. The late-stage volatility decay pattern persists: AI text (red) exhibits steeper decay in derivative and local standard deviation features compared to human text (blue), with pronounced separation in the second half (highlighted in yellow).

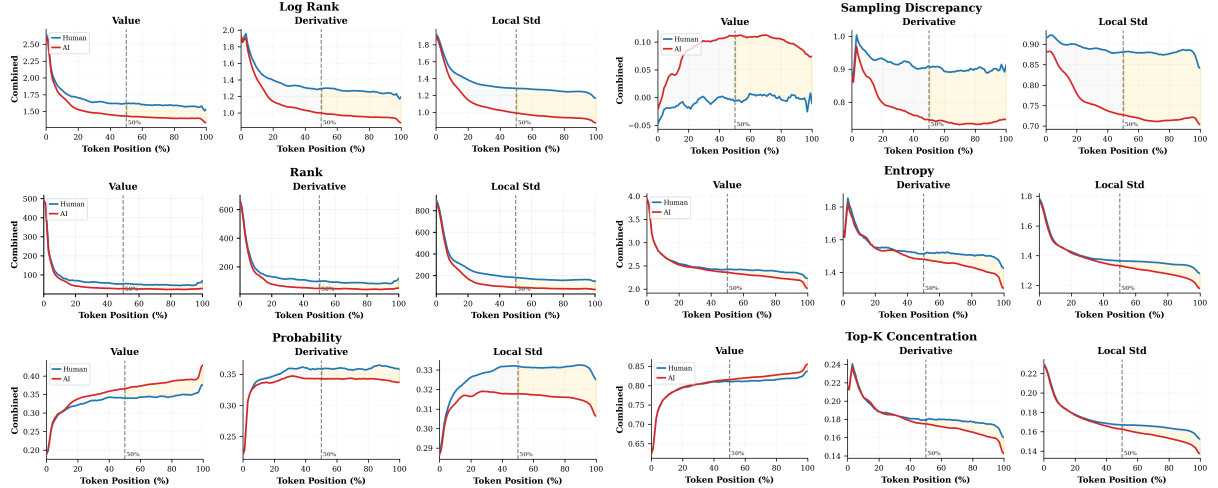


Figure 11: Temporal dynamics on EvoBench using Falcon-7B as surrogate model. Despite different model architecture and training data, the temporal patterns remain consistent with Llama-3-8B and GPT-J-6B results, confirming the surrogate-independent nature of late-stage volatility decay.

no generation-time/scoring gap. (iii) The signal transfers to other scorers and attenuates monotonically as the scorer diverges from the generator (self > cross-model > cross-family)—exactly the behavior expected of a genuine generation-side signal seen through an increasingly imperfect surrogate—while the second-half human–AI gap remains clearly negative even for the cross-family scorer. (iv) Human text does not contract under any scorer (all $|\text{decay}| \leq 1.9\%$). Together with the cross-surrogate results above and the frontier-model results in Appendix O, this supports the interpretation of Section 2: late-stage volatility decay is a property of the generation process that transfers to black-box surrogates, rather than an artifact of

surrogate scoring.

O Generalization to Frontier Models

To further validate the universality of late-stage volatility decay, we extend our analysis to frontier models released in late 2024 and early 2025, with particular attention to reasoning-enhanced models. We collect text samples from MIRAGE (Fu et al., 2025), a recent benchmark containing parallel human-AI pairs across 17 state-of-the-art generators.

Table 26 presents the late-stage volatility decay statistics across 13 frontier models. The phenomenon persists universally, with decay ratios ranging from 1.0 to 3.0. Critically, we

Family	Generator	Derivative				Local Std			
		H-decay	A-decay	Ratio	Gap%	H-decay	A-decay	Ratio	Gap%
OpenAI	GPT-4o	−10.3%	−26.2%	2.5	−27	−10.4%	−28.3%	2.7	−29
	GPT-4o-mini	−10.5%	−21.8%	2.1	−24	−10.5%	−23.4%	2.2	−26
	GPT-o3-mini [†]	−10.4%	−22.5%	2.2	−23	−10.6%	−24.3%	2.3	−25
Anthropic	Claude-3.5-Haiku	−10.5%	−24.2%	2.3	−24	−10.8%	−26.8%	2.5	−28
	Claude-3.7-Sonnet	−10.5%	−24.8%	2.4	−24	−10.6%	−26.9%	2.5	−27
Google	Gemini-2.0-Flash	−10.6%	−28.7%	2.6	−24	−10.5%	−30.6%	2.8	−26
	Gemini-2.0-Flash-Lite	−10.6%	−28.8%	2.6	−23	−10.7%	−30.2%	2.8	−26
DeepSeek	DeepSeek-V3	−11.0%	−24.4%	1.8	−31	−10.6%	−25.3%	1.9	−32
	DeepSeek-R1 [†]	−10.0%	−10.9%	1.0	−5	−10.2%	−15.1%	1.4	−11
Meta	Llama-3.1-8B-Instruct	−11.0%	−29.2%	2.2	−43	−10.7%	−29.2%	2.4	−42
Alibaba	Qwen2.5-7B-Instruct	−11.0%	−29.6%	2.3	−33	−10.8%	−31.1%	2.4	−35
	QwQ-Plus [†]	−10.3%	−14.6%	1.3	−12	−10.7%	−17.9%	1.5	−18
ByteDance	Doubao-1.5-Pro-32K	−10.0%	−32.2%	3.0	−30	−10.1%	−32.7%	3.0	−30
Average (All)		−10.5%	−24.5%	2.2	−24	−10.6%	−26.3%	2.3	−27
Average (Reasoning [†])		−10.2%	−16.0%	1.5	−13	−10.5%	−19.1%	1.7	−18

Table 26: Late-stage volatility decay across frontier models on MIRAGE. *H-decay/A-decay*: percentage decrease from first to second half for human/AI text. *Ratio*: AI-to-human decay ratio. *Gap%*: relative human-AI difference in the second half. [†]Reasoning-enhanced models.

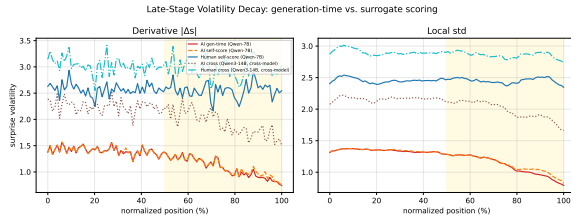


Figure 12: Surprise-volatility trajectories (left: derivative $|\Delta s|$; right: local std) across normalized positions for AI continuations under generation-time logging, self-scoring, and cross-model/cross-family scoring, together with the corresponding human continuations. The generation-time and self-score curves for AI text coincide almost exactly and decay in the late stage (shaded), while human curves under every scorer remain flat.

find that late-stage volatility decay extends to reasoning-enhanced models (including GPT-o3-mini, DeepSeek-R1, and QwQ-Plus), which represent a distinct generation paradigm involving extended chain-of-thought processes. While these reasoning models exhibit somewhat attenuated decay ratios at 1.0–2.3 compared to standard models at 1.8–3.0, they nonetheless display the fundamental pattern: AI-generated text stabilizes more than human text toward sequence end. The extended reasoning chains may introduce additional variabil-

ity that partially masks the decay signal, yet the underlying phenomenon remains detectable.

Figure 13 visualizes the temporal dynamics of a representative subset of models. Across all model families, AI-generated text consistently exhibits a steeper decay in both the derivative and the local standard deviation, with the separation between AI and human text becoming more pronounced in the latter half of the sequence. This trend persists regardless of architectural variations or the presence of explicit reasoning mechanisms.

The consistency of late-stage volatility decay across this diverse set of frontier models—spanning different organizations, architectures, scales, and training paradigms—provides strong evidence that this phenomenon is a robust regularity consistent with autoregressive language generation rather than an artifact of specific model designs.

P Additional Statements

Potential Risks. Our method is designed for AI-generated text detection research and should be used responsibly. Like all detection methods, it may produce false positives or negatives and should not be the sole basis for consequential decisions.

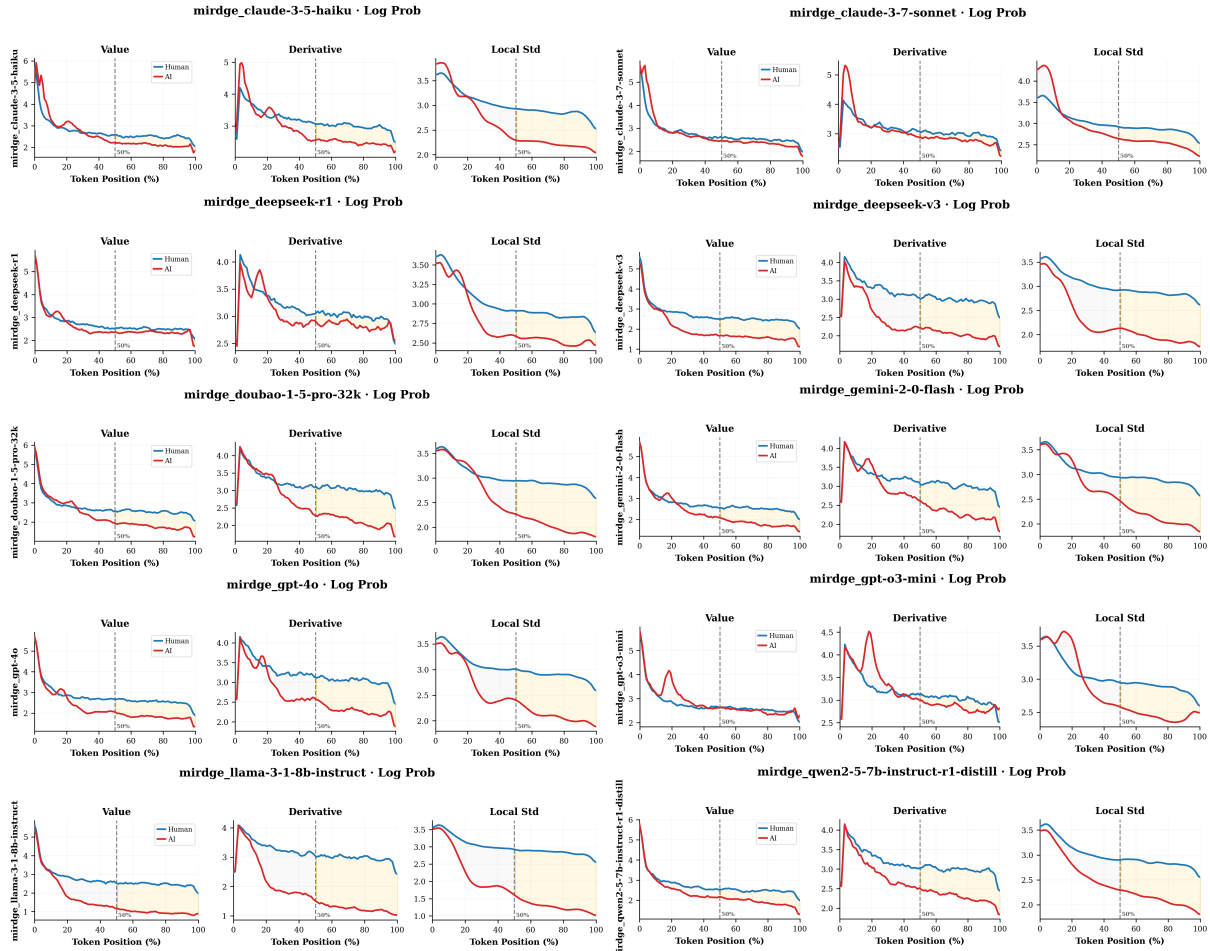


Figure 13: Temporal dynamics of log probability across frontier models from MIRAGE. Each row shows a different generator. The late-stage volatility decay pattern persists universally, including for reasoning models such as DeepSeek-R1 and GPT-o3-mini.

Model Size and Computational Budget. Our experiments rely on Llama-3-8B-Instruct as the surrogate model for computing token-level statistics. All inference was conducted on one NVIDIA H100 GPU. The choice of surrogate model affects detection performance, and we acknowledge that results may vary with different model sizes or architectures.

Experimental Reproducibility. Our approach performs zero-shot detection without requiring training, which ensures stable and deterministic results. All reported point-estimate results are from single runs, as the absence of stochastic training procedures eliminates the need for multiple runs. Bootstrap-based 95% confidence intervals for the main results are reported in Appendix G. Our implementation of TSD and all baselines, together with the evaluation scripts, is publicly available at <https://github.com/skJack/TSD>.

Use of AI Assistants. We used AI assistants to aid in manuscript writing and code refinement. These tools helped with language polishing, clarity improvements, and debugging assistance. All core research ideas, experimental design, and analytical conclusions are the authors' own work.